CZECH UNIVERSITY OF LIFE SCIENCES PRAGUE

FACULTY OF ECONOMICS AND MANAGEMENT

Data-driven decision support systems and predictive modelling in dairy herd health

DISSERTATION THESIS

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Prague 2025

Acknowledgments:

I dedicate this thesis to my parents, Petr and Zdeňka Sarovým, who had to give up everything when I was accepted to this university. Along with my three siblings, they are the reason why I am here today. I thank them for everything they have sacrificed for us. They could have accomplished so much more, but instead, they decided to live vicariously through their children. With this thesis, I am honouring their sacrifice.

I would also like to extend my heartfelt gratitude to my excellent supervisor, Professor Helena Brožová, whose boundless patience and unwavering support have guided me throughout this research journey. To Associate Professor Luděk Stádník, for his endless kindness and encouragement. One of mine deepest appreciation goes to Dr. Nadežda Firsová, whose countless hours of mentorship in research excellence at the National Technical Library have profoundly shaped my understanding and dedication to scientific work. My deep gratitude goes to Associate Professor Robert Hlavatý, who played a key role in the most critical moments of this dissertation — always hand in hand with his exceptional human approach, brilliant reasoning, and instant understanding of the problem at hand, naturally suggesting the next steps forward. I also wish to express my sincere thanks to Ing. Ladislav Šána, the unsung hero of the faculty. Good things don't happen by chance, but thanks to the silent dedication and tireless effort of people like him. His work, often invisible to others, has made a tangible difference in making our academic journeys smoother and more humane. I also extend my sincere thanks to Associate Professor Tatiana Valentine Guy and the Department of Adaptive Systems at the Institute of Information Theory and Automation of the Czech Academy of Sciences. Their scientific support and guidance during the most desperate moments of my PhD journey were a beacon of hope. Their kindness, expertise, and encouragement gave me strength and direction when I needed it most.

Thank you from the bottom of my heart. In these lines lies the main motivation for this PhD and for the 38-year-old decision — a decision that gave life to my siblings including myself. Without it, these lines as well as work would have never seen the light of day.

With all my honour to your excellent personalities,

Your son,

Jan

Abstract:

This dissertation explores the development of Decision Support Systems (DSSs) for herd health management in dairy farming through innovative data-driven approaches. In the first stage of this research, a comprehensive disease scoring system was introduced to categorise and assess disease severity and impact. In the analysis of a five-year dataset containing over 2,500 records of dairy cow health, diseases were classified into key categories, such as lameness, mastitis, and reproductive disorders, among others, to create an informed foundation for health management. Incorporating this scoring system, the resulting DSS provides dairy farmers with timely insights into disease trends, enabling targeted interventions based on observed patterns. In the second stage, data availability challenges were addressed through predictive modelling with Markov chains to estimate disease probability. Following disease categorisation and optimal model selection based on Chebyshev distance minimisation, the DSS achieved accurate projections for most diseases. This predictive component not only proves suitable for further decision-making processes, such as treatment costs, but also supports evidence-based decision-making, thereby improving herd health outcomes. In the third stage of this dissertation, the main research goal was to develop a web-based DSS integrating predictive modelling and descriptive analysis to enhance herd health management in dairy farming. The system combines machine learning techniques, particularly Long Short-Term Memory (LSTM) neural networks, to forecast disease progression using historical health data. Integrating real-time data processing through a scalable web platform, the DSS offers dairy farmers a user-friendly tool for proactive decision-making. The system architecture, built with a Flask backend and a React frontend, incorporates data preprocessing, predictive modelling, and cost analysis. With a mean absolute error of 6.66 and a median absolute deviation of 2.35 across predictions, the DSS reliably forecasts disease outcomes and optimises treatment costs through linear trend models. Additionally, this system analyses different treatment scenarios, calculates medication dosages, and identifies cost-effective supplier selections. As such, this DSS empowers dairy farmers with data-driven insights and decision-making capabilities to improve herd health management, reduce treatment costs, and enhance overall farm productivity.

Keywords: dairy cows, dairy diseases, dairy herd health, decision support systems, Markov chains, predictive model

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Introduction

Effective herd health management requires access to accurate and relevant information. This information supports decision-making aimed at improving animal health and productivity, thereby enhancing the economic efficiency of the farm. With the advancement of data technologies, farmers can better analyse herd health and prevent potential health issues, enhancing animal welfare and dairy farming sustainability.

In modern dairy farming, herd health management promotes farm productivity and economic sustainability. Health challenges can impose a significant financial burden and often decrease production. Therefore, dairy farmers must proactively pursue health management strategies to maintain both the economic viability of their farms and animal well-being.

In dairy herd management, early diagnosis and effective prevention remain major challenges. Traditional methods for assessing and predicting health risks in dairy herds often lack the precision needed to meet the demands of proactive herd health management. As a result, farmers frequently find themselves reacting to health issues rather than preventing them, which can lead to higher treatment costs and reduced productivity. This reactive approach affects the economic output and welfare of dairy herds, underscoring the importance of timely interventions.

Several factors influence herd health, including nutrition, housing, genetics, and farming conditions. These dynamic and interconnected factors complicate disease prediction and management. To prevent health challenges and improve overall herd health, dairy farmers must access precise data for timely decision-making. Advances in data analytics and automation have opened up new opportunities for monitoring animal health, providing comprehensive information on the well-being of individual animals and the entire herd. Yet, despite these technological advancements, no comprehensive methodology is available for effectively leveraging available data in herd health management. Nevertheless, implementing standardised procedures and decision support systems (DSSs) may significantly enhance the ability of dairy farmers to proactively address health concerns and to optimise herd health care at the farm level. This dissertation reports efforts made to address these challenges by developing a data-driven support tool integrating health scoring with predictive modelling.

Harnessing data to assess health risks and forecast potential issues, the proposed system aims to improve proactive health interventions and assist dairy farmers in strategic treatment planning.

Through structured data collection and analysis, dairy farmers can effectively monitor herd health and make informed decisions to support prevention and treatment strategies. DSSs based on accurately gathered and interpreted data facilitate the identification of health patterns and support sustainable management in dairy farming, benefiting both the economic outlook of the farm and animal welfare. By optimising operational processes and minimising the need for emergency interventions, these systems can help to reduce costs and maximise the positive impacts of data-driven health management strategies in dairy farming.

Dissertation Objectives

The literature review identifies a set of shortcomings in current Decision Support Systems (DSSs) for dairy herd health management. First, most existing DSSs lack robust predictive capabilities and rely solely on retrospective data, offering limited utility for proactive intervention (Kamilaris et al., 2018; Niloofar et al., 2021; Ferris et al., 2020). Second, there is a general absence of structured scoring mechanisms to assess disease severity and prioritise interventions, despite the complexity and variability of herd health issues (Alawneh et al., 2018; S. Balhara et al., 2021). Third, DSSs are often designed for high-tech farms with advanced infrastructure, leaving small or traditional farms without accessible solutions (Rupnik et al., 2019; Cabrera, 2018). Fourth, economic dimensions such as treatment cost simulations, medication dosages, and supplier optimisation are rarely integrated into herd health decision-making (Giordano et al., 2012; Gargiulo et al., 2022; Louta et al., 2023a). These gaps clearly indicate a need for a comprehensive, data-driven, and economically integrated DSS that supports predictive modelling and health scoring while remaining accessible to farms with varying technological capacities.

General Objective

To design and develop a comprehensive data-driven Decision Support System (DSS) that integrates disease scoring, predictive modelling, and cost analysis to support timely, evidence-based, and economically sound decisions for herd health management in dairy farming.

Specific Objectives

The first objective of this dissertation is to develop an innovative disease scoring system leveraging predictive models for early disease detection and prevention. This scoring system is designed to quantify the severity and impact of individual diseases on herd productivity, enabling farmers to prioritise interventions based on disease severity. This approach aims to create a reliable, real-time solution for herd health management, empowering farmers with tailored insights for immediate health management.

The second objective consists of using predictive modelling to forecast disease occurrences in herds. Although DSS solutions typically rely on historical data for health predictions, this research aims to validate the effectiveness of specific predictive models under varied farm conditions. To this end, key disease occurrence factors will be identified in the experimental validation of the model so that farmers can anticipate and prevent the impact of potential health problems on herd productivity.

The third research objective lies in developing a web-based DSS platform integrating both descriptive and predictive analysis with real-time herd health data. This platform should provide a user-friendly interface where farm managers can access disease predictions, severity scoring, and management recommendations. With these parameters, dairy farmers may implement targeted interventions based on preset thresholds, alerts, and data-driven insights from both current and predicted health statuses.

Ultimately, this dissertation aims to propose methods and recommendations to enhance the functionality and efficiency of DSSs for dairy herd health management. Achieving this goal will require concerted research efforts to address technical and economic limitations that hinder practical applications of DSSs, including user interface, computational requirements, and integration capabilities. Further studies may explore automated collaboration among components, focusing on trend prediction in health metrics and spatial relationships in herds.

Methodology

In this dissertation, theoretical, empirical, and applied approaches were used to develop a DSS for dairy herd health management. For all research questions, data collection is described at the start of this chapter. Subsequently, specific research approaches and scientific methods applied to answer each research question are detailed below. This methodology was followed to ensure that the DSS for predicting and assessing herd health was as effective as possible.

Data Collection Description for Quantitative Research

Data were gathered using a quantitative approach to objectively measure disease incidence and severity in a dairy herd. Quantitative data are essential for developing predictive models and DSSs because they provide precise numerical information on the frequency and duration of individual diseases. This approach enables robust analysis and statistical data processing (Creswell & Creswell, 2017).

Creating an accurate predictive model required collecting a complete set of data on herd health, including disease diagnoses and related parameters, such as type, diagnosis, duration and severity of disease, in addition to disease frequency and distribution over different time periods. These data were collected from veterinary records and included disease incidence as a function of factors like lactation stage and season. These data are crucial for categorising diseases and establishing probability models to predict herd health trends.

Data Sources

The primary source of information consisted of dairy cow health records collected over five to six years on a Czech farm. These records documented disease diagnoses, occurrence dates, and animal identifiers. The first study covered 2,558 records for 798 cows, while the second study involved 36 types of diseases for 750 cows recorded over six years. These data provided reference points for assessing the performance and accuracy of the new model under real-world conditions.

Data Collection Methods

Quantitative techniques, including regular health monitoring, were used to collect data on the farm. Disease categorisation and quantitative data collection facilitated the development of predictive models based on statistical analysis of historical disease data. These data were processed through Markov chains for probability estimation of disease occurrence based on historical trends.

Data Processing and Cleaning

Data were carefully pre-processed to ensure quality and accuracy. Preprocessing included format standardisation, duplicate removal, and consistency adjustments. These steps minimised bias and errors from incomplete or inaccurate records, supporting an accurate quantitative analysis. As outlined in Deep Learning by (Goodfellow et al., 2016), data cleaning and standardisation procedures helped to improve model accuracy.

Data Collection Limitations

Data collection on farms faces several challenges, including gaps in records and varying methods for animal health documentation across farms. These inconsistencies were partly addressed by standardising data collection methods and introducing a general assessment model applicable across various operations for farm-to-farm comparisons. However, farmers still express concerns about the lack of control over their data, which may impact their willingness to share such information. According to a previous study, 66% of farmers feel they lack full control over their "data chain of custody" once data are accessible to third parties, with only 19% signing formal data-sharing agreements. This sense of losing control can hamper their willingness to openly share data, which is crucial for developing robust predictive modelling (Fadul-Pacheco et al., 2022).

3.1 Research Question 1: What key characteristics should a DSS based on a new disease scoring system for proactive farm management?

The aim of this part of the research was to develop a quantitative disease scoring system that enables dairy farmers to proactively monitor and manage herd health. The methodology combines theoretical justification with applied development and empirical validation using real-world data. This hybrid approach ensures both scientific rigor and practical usability of the proposed Decision Support System (DSS).

Research Approaches

1. **Theoretical Approach:** The disease scoring system will be built upon a thorough theoretical framework, including the examination of existing disease classification models and health assessment methods. This approach will involve a critical analysis of the scientific literature and state-of-the-art methodologies in veterinary science to identify gaps and improve current disease assessment techniques. The theoretical approach will enable the

formulation of robust criteria for assessing cattle health, which will be integral to the scoring system.

2. **Applied Approach:** To develop a practical tool for farmers to make informed decisions about health interventions, the disease scoring system will be designed to simplify complex health data and provide actionable insights readily implemented on farms. This applied approach will bridge the gap between theory and practice, ensuring the relevance and usability of this tool in real-world agricultural settings.

Data Collection and Preprocessing

Health data were collected over a five-year period from a dairy farm in the Czech Republic. The dataset included 2,558 disease entries for 798 cows, each annotated with disease type, date, and treatment. The records, originally in PDF and Excel formats, were digitized and standardized into structured CSV using OCR techniques and data cleaning scripts written in Python.

Disease Categorization and Scoring Design

A total of 125 distinct disease types were identified and manually classified into six main disease categories in consultation with licensed veterinarians:

- Lameness
- Mastitis
- Reproductive diseases
- Digestive system diseases
- Postpartum complications
- Other diseases

Each disease was assigned a severity score on a scale from 1.0 to 3.0, with 0.5 increments allowed. These scores were determined by a veterinary panel based on three key criteria: (1) impact on milk production, (2) treatment cost, and (3) physiological severity or risk. For example, severe mastitis was scored 3.0, while mild fever was scored 1.0.

Monthly Disease Burden Calculation

For each cow and each month, a cumulative disease score was calculated by summing severity scores of all reported diseases. This resulted in a monthly time series of herd health burden per animal. These data were stored in matrix format with cows as rows and months as columns, enabling temporal analysis and visualization.

Statistical Trend Analysis

To assess health dynamics over time, a linear regression model was applied to each cow's time series. The slope of the fitted line was interpreted as an indicator of health trend:

- Positive slope: increasing disease burden (worsening health)
- Negative slope: decreasing burden (improving health)
- Near-zero slope: stable condition

Trend analysis was implemented in Python using the statsmodels.OLS module. Confidence intervals and R^2 metrics were also computed to evaluate model fit.

Visualization and Implementation

The system was developed using the following tools and libraries:

- **Data manipulation**: pandas, numpy
- **Statistical modelling**: statsmodels
- **Visualization**: matplotlib, seaborn, plotly
- **Implementation environment**: Python 3.11, Visual Studio Code
- **Output format**: interactive dashboards (Plotly Dash, Streamlit)

All graphs and outputs were exported as part of a prototype DSS for stakeholder presentation. Outputs included individual cow scores, herd averages, category-specific summaries, and alert flags for negative health trends.

Comparative Evaluation Within the Farm

To enable consistent interpretation over time, monthly disease scores were normalized by the number of animals in the herd and adjusted for calendar months. This normalization allowed for seasonal comparisons and identification of high-risk periods. The system supports internal farm decision-making by highlighting months or categories with significant deviations from the herd's baseline health status. This methodology will combine quantitative scoring, expert veterinary input, and statistical analysis to provide a robust, adaptable tool for proactive dairy herd health management.

3.2 Research Question 2: How can a predictive mathematical model be developed to forecast the incidence of diseases in dairy herds?

This research question aims to address the challenge of forecasting disease occurrences in dairy cattle using mathematically grounded and computationally efficient predictive models. While machine learning offers powerful alternatives, its complexity and data demands are often unsuitable for small to medium-sized dairy farms. Instead, this study developed an interpretable and robust predictive framework based on discrete Markov chains, suitable for real-world deployment on farms with varying levels of digital infrastructure.

Research Approaches

1. **Theoretical Approach:** The predictive modelling approach will be based on the theoretical foundations of stochastic processes and probability theory, specifically discrete Markov chains. Both homogeneous (HMC) and non-homogeneous (NHMC) Markov chain models will be considered. The selection between these models will depend on the seasonal dynamics of the disease occurrence. The methodology will also include the derivation of mathematical expressions for state transitions and accuracy evaluation using Chebyshev distance. This theory-driven approach will facilitate a framework suitable for modelling temporal health patterns in dairy herds.

2. **Empirical Approach:** Data will be collected from a dairy farm in the Czech Republic for a herd of 750 cows over a six-year period (2018–2023), comprising 2,167 consecutive days. This empirical data will allow the construction of daily time series for 36 diseases. The datasets will be cleaned and pre-processed using Python. Empirical analysis will include non-parametric statistical testing (Kruskal–Wallis test) to detect significant seasonal changes. These findings will inform model parameterization and selection.

Data Preparation and Encoding

The dataset was extracted from the farm's digital health record system and structured into time series using Python. Each disease was treated as an independent sequence. Data processing involved:

- Cleaning and de-duplication using `pandas`
- Time alignment and resampling using `datetime` and `resample`
- Normalization of disease labels using string matching and domain-specific mapping tables

- Encoding of disease presence as integer state vectors

Diseases were filtered for modelling based on two representation criteria:

- **Q-index**: The fraction of calendar quarters where the disease occurred (≥ 0.5)
- **D-index**: The proportion of days with disease presence across the six-year period (≥ 0.01)

Only diseases exceeding both thresholds were modelled using Markov chains. For rare or highly sporadic diseases, a Bernoulli probabilistic model was used instead, calculating daily risk from historical relative frequency.

Modelling Strategy and Implementation

Selected diseases were modelled using homogeneous and non-homogeneous Markov chains, depending on their seasonality. For each disease, historical transitions between states were tabulated to estimate the likelihood of change over time. When clear seasonal variation was detected, separate models were developed for each quarter of the year to better capture these dynamics.

For diseases with sporadic occurrence, a simpler probabilistic model was applied based on historical relative frequency. These models were less complex but sufficient for forecasting the probability of occurrence in the short term.

Evaluation and Validation

To ensure model accuracy and relevance, several evaluation techniques were applied. A portion of the dataset was reserved for testing purposes, allowing comparisons between predicted and observed disease states. The performance of each model was assessed using distributional distance metrics.

Seasonal effects were statistically confirmed using non-parametric tests, specifically the Kruskal–Wallis test, to support the decision on whether to apply seasonal modelling. The results of the modelling process were further validated through graphical diagnostics and residual analysis.

Software Tools and Libraries

The modelling process was implemented entirely in Python, utilizing well-established libraries including:

- pandas and numpy for data manipulation
- scipy and statsmodels for statistical operations

- matplotlib and seaborn for visualization
- scikit-learn for reference metrics and supplementary evaluation

Output and Integration

Final outputs of the modelling included daily forecasts of disease occurrence, expected numbers of affected cows, and confidence ranges. These outputs were saved in tabular format and visualized using time series plots and probability heatmaps. The predictions were subsequently integrated into the Decision Support System platform developed in other parts of the dissertation, allowing real-time use by farm managers and veterinary staff. This methodology offers a lightweight and interpretable solution for forecasting dairy herd diseases. It provides a practical foundation for data-informed herd health management, enabling proactive intervention and better planning of veterinary and operational resources.

3.3 Research Question 3: What are the key features a web-based DSS platform should have to effectively integrate predictive modelling with descriptive analysis for farm management?

This research question addresses the development of a web-based Decision Support System (DSS) designed to support proactive and data-driven decision-making in dairy herd health management. The proposed DSS integrates predictive modelling, descriptive analytics, and cost analysis to assist farm managers in planning veterinary interventions, reducing treatment expenses, and improving animal health outcomes.

Research Approaches

1. **Applied Approach:** The DSS will be designed to support real-time decision-making for herd health by integrating data from farm records, veterinary reports, and economic variables. This web-based platform will combine predictive modelling, descriptive analytics, and cost analysis to empower dairy farmers to make timely and informed decisions. The platform will be tailored to real-world usability through a combination of AI-powered backend systems and a user-friendly frontend interface.

2. **Empirical Approach:** The DSS will be tested using real-world veterinary records collected over a five-year period from a dairy farm in western Bohemia. Data will be obtained from digital and manual sources, including farm management systems and treatment logs. The

system's usability and performance will be iteratively improved based on feedback from practical deployments and simulated decision scenarios.

Data Collection and Preparation

The system processes structured datasets that include information about disease cases, medications used, dosages, suppliers, and treatment outcomes. All data were harmonized into a consistent schema and preprocessed using Python scripts. Preprocessing included de-duplication, correction of inconsistent entries, and transformation into temporal formats appropriate for modelling and analysis. Key data fields include: diagnosis date, disease type, dosage, treatment duration, medication cost, and supplier ID.

System Architecture

The DSS system was developed as a full-stack web application. The backend is built with Flask (Python) and handles data input/output, modelling processes, and business logic. The frontend is implemented in React, providing an interactive dashboard for farmers. The entire platform is deployed on Microsoft Azure to ensure accessibility, scalability, and data security.

Predictive Modelling Component

A Long Short-Term Memory (LSTM) neural network was implemented for disease forecasting. The model was trained on historical time series of disease records to learn temporal dependencies and trends in disease patterns. The LSTM outputs were used to predict likely disease incidences, which were then combined with descriptive and economic data to support operational planning. Additionally, linear regression models were used to project longer-term cost trends and disease burden trajectories.

Cost and Treatment Simulation

Based on disease predictions, the system estimates required medication types and quantities. Treatment protocols were mapped to each disease type and linked to medication dosage guidelines. The DSS calculates expected treatment costs for each predicted scenario. It also enables supplier comparison by integrating price data, allowing the identification of cost-effective purchasing strategies.

Scenario Analysis

Users can create and compare alternative treatment scenarios by modifying input parameters, such as disease rates or supplier contracts. For each scenario, the system generates dynamic forecasts of disease burden, medication volumes, and projected costs. These simulations help in evaluating preventive strategies and selecting optimal actions before disease outbreaks occur.

Visualization and User Interface

The system features interactive dashboards with real-time health monitoring visualizations, predicted disease trends, treatment plan recommendations, and cost comparisons. Visual components were implemented using React-compatible charting libraries and include timeline charts, heatmaps, and scenario comparison tables. The interface supports multiple languages and is designed for use on both desktop and mobile devices. By integrating machine learning, economic modelling, and practical usability, this web-based DSS represents a comprehensive solution for managing dairy herd health. It enables farmers to act on reliable forecasts, plan budgets more effectively, and reduce risks through scenario-based planning.

Summary of the Methodological Approach

This dissertation combined theoretical and empirical research in the development of a practical tool for dairy herd health management. Each scientific method helped to achieve a specific goal, facilitating the construction of a DSS based on theoretical foundations and empirically validated data.

Literature Review

Decision Support Systems

Decision Support Systems (DSSs) are interactive computer-based tools designed to assist individuals and organizations in making informed, data-driven decisions, especially in contexts that are complex, dynamic, or partially structured. First introduced in the 1970s, DSSs emerged from the confluence of information systems research and decision theory. (Keen & Scott Morton, 1978) described them as systems that help users address semi-structured problems—those for which parts of the decision process are known, but others require human judgment, adaptation, or creative input.

Early DSSs were relatively simple systems that combined basic data processing with predefined models, enabling users to manipulate inputs and observe resulting outcomes. As computing technologies advanced, DSSs evolved to incorporate increasingly sophisticated components such as simulation models, optimization algorithms, and graphical user interfaces (Power, 2002). Their development paralleled milestones in data science, systems engineering, and organizational behaviour, establishing DSSs as foundational tools for complex decision environments.

A key advantage of DSSs lies in their ability to integrate and analyse diverse sources of information—ranging from historical records and live sensor data to user-generated inputs—and transform them into actionable insights. By structuring decision alternatives, forecasting possible outcomes, and evaluating trade-offs, DSSs support both strategic and operational decision-making. They also enhance transparency and reproducibility in complex choices, thereby strengthening the basis for accountability and evidence-based practice (Turban et al., 2010). In the modern context, DSSs are deployed across a wide spectrum of domains, including healthcare (e.g., clinical decision support), finance (e.g., risk management tools), logistics (e.g., route and inventory optimization), and agriculture (e.g., crop planning and livestock health monitoring).

Contemporary DSS architectures increasingly exploit the potential of cloud computing, artificial intelligence, and real-time data integration. This has led to the development of adaptive and learning-based DSSs capable of adjusting their outputs as new data become available or environmental conditions change (Power, 2008) and (Kamilaris et al., 2018). Moreover, the expansion of the Internet of Things (IoT) has further enhanced the functionality of DSSs, enabling the incorporation of continuous data streams from distributed sensors and systems.

This has proven particularly impactful in sectors where spatial and temporal variability are central—such as precision agriculture, environmental modelling, and urban infrastructure planning. Overall, DSSs have evolved into essential components of digital transformation strategies. Their role is not limited to passive information retrieval, but extends to active support for scenario simulation, risk assessment, resource optimization, and collaborative decision-making. As digital ecosystems become more complex and data-rich, the value of robust, transparent, and context-aware DSSs continues to grow.

Classification of Decision Support Systems

Decision Support Systems (DSSs) have been classified in various ways depending on their underlying architecture, mode of operation, and the type of support they provide to decision-makers. One of the most widely accepted classification frameworks was introduced by (Power, 2002) and later elaborated by (Turban et al., 2011), which distinguishes DSSs according to the dominant component that drives the support they offer.

The first category, data-driven DSSs, primarily focuses on the collection, storage, retrieval, and analysis of large volumes of structured data. These systems are typically built on relational databases, data warehouses, or online analytical processing (OLAP) technologies. Their primary function is to enable users to perform queries, generate reports, and explore trends in historical or real-time data. By providing timely and flexible access to accurate and relevant information, data-driven DSSs support operational and tactical decision-making in environments where quantitative indicators are central (Power, 2002) and (Turban et al., 2011).

Model-driven DSSs, on the other hand, rely on mathematical, statistical, or simulation models to evaluate scenarios and support decision-making. These systems emphasize the application of analytical models rather than direct data manipulation. They are particularly useful in situations where decision-makers need to assess alternative strategies, perform sensitivity analysis, or solve optimisation problems. The primary value of model-driven DSSs lies in their capacity to formalize complex relationships among decision variables and to evaluate the consequences of different courses of action under defined constraints (Shim et al., 2002) and (Marakas, 2003).

Knowledge-driven DSSs—also known as expert systems—are designed to provide specialized recommendations or classifications based on domain-specific knowledge. They operate using encoded rules, inference engines, and sometimes ontologies that emulate human expert reasoning. These systems are suitable for contexts in which expertise can be formalized and consistently applied to new cases. They are typically used in diagnostic and advisory tasks, where the ability to simulate expert judgment is crucial for supporting semi-structured decision processes (Holsapple, 2008).

Document-driven DSSs support decision-making through the retrieval and analysis of unstructured textual information. These systems manage collections of documents such as policies, regulations, manuals, or case reports, and facilitate access to relevant information through search engines, indexing mechanisms, and sometimes natural language processing. In domains where decision-making is grounded in qualitative or textual evidence, such as legal, administrative, or policy environments, document-driven DSSs play a critical role (Turban et al., 2011) and (Olsina et al., 2006).

The final category, communication-driven DSSs, is designed to facilitate collaborative decision-making among multiple stakeholders. These systems provide platforms for information exchange, coordination, and consensus-building, often through tools such as groupware, video conferencing, messaging systems, and collaborative interfaces. Communication-driven DSSs are particularly relevant in distributed or multidisciplinary environments, where decision processes require the integration of diverse perspectives and real-time interaction (DeSanctis & Gallupe, 1987) and (Shim et al., 2002).

This classification framework provides a conceptual foundation for understanding the diversity of DSS architectures and functionalities. By identifying the dominant mechanism—whether it is data, models, knowledge, documents, or communication—researchers and practitioners can better align DSS design and implementation with the specific needs of decision contexts and user requirements.

Decision Support Systems in Agriculture

Agricultural Decision Support Systems (DSSs) have rapidly evolved to manage the growing complexity of modern farming under pressures like climate change, volatile markets, and sustainability goals. These computer-based tools integrate diverse data – from weather and soil sensors to crop models and economic metrics – to provide tailored recommendations for farm decision-making (Petraki et al., 2025a). By synthesizing information across biological, environmental, and economic domains, DSSs help farmers make informed decisions on crop management, resource use, and investments, thereby improving both productivity and resilience.

DSS Applications in Crop Production

In crop production, DSSs assist farmers with decisions on sowing dates, fertilization, pest control, and yield forecasting. A prominent trend is the use of machine learning (ML) to predict crop yields and optimize management. For example, an intelligent DSS for crop yield prediction combined multiple ML algorithms (including ensemble techniques) and achieved nearly 89% accuracy in forecasting yields (Anbananthen et al., 2021). This system was deployed as a user-friendly web-based application, allowing farmers to easily input field data and receive fast, accurate yield predictions before planting. Such tools enable growers to plan crop choices and management practices with better insight into expected outcomes, reducing risk.

Another cornerstone of crop DSSs is simulation modeling for growth and yield. Robust crop simulation models (e.g. APSIM, WOFOST) are now integrated into DSS platforms to support decisions under varying conditions. (Banerjee et al., 2024) examined state-of-the-art crop modeling tools, highlighting their utility in growth forecasting, nutrient management, and yield prediction across different climates. One widely used system is DSSAT (Decision Support System for Agrotechnology Transfer), which includes models for over 40 crops. The DSSAT platform (Abayechaw, 2021) has been applied worldwide to simulate how different planting dates, crop varieties, or input levels will affect yields (Jones et al., 2003). By integrating weather, soil, and management data, these models let farmers ask "what if" questions and virtually test strategies. DSSAT continues to be a foundational tool in farm-level DSSs, with tens of thousands of users in over 190 countries. Its longevity and ongoing updates underscore the importance of simulation-based DSSs in handling climate variability and site-specific planning. Notably, even as newer AI-driven tools emerge, these mechanistic models remain critical for scenario analysis and understanding crop responses in a scientifically robust way.

DSS Applications in Irrigation Management

Efficient water management is another domain where DSSs have made significant impact. Irrigation DSSs combine weather forecasts, soil moisture data, and crop models to optimize when and how much to irrigate. By providing precise scheduling recommendations, they aim to maximize yield per unit of water – a key goal under climate-induced water scarcity. For instance, a recent study showed that using a Decision Support System for Irrigation Scheduling (DSSIS) in cotton fields increased seed cotton yield by 32% and boosted water productivity by 20% compared to relying on soil moisture sensors alone (Petraki et al., 2025b). This demonstrates how data-driven scheduling can outperform even modern sensor-based practice by synthesizing additional factors (weather predictions, crop growth stages, etc.) into the decision.

Several established tools are widely used for irrigation DSSs. The FAO's CropWat program and the more crop-focused AquaCrop model are two examples that have been deployed for optimizing on-farm water use. Studies in semi-arid regions have found that these models provide very similar guidance on irrigation requirements, but AquaCrop has an edge by accounting for factors like crop fertility and salinity, resulting in better water-use efficiency (Amirouche et al., 2023). In one 2023 case, an AquaCrop-based DSS in the Sahel helped farmers adjust irrigation based on five-day weather updates, leading to yield increases in tomato, maize, and quinoa and higher water productivity (Alvar-Beltrán et al., 2023). Such precision irrigation systems demonstrate substantial efficiency gains: by minimizing water stress and only applying water when and where needed, they save resources while maintaining or improving yields. In practice, these DSSs often deliver advice via mobile apps or dashboards to extension agents and farmers in real time. Overall, the integration of predictive models (for evapotranspiration and crop growth) with on-ground sensor data has made irrigation management more data-driven. As a result, farmers can achieve "more crop per drop," which is crucial for sustainability in water-limited areas.

DSS Applications in Livestock Farming

Recent advances in livestock-focused Decision Support Systems (DSSs) combine IoT sensors**,** mobile applications**,** and AI-based analytics to assist with breeding, health monitoring, and real-time herd management. For example, (Panda et al., 2024) developed a DSS using RFID telemetry and geospatial data to detect abnormal animal behavior and notify farmers via a mobile app for early intervention. Another important development is the use of wearable devices like the RumiWatch halter and pedometer, which were validated during grazing in 2024 and demonstrated high accuracy (correlation coefficients ≥ 0.91) for rumination and locomotion monitoring (Pichlbauer et al., 2024).

DSS Integration of Economic and Risk Analysis

Recent developments in Decision Support Systems (DSSs) have increasingly incorporated economic and risk analysis modules to aid farmers in making more strategic and sustainable choices. Notably, a 2024 study of pesticide management DSS adoption found that platforms embedding economic evaluation tools, such as ROI simulators and cost–benefit analysis, significantly increased farmers' willingness to adopt new technologies, particularly when returns were quantified under variable input-cost scenarios (Akaka et al., 2024). This aligns with broader findings that DSS modules displaying cost–benefit dashboards and clearly demonstrating potential financial gains drive user trust and encourage practical uptake.

Risk-sensitive features are also key: (Alvar-Beltrán et al., 2023) DSS tools that simulate water stress and market fluctuation scenarios offer farmers insights into yield stability and resilience. For example, an AquaCrop-based DSS deployed in the Sahel region in 2023 enabled farmers to assess water-stress impacts across crops like tomato and maize, thus improving adaptation strategies during dry spells. Similarly, (Papadopoulos et al., 2024) economic and environmental analysis of digital agricultural technologies highlights how tools combining profit variability and climate risk modeling help farmers anticipate income changes under drought or price volatility.

By weaving together agronomic advice with financial insight and scenario-driven risk metrics, modern DSSs empower farmers to make decisions that are not only biologically sound but economically robust, supporting more resilient and sustainable farming systems.

Trends and Emerging Directions in Agricultural DSSs

In recent years, several key trends have emerged that reshape how DSSs are developed and deployed in agriculture.

First, artificial intelligence (AI) and machine learning (ML) are now core to many DSS platforms. (Javaid et al., 2022) highlight the role of ML in predictive tasks such as disease identification, yield estimation, and irrigation scheduling. AI-driven systems offer enhanced adaptability and precision, particularly when combined with big data sources such as satellite imagery or historical farm data.

Second, the proliferation of Internet of Things (IoT) technologies has expanded the availability of real-time, in-field data. These include soil moisture sensors, GPS tracking, and wearable health monitors for livestock. (Ahmed & Shakoor, 2025) describe how IoT data streams feed directly into DSS platforms, which then process this information using cloud infrastructure to deliver immediate, context-aware recommendations.

Third, the transition to cloud-based and web-accessible DSS platforms improves usability and scalability. Tools like those described by (Anbananthen et al., 2021) are now often delivered via mobile apps or browser dashboards, with minimal installation or technical barriers. This shift increases adoption among farmers by improving access and allowing seamless updates. (Hamadani

& Ganai, 2022) also demonstrate successful integration of mobile interfaces in livestock management DSSs.

Fourth, DSSs increasingly support sustainability goals. Recent systems assist with climate-smart practices, resource recycling, and emissions reduction. For example, (Tagarakis et al., 2021) proposed a DSS for circular agriculture, integrating livestock manure data and crop nutrient needs to minimise waste and input costs. Similarly, (Petraki et al., 2025b) provide a review of agroecological DSSs that support biodiversity, soil health, and adaptive responses to climate risks.

Finally, there is a growing emphasis on participatory and user-centred DSS design. (McGrath et al., 2025) and (Gonzalez et al., 2024) both stress the importance of co-creation with farmers to ensure DSS outputs are practical and locally relevant. DSS development now often includes usability testing, interface simplification, and multi-language support to enhance adoption.

In summary, DSSs are evolving into intelligent, accessible, and sustainability-aligned tools. These developments position them as vital enablers of data-driven, resilient agriculture in the face of ongoing environmental and economic challenges.

DSSs in Dairy Farming

In dairy farming, DSSs help to solve a wide range of problems (Rupnik et al., 2019) by providing farmers with highly user-friendly platforms (Gargiulo et al., 2022) with simple answers to complex questions. Leveraging the latest software and the best scientific information available (Cabrera, 2018), DSS also provide dairy farming stakeholders with crucial feedback (Gutiérrez et al., 2019).

Data-Driven DSS in Dairy Farming

In Precision Livestock Farming, the main research areas of data-driven DSS focus on enhancing dairy cow health and welfare (Krueger et al., 2020), as shown in a recent study (Niloofar et al., 2021). But data-driven DSSs also promote cow productivity, thereby enhancing overall farm performance and other economic parameters (Niloofar et al., 2021). In dairy farms, data-driven DSS can also identify “elite” animals with the necessary physical characteristics for the best economic prosperity, based on criteria specified by the dairy farmers (A. P. Balhara Sunesh; Singh, Rishi Pal; Ruhil, 2021).

Herd Health Management with DSS

Data-driven DSS are primarily developed to improve decision-making and economic outcomes (Cabrera, 2018). But when applied in dairy farms, DSS become herd health advisors (Alawneh et al., 2018). Among currently implemented solutions a unique DSS known as Dairy Brain (Ferris et al., 2020) stands out for combining data analytics and decision-making in powerful tool for promoting effective management of cow and dairy herd.

Despite advances such as automated milking systems (AMSs), DSSs remain crucial for the economic viability of dairy farms and for the integration of these advances with biological process (Gargiulo et al., 2022). DSS developers focused on economic optimisation have developed a web-based DSS termed Integrated Management Model for assistance of dairy farmers based on empirically determined predictive equations combining productivity and AMS profitability factors with stochastic simulation and optimisation modelling.

Classification of DSS in Dairy Research

In dairy farming research, DSSs can be divided by aim of application, including feed efficiency, culling, and other dairy operations (Ferris et al., 2020), into several groups, such as Integrated DSSs (IDSSs). IDSSs receive a continuous data batch from on- and off-farm data gathering systems (Baldin et al., 2021). In contrast, other DSSs classify cattle health based on an artificial neural network (Pimpa, 2019) or support dairy farmers in their decision-making process by sharing real-time farm data for farm management at both individual and herd levels, as exemplified by “Dairy Brain” (Ferris et al., 2020). More recently, researchers have developed a herd management system (HMS) to improve cow and pasture performance by remote monitoring (Asher & Brosh, 2022). These advances show that data-driven DSS can provide farmers with actionable insights, often in real-time.

Decision Support System in the Dissertation

The dissertation focuses on the design and implementation of a decision support system (DSS) for managing herd health in dairy farms. The system combines data-driven methods with predictive modelling to support strategic decision-making related to disease monitoring, treatment planning, and cost optimization. The DSS integrates various components including data processing, trend analysis, and scenario simulations, enabling users to better manage disease risks and treatment strategies. Through this approach, the research contributes to the development of practical tools for improving animal welfare, reducing veterinary costs, and enhancing overall farm productivity.

Results

The results of this dissertation were published by the author in two articles: "A decision support system based on disease scoring enables dairy farmers to proactively improve herd health," published in the *Czech Journal of Animal Science* (2024), and "Discrete Homogeneous and Non-Homogeneous Markov Chains Enhance Predictive Modelling for Dairy Cow Diseases," published in *Animals* (2024). Both peer-reviewed publications are indexed in the Scopus and Web of Science databases. The author has made a substantial contribution to these publications, which report findings directly related to his dissertation. In addition, the author has penned a third article entitled “A decision support system for herd health management for dairy farms (2024)”, also published in the *Czech Journal of Animal Science*. The results presented in these articles will be analysed in a mini-discussion format to highlight their relevance, benefits, and connection to the dissertation objectives.

Overview of article number 1

A Decision Support System Based on Disease Scoring Enables Dairy Farmers to Proactively Improve Herd Health

This study focused on developing and validating a new disease scoring metric to support decision-making regarding dairy herd health, enabling farmers to respond based on clearly defined disease severity data. The study demonstrated that a DSS based on disease scoring could effectively convey interpretable information, promoting preventive measures and optimise herd health. Five years of data from 2,558 disease records were collected and classified into six disease categories (lameness, mastitis, postpartum diseases, digestive system diseases, reproductive diseases, and other diseases). This approach improved monitoring of individual disease categories and created conditions for targeted veterinary interventions. Although some categories, such as postpartum diseases, increase due to changes in reproduction management, positive trends in disease scores were observed during the monitoring period. When generalising the approach, this DSS proved applicable as a universal tool for monitoring and managing dairy cow herd health, thus helping to improve farm management efficiency. As such, this DSS fosters operational optimisation and herd productivity by improving planning and reducing disease occurrence through targeted interventions.

Overview of article number 2

Discrete Homogeneous and Non-Homogeneous Markov Chains Enhance Predictive Modelling for Dairy Cow Diseases

This study aimed to improve dairy cow disease prediction and management through a discrete Markov chain-based model. By selecting both Homogeneous (HMC) and Non-Homogeneous Markov Chains (NHMC), this research study tackled disease prediction, which relies on data consistency across farms of various technological capacities. This model provided reliable forecasts on disease trends by accounting for the state of diseases in previous periods. As such, this tool is adaptable to diverse farm environments, including those with limited technological infrastructure. To achieve this goal, historical data on 19 common diseases were aggregated, and Chebyshev distance minimisation was used to refine the prediction model until reaching an error margin lower than 15% in 14 diseases. This level of accuracy enables practical applications for monitoring herd health, estimating treatment needs, and reducing operational costs. Thanks to its adaptability, this model can be integrated as a core component of DSSs on low-tech farms, projecting antibiotic costs and informing strategic decisions. Furthermore, the predictive accuracy of this Markov chain model underscores its potential for evaluating whole herds globally and its ability to support proactive management through effective disease monitoring and risk mitigation strategies. While the transition probability matrix may require periodic updates, the model remains a feasible alternative to higher-tech systems, such as Precision Livestock Farming (PLF). Based on these results, integrating such predictive models into a Dairy Disease DSS may significantly advance herd health management across varying farm types by providing a cost-effective tool for both disease prediction and planning.

Overview of article number 3

A Decision Support System for Herd Health Management For Dairy Farms

This study was designed to develop an accessible, web-based Decision Support System (DSS) for dairy farmers, enabling real-time decision-making for herd health management. While industrial dairy farms often utilise advanced monitoring systems, they lack user-friendly platforms for farmers to actively manage disease prevention and optimise treatment strategies. This study aimed to bridge this gap by creating a machine learning-powered DSS integrating both predictive modelling and cost analysis into a scalable web application. The system architecture consists of a Flask backend and a React frontend, enabling efficient data integration, preprocessing, and predictive analysis through cloud-based storage. The predictive capabilities are driven by Long Short-Term Memory (LSTM) neural networks, which forecast disease progression with high accuracy, achieving a mean absolute error of 6.66 and a median absolute deviation of 2.35. Additionally, the system includes a linear trend model to project reductions in treatment costs. Using this system, farmers can streamline supplier selection, calculate medication dosages, and simulate treatment scenarios. The results demonstrate that this web-based DSS provides dairy farmers with an essential tool for improving herd health management by predicting diseases, optimising prevention strategies, and reducing overall costs. The system identifies high-cost diseases and potential savings, making it a cost-effective solution for farms of varying technological capacities. This research supports proactive veterinary planning and enhances both animal welfare and farm productivity.

[redacted]

https://doi.org/10.17221/53/2024-CJAS

A decision support system based on disease scoring enables dairy farmers to proactively improve herd health

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Citation: Saro J., Stádník L., Bláhová P., Huguet S., Brožová H., Ducháček J. (2024): A decision support system based on disease scoring enables dairy farmers to proactively improve herd health. Czech J. Anim. Sci., 69: 165–177

Abstract: Decision support systems (DSSs) enable dairy farmers to make informed and timely decisions on herd health management. However, the lack of a disease scoring system by category and severity limits the application of this approach. In this study, we developed an innovative approach to dairy herd health management by establishing a novel scoring system for dairy herd health management aimed at providing a more nuanced understanding of disease impact. For this purpose, we retrieved 5-year data from 2 558 disease diary records of 798 primiparous and multiparous cows housed on a Czech farm and classified 125 production diseases into six categories, namely lameness, mastitis, postpartum diseases, digestive system, reproductive diseases and other diseases. Based on this metric, we developed a data-driven DSS for farm management. Using this DSS, we identified markers of disease categories for efficient veterinary monitoring on dairy farms. This DSS highlighted a decreasing trend of average monthly disease scores, yet the prevalence of postpartum and other diseases increased during the same period, due to changes in reproduction management within the herd. These findings underscore the need for data-driven targeted interventions for promoting the herd health. Therefore, our scoring model not only provides a comprehensive framework for dairy herd health monitoring and improvement but also advances dairy farming by providing a decision support system easily applicable to dairy farms based on available data recorded in disease diaries.

Keywords: dairy cows; descriptive analysis; disease scoring system; farm management; production disease

Dairy herd health management (Bowen 2016; Damiaans et al. 2020) is crucial for effective farm management (Ferchiou et al. 2021) within the precision farming approach (Loucka et al. 2023).

To this end, new approaches have recently been developed towards sustainable dairy farming (Ufitikirezi et al. 2024) based on data-driven decision making by applying artificial intelligence (AI), data analysis, and big data analysis (Cabrera 2021). Case in point, machine learning can predict health trends at dairy herd and individual cow levels (Parker Gaddis et al. 2016), for example according to monitoring of eating and rumination time (Codl et al. 2023).

https://doi.org/10.17221/53/2024-CJAS

Improving the herd health management using the general resilience of dairy cows (Kasna et al. 2022) requires the more closely monitoring of production diseases (Islam et al. 2020). Production diseases, such as mastitis, lameness, reproductive disorders and vulval discharge, decrease milk production, having a major economic impact on a dairy farm (Kossaibati and Esslemont 1997; Kasna et al. 2023). Previous studies have shown both the combined, long-term effects of these diseases (Carvalho et al. 2019) and the economic impact of individual diseases, including lameness (Robcis et al. 2023) and postpartum diseases on the herd size (Dubuc and Denis-Robichaud 2017). Research efforts have also been made to classify production diseases into 5 categories and to assess their effects on production and reproduction (Masia et al. 2022).

In dairy farming, several studies have developed scoring systems, such as the KalfOK system, to evaluate the quality of young cattle in dairy herds using 12 key indicators (Santman-Berends et al. 2018) towards improving animal health and welfare on farms. Some authors (Moller et al. 2023) calculated the agreement between 2 scoring systems for calves, namely a Visual Analog Scale (VAS) and the Wisconsin Calf Health Scoring Chart (WCHSC). Other authors scored the herd health using qualitative research based on questionnaires examining the risks of intramammary infections and subclinical mastitis in areas with herds of different sizes and characteristics (Savignano et al. 2008). Overall dairy herd health was also directly compared between dairy farms using scoring systems in Serbia (Stankovic et al. 2014) and France (Coignard et al. 2013), but not in the Czech Republic.

Decision support systems (DSSs) have been developed for controlling individual diseases, including the bovine pestivirus syndrome (Bennett 1992) and mastitis (Allore et al. 1995). DSSs enable farmers to design a targeted control strategy by providing them with reference values for comparison. Another DSS for tracking the dairy herd health at dairy cow or herd levels known as Dairy Brain (Ferris et al. 2020) uses near-real-time data streams to generate decision support information for farm management. DSS monitoring of dairy herd health improves the cow and herd health, decreasing the number of cows for transport Cockram (2021). However, the lack of a disease scoring system by category and severity limits the application of this approach. Moreover, such research has never been conducted on Czech farms, promoting DSS-based monitoring of production diseases in this context.

Considering the above, this study aims to improve the herd health by developing a DSS based on a new dairy disease scoring system for proactive farm management. We developed this new scoring system for the data analysis of dairy herd health by retrieving available data from dairy disease records, a common standard on Czech farms. This scoring model-based DSS is a novel method for data-driven decision making in dairy farm management.

MATERIAL AND METHODS

In this study, we extracted data on a herd of 798 primiparous and multiparous cows recorded for 5 years, from March 2018 to April 2022, in the disease diary using the middleware application "Portal farmáře". The disease data included cow identification, date of disease diagnosis, and the type of disease, totalling 125 disease types. These data were initially classified into 5 disease groups, namely reproductive diseases, digestive tract, lameness, mastitis, and postpartum diseases, as outlined in Table 1. Figure 1 shows a flowchart of the digitalisation and data processing procedure from the dairy disease records to the final scoring results. Our scoring model may be used to compare the dairy herd health between various farms, thereby identifying differences and the farms with the healthiest herds whose procedures should be adopted by farms with less healthy dairy herds. Another potential application of our scoring model is the development of a common metric per cow as a comparable parameter among several farms towards establishing shared animal health criteria.

Data preprocessing

All data were prepared data for developing the scoring model in this study. The disease records were converted from PDF files into an Excel spreadsheet. Then, all duplicities were removed during the data filtering step (Lee et al. 2020). As a result, 125 diseases were identified in a total of 2 558 disease records and classified into 6 categories, the five categories described above and a category entitled "other diseases".

https://doi.org/10.17221/53/2024-CJAS

Table 1. Basic statistics for the ovarian response, and the number of recovered embryos per cow per flushing

Disease	Disease category	Disease severity
Abscess in the subcutaneous tissue	other diseases	1
Acidosis (metabolic acidosis) – rumen content	other diseases	1
Acyclicity	reproduction diseases	2
Acarosis – infestation by arthropods (parasitic conditions, mainly affecting the skin)	other diseases	1
Acute ruminal acidosis (lactic acidosis)	digestive system	3
Acute catarrhal mastitis	mastitis	3
Arthritis – joint inflammation	lameness	3
Arthrosis	lameness	1
Aseptic inflammation of the flexor tendon sheath (*Tendovaginitis flexorum digitalis nonpurulenta*)	lameness	1
Atypical puerperal paresis	postpartum diseases	2.5
Bronchopneumonia – lung inflammation	other diseases	2
Cystitis – bladder inflammation	other diseases	1.5
Cysts – ovarian cyst syndrome	reproduction diseases	2
Digital dermatitis (DD)	lameness	2
Digital dermatitis M-1 stage – initial DD (M1)	lameness	2
Digital dermatitis M-2 stage – typical DD (M2)	lameness	2
Dislocation of the spleen	postpartum diseases	3
E3 – purulent endometritis	reproduction diseases	2
E4 – pyometra	reproduction diseases	2
Endometritis (after the 20^{th} day postpartum)	reproduction diseases	2
Subcutaneous hematoma	other diseases	1.5
Haemorrhagic enteritis (diarrhoea with blood)	digestive system	3
Haemorrhagic mastitis	mastitis	3
Purulent hollow organ wall (bovine contagious abortion) (wall ulcer)	lameness	2
Purulent joint inflammation of the claw	lameness	3
Fever/elevated temperature	other diseases	2
Low-grade fever/temperature increase up to 1 °C	other diseases	1
Moderate fever/temperature increase up to 2 °C	other diseases	1
Very high fever/temperature increase over 3 °C	other diseases	1
High fever/temperature increase up to 3 °C	other diseases	1
Foot ulcer – Rusterholz ulcer (RV)	lameness	2
Foot ulcer – atypical localization	lameness	2
Chronic and latent ruminal acidosis (SARA) – with increased DM	other diseases	2
Chronic catarrhal mastitis	mastitis	2
Indigestion/reduced ruminal activity in cattle	digestive system	1.5
Intertrigo (inguinal dermatitis)	other diseases	1
Other calving disorders	postpartum diseases	2
Other disorders in energy metabolism, carbohydrate, and fat metabolism	other diseases	1
Catarrhal enteritis (diarrhoea)	digestive system	2.5
Ketosis – clinical primary	postpartum diseases	2
Ketosis – clinical primary – severe	postpartum diseases	2
Ketosis – clinical primary – mild	postpartum diseases	2
Ketosis – clinical primary – moderate	postpartum diseases	2
Ketosis – subclinical primary	postpartum diseases	2

https://doi.org/10.17221/53/2024-CJAS

Table 1 to be continued

Disease	Disease category	Disease severity
Ketosis – subclinical primary – moderate	postpartum diseases	2
Contractures of flexor tendon sheaths (overstraining)	lameness	1.5
Blood in milk – haemolactia	mastitis	1
Limping	lameness	2
Mild mastitis – acute	mastitis	1
Clinical mastitis	mastitis	2
Mastitis without microbiological findings	mastitis	1
Mastitis with isolated G+ golden Staphylococcus	mastitis	3
Metritis + putrid discharge	mastitis	1.5
Metritis + purulent discharge	mastitis	1.5
Metritis = postpartum uterine inflammation	postpartum diseases	2
Mild lameness = grade 1	lameness	1
Mild ruminal stasis	digestive system	1
Dead foetus – internal	postpartum diseases	3
Necrobacillosis of interdigital space (N)	lameness	2.5
Necrosis of claw tip (NS)	lameness	2.5
Oral cavity diseases	other diseases	1.5
Joint diseases	lameness	1.5
Musculoskeletal disorders (except hooves), lameness	lameness	1.5
Muscle diseases	lameness	1.5
Tendon diseases	lameness	1.5
Oedema – udder oedema around calving	postpartum diseases	1
Papillomatosis	other diseases	1
Parasitic diseases	other diseases	1.5
Sole ulcer (PV)	lameness	2
Periarthritis – inflammation around the joint	lameness	1.5
Peritarsitis – inflammation around the hock	lameness	1.5
Bruising/contusion – contusion	other diseases	2
Polyarthritis – joint inflammation	other diseases	2.5
Uterine injury during calving	postpartum diseases	2.5
Vaginal injury during calving	postpartum diseases	1.5
Vulvar injury during calving	postpartum diseases	1.5
Calving disorders	postpartum diseases	1.5
Vascular disorders	other diseases	1.5
Spontaneous dislocation of the spleen	postpartum diseases	3
Prolonged uterine involution	reproduction diseases	1.5
Decrease in productive performance	other diseases	1
Rumen tympany (acute)	digestive system	3
Diarrhoea	digestive system	2
Pyelonephritis – kidney pelvis inflammation	other diseases	3
Recurring chronic tympany	digestive system	2.5
Secondary ketosis – moderate	postpartum diseases	2
Moderate (catarrhal) mastitis – acute	mastitis	3
Moderate lameness = grade 2	lameness	2.5
Severe (catarrhal) mastitis – acute	mastitis	3

https://doi.org/10.17221/53/2024-CJAS

Table 1 to be continued

Disease	Disease category	Disease severity
Severe mastitis (parenchymatous)	mastitis	3
Severe lameness = grade 3	lameness	2.5
White line disease (T)	lameness	1
Rumen tympany (= bloating)	digestive system	2
Typical puerperal paresis (stages 1 and 2)	postpartum diseases	2
Recumbency – puerperal paresis	postpartum diseases	2
Recumbency postpartum – other than paresis	postpartum diseases	2
Recumbency due to musculoskeletal disease	lameness	3
Claw ulcer (V)	lameness	2
Claw tip ulcer (VS)	lameness	2.5
Claw tip ulcer/necrosis (VS/NS)	lameness	2.5
Uterine prolapse	postpartum diseases	2.5
Markedly reduced ruminal activity	other diseases	1.5
Uterine retention	postpartum diseases	2
Intestinal inflammation – enteritis (diarrhoea)	digestive system	2
Cessation of ruminal activity	digestive system	1
Mammary gland quarter/body injuries	other diseases	2
Skin, subcutaneous, and fur injuries	other diseases	1.5
Pelvic injuries	other diseases	2.5
Musculoskeletal injuries	lameness	2
Teat injuries	other diseases	2
Udder injuries	other diseases	2

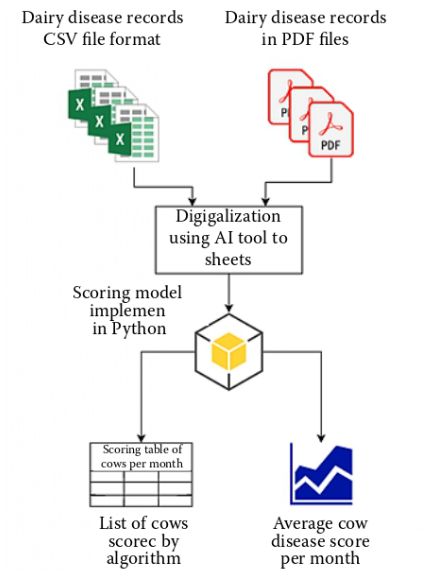

Figure 1. Flowchart of the digitalisation process of dairy disease records

Data categorization and disease scoring

Our novel scoring system of dairy herd health was created as shown in Figure 2. In the first step, all diseases were listed. In the second step, the diseases were scored with a severity number expressing how serious the disease is for the life cycle of a dairy cow.

All diseases were assessed and scored by a veterinarian. Once scored, the diseases were then classified into 6 disease categories (Table 2), according to Shabalina et al. (2020).

Expression of mathematical scoring model

The scoring expression has the following data structure:
- Cow identification.
- Date of disease occurrence.
- Disease name.
- Disease category.
- Disease severity score.

https://doi.org/10.17221/53/2024-CJAS

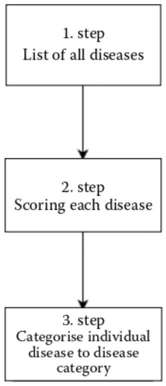

Figure 2. Stages of the overall scoring system of dairy diseases

Mathematical formula of scoring system

- Set of diseases D: This is the set of all possible disease names.
- Cow set C: This set represents all cows in the herd.
- Disease severity score $S(D)$: this score is assessed as described in Table 3.
- Sum scores of diseases of cow count per day:

$$S_l = \sum_{k=1}^{C}\sum_{j=1}^{M}\sum_{i=1}^{D} S(D_i)_{j,k} \tag{1}$$

where:
$S(D_i)_{j,k}$ – occurrence of disease i with score $S(D_i)$ and of cow k from all cows C on day j from all days in month M.

- Average score per cow k in month:

$$O_l = \frac{S_l}{C} \tag{2}$$

where:
O_l – the sum score in month l.

- Sum of scores per cow k in month l: $S_{l,k}$.

The formula for calculating the trend of diseases

$$SSR = \sum_{i=1}^{m}\left(O_l - \left(\beta_0 + \beta_1 . l\right)\right)^2 \tag{3}$$

where:
$l \in (1, m)$;
m – the last month;
O_l – the observed average score per cow in month l;
l – the month index or time variable;
β_0 and β_1 – the coefficients determined using the least squares method;

$$T = \beta_0 \text{ and } \beta_1 .\ l$$

where:
T – the calculated trend of several months;
$\beta_1 > 0$ – suggest an increasing trend of average scores over the months;
$\beta_1 < 0$ – suggests a decreasing trend;
$\beta_1 \approx 0$ – indicates a stable trend, with no significant increase or decrease over time.

Table 2. Disease categories and descriptions

Disease category	Group description
Lameness (Sahar et al. 2022)	diseases related to the cow's locomotor apparatus
Mastitis (De Vliegher et al. 2012)	various difficulties associated with mastitis
Postpartum diseases (Dubuc et al. 2011)	diseases occurring after calf birth
Digestive system (Hall and Mertens 2017)	diseases related to the digestive tract
Reproductive diseases (Gilbert 2016)	conditions affecting the reproductive system, including fertility problems and complications during pregnancy
Other diseases	other disease types occurring during the lifetime of a cow

Table 3. Disease score expressing the levels of disease severity

Disease severity score	Group description
1	mild disease
1.5	mild-to-moderate disease
2	moderate disease
2.5	moderate-to-severe disease
3	severe disease (high risk of culling)

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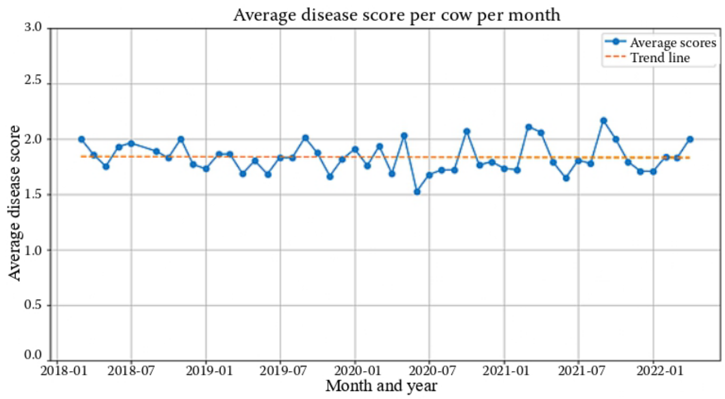

Figure 3. Average disease score per month

RESULTS

The time series of average disease scores per cow per month is shown in Figure 3.

The average disease scores per cow ranged from 1.2 to 2.4. The trend line was calculated by linear regression. The monthly trend of average disease scores per cow in a dairy herd decreased for more than 5 years. Based on this information, farmers can improve their herd health from a long-term perspective. The average disease score was 1.83, with a minimum of 1.53 and maximum of 2.17. The equation of the linear trend line is also included in the legend:

$$T = 1.84 - 6.5.\ 10^{-6}x \quad (4)$$

Resultant $P = 0.89$ expressed that no significant trend was detected.

Table 4. Trends of disease categories

Disease category	Disease category severity	Trend line equation	Slope *P*-value	Trend detection
Digestive system	moderate	$y = -0.006\ 73x + 1.00$	0.680 587	no significant trend
	severe	$y = 0.000\ 61x + 0.84$	0.972 524	no significant trend
Lameness	mild	$y = 0.004\ 54x + 1.16$	0.786 799	no significant trend
	moderate	$y = -0.081\ 84x + 8.83$	0.314 342	no significant trend
	severe	$y = -0.001\ 22x + 0.52$	0.942 695	no significant trend
Mastitis	mild	$y = 0.067\ 76x + 9.15$	0.438 122	significant decreasing trend
	moderate	$y = -0.285\ 31x + 11.38$	0.000 152	significant increasing trend
	severe	$y = 0.393\ 67x + 11.37$	0.003 932	no significant trend
Other diseases	mild	$y = 0.026\ 79x + 5.12$	0.634 769	no significant trend
	moderate	$y = 0.038\ 11x + 0.70$	0.053 738	no significant trend
	severe	$y = 0.000\ 61x + 0.17$	0.934 569	no significant trend
Postpartum diseases	mild	$y = 0.005\ 10x + 0.48$	0.672 440	no significant trend
	moderate	$y = 0.015\ 92x + 3.50$	0.704 176	no significant trend
	severe	$y = 0.034\ 29x + 1.50$	0.210 044	no significant trend
Reproduction diseases	mild	$y = -0.000\ 77x + 0.05$	0.727 673	no significant trend
	moderate	$y = -0.172\ 24x + 10.95$	0.028 302	significant decreasing trend

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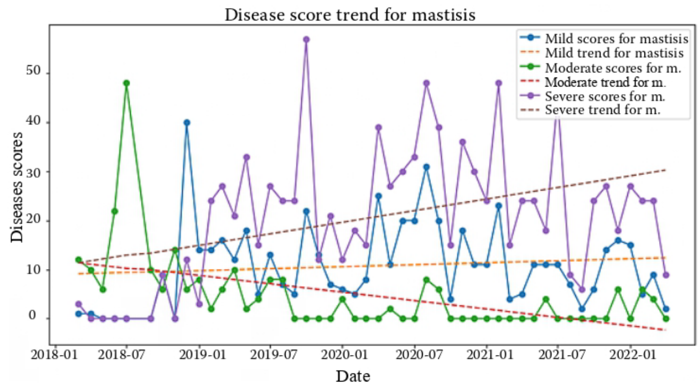

Figure 6. Sum of scores for mastitis disease category

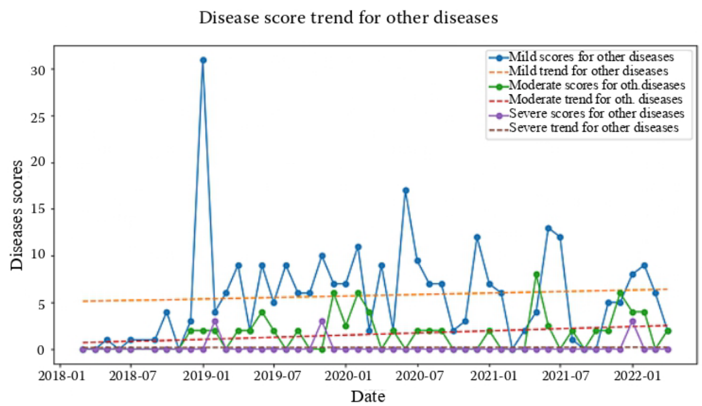

Figure 7. Sum of scores for "Other diseases" category

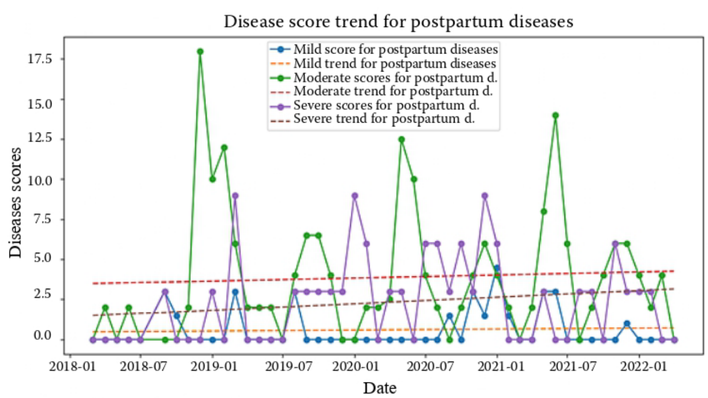

Figure 8. Sum of scores for postpartum disease category

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Evaluation of total disease scores in the dairy cow population

Disease severity was classified using score intervals outlined in the following charts and tables. The DSS system was defined based on three disease severity levels: "Mild", "Moderate", and "Severe". The "Mild" category included scores from 1 to 1.5, indicating the lowest severity. Scores between 2 and 2.5 were classified as "Moderate" disease severity. Lastly, disease severity scores equal to 3 were categorised as "Severe", representing the highest severity level.

This scoring system aims to provide a more nuanced understanding of disease impact.

Table 4 presents the results of trends by production disease category. The DSS provides mastitis control, primarily at the moderate level. However, other diseases showed an overall increase in prevalence across all severity levels. Postpartum diseases showed increased rates, indicating the need for targeted interventions. In contrast, DSS highlighted a decrease in reproductive diseases, particularly at the moderate level. These findings underscore the need for tailored DSS strategies aimed at addressing specific health concerns and the complexity of dairy cow management in promoting the overall herd health.

Figure 4 shows a decreasing trend of moderate diseases of the digestive system, albeit with a slight

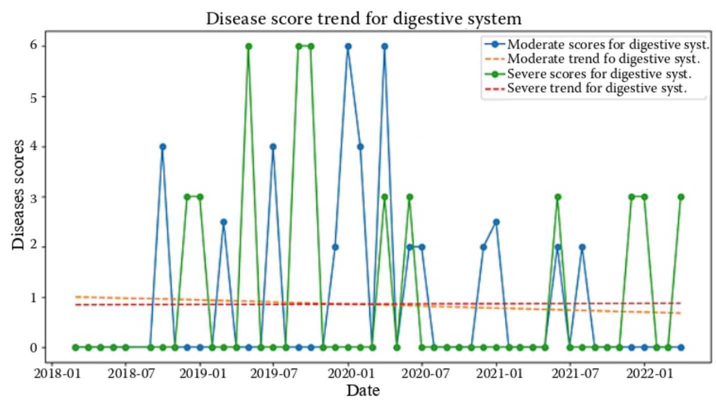

Figure 4. Sum of scores for digestive system

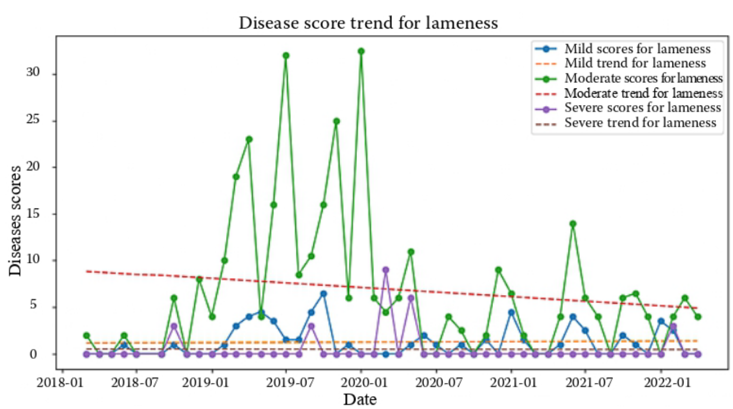

Figure 5. Sum of scores and trends for lameness

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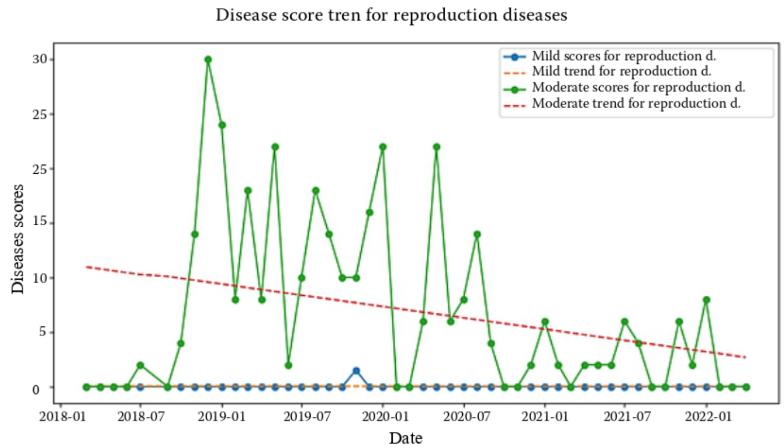

Figure 9. Sum of scores for reproductive disease category

increase in severe diseases of this category. These results demonstrate that our DSS enables farmers to identify differences in disease severity within the same category.

Figure 5 shows a marked decrease in moderate lameness diseases, which account for most diseases in this category. Notwithstanding this prevailing decrease, the remaining severe and mild lameness diseases increased slightly over time. These findings support our assertion above that a scoring model-based DSS enables farmers to differentiate diseases by severity in the same category, regardless of the category.

Figure 6 shows that severe mastitis displayed an increasing trend. Conversely, moderate mastitis significantly decreased over time, whereas mild disease scores showed a nearly linear trend.

In the category of "Other diseases", the score trends shown in Figure 7 slightly increased over time across all disease severities. However, mild diseases had higher scores than moderate diseases in nearly all months of the studied period. Furthermore, severe diseases almost invariably scored 0, except for two months.

The scores of postpartum diseases slightly increased over time, regardless of the disease severity. Nevertheless, the most significant increase was observed in the scores of severe postpartum diseases (purple), as shown in Figure 8.

The category of reproductive diseases showed decreasing trends for all disease severities in Figure 9.

DISCUSSION

Using this scoring model-based DSS, dairy farmers can set al.rt levels for specific trends on a single farm or a set of farms according to a common metric of the dairy herd health. These alert thresholds can be defined by farm management (McBride and Johnson 2006) based on critical states previously identified by farm and by disease category.

Our analysis revealed an average overall disease score of 4.27, indicating the average level of disease burden in this dairy cow population. The 95% confidence interval of the average scores ranged from 0 to 12.39, suggesting a considerable spread in disease severity among the cows. These findings indicate a varied health status within the population and highlight the need for a differentiated approach to health management and disease treatment. A different outcome in reproductive diseases is the result of a change in the approach, and this new method of monitoring through a metric approach allows for tracking changes in disease incidence over time.

The novel overall scoring model proposed in this study can be used by dairy farmers, dairy farm consultants and veterinary staff (Armengol et al. 2022) to monitor the dairy herd health status. The other scoring systems also have cumulative scoring units. In addition, the disease severity score can be modified to meet veterinary needs. The scoring system designed in this study also defined an overall score.

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The practical results of scoring metrics are useful for decision-making of dairy farmers according to herd health trends (Cabrera 2021) and for diagnosing and improving the dairy herd health by decreasing disease trends (Enevoldsen et al. 1995). Decreasing disease trends increases animal health and welfare and decreases the number of cows selected for culling and requiring transport to a slaughterhouse (Cockram 2021), therefore it brings a positive impact on the herd-level economics. This proactive monitoring approach helps to increase milk yields by improving the cow health (De Vliegher et al. 2012), and prevents global warming by a decreased use of antibiotics (Park 2022) and/or by achieving the more effective application of timed artificial insemination protocols (Boudaoud 2023).

Figures 4–9 show trends by disease category. These results can be used for decision-making based on herd health trends broken down into different classes of diseases.

These trends are starting points for projections about dairy herds in longer time periods and may be used as metrics for decision-making about the current status of dairy herd health in combination with farm alerts (Eckelkamp and Bewley 2020). Such alerts enable farmers to quickly apply practical prevention measures for decreasing disease scores in specific categories. This framework provides a DSS for dairy farm management to evaluate the effectiveness of veterinary treatments of production diseases.

CONCLUSION

Our novel overall scoring framework for DSS enables dairy farmers to proactively improve the herd health. Such a data-driven DSS can be applied to a wide research area as a universal comparison methodology for dairy farm herd health management by monitoring the dairy herd health status using severity disease metrics over long periods. Therefore, these findings overcome limitations associated with the lack of digitalisation of disease data and electronic records with insufficient metadata on disease severity. The significance of the observed results and relationships is based on the generally accepted assumption of correlations between milk yield, reproduction, and the health of dairy cows, as confirmed by numerous studies, such as Vacek et al. (2007). This fact is practically utilised in the management and breeding of Holstein cattle through the use of selection indices (Pribyl et al. 2004).

Conflict of interest

The authors declare no conflict of interest.

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Received: April 12, 2024
Accepted: May 22, 2024
Published online: May 31, 2024

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Discrete Homogeneous and Non-Homogeneous Markov Chains Enhance Predictive Modelling for Dairy Cow Diseases

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Simple Summary: Managing cow diseases effectively remains a major challenge in dairy farming. Our study introduces a simple model for predicting dairy cow diseases. To develop this model, we used categorized data and Markov chains to select the best prediction model based on minimal error distance. The results show that our model is not only highly accurate and reliable but also easy to use, even in low-tech farms. Our methodological approach can capture various data structures in different volumes and qualities, demonstrating its versatility and adaptability to a wide range of herd sizes. This universal applicability enables us to evaluate entire herds, regardless of size. Furthermore, while each farm records diseases differently, our model can accommodate these variations. As such, this model may help dairy farmers manage herd health, predict antibiotic costs, and plan farming strategies.

Abstract: Modelling and predicting dairy cow diseases empowers farmers with valuable information for herd health management, thereby decreasing costs and increasing profits. For this purpose, predictive models were developed based on machine learning algorithms. However, machine-learning based approaches require the development of a specific model for each disease, and their consistency is limited by low farm data availability. To overcome this lack of complete and accurate data, we developed a predictive model based on discrete Homogeneous and Non-homogeneous Markov chains. After aggregating data into categories, we developed a method for defining the adequate number of Markov chain states. Subsequently, we selected the best prediction model through Chebyshev distance minimization. For 14 of 19 diseases, less than 15% maximum differences were measured between the last month of actual and predicted disease data. This model can be easily implemented in low-tech dairy farms to project costs with antibiotics and other treatments. Furthermore, the model's adaptability allows it to be extended to other disease types or conditions with minimal adjustments. Therefore, including this predictive model for dairy cow diseases in decision support systems may enhance herd health management and streamline the design of evidence-based farming strategies.

Keywords: dairy cows; herd health status; dairy diseases; Markov chains; predictive model; decision support systems

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Citation: Saro, J.; Ducháček, J.; Brožová, H.; Stádník, L.; Bláhová, P.; Horáková, T.; Hlavatý, R. Discrete Homogeneous and Non-Homogeneous Markov Chains Enhance Predictive Modelling for Dairy Cow Diseases. *Animals* **2024**, *14*, 2542. https://doi.org/10.3390/ani14172542

Academic Editors: Ewa Tomaszewska, Beata Łebkowska-Wieruszewska, Tomasz Szponder and Joanna Wessely-Szponder

Received: 6 August 2024
Revised: 29 August 2024
Accepted: 30 August 2024
Published: 1 September 2024

1. Introduction

Dairy farming improves human welfare globally. Directly or indirectly, the dairy sector employs approximately 240 million people and provides a livelihood for up to one billion people worldwide. Furthermore, milk production promotes female empowerment [1], as

2. Materials and Methods

2.1. Data Description

A dataset of 36 diseases was collected for 750 dairy cows of a herd housed in a farm located in the Czech Republic during the six-year period from 1 January 2018 to 7 December 2023, totaling 2167 days. This dataset contained the count of occurrences of each dairy cow disease monitored daily during the study period.

The data were continuously collected by the dairy farm's zootechnician and subsequently processed using Python scripts. During the data pre-processing stage, it was essential to carry out extensive data cleaning, including the standardization of data formats and the removal of duplicate entries. These steps were critical to ensure the reliability and consistency of the dataset used in our analysis.

Table 1 presents a statistical summary of these disease data.

Table 1. Basic statistics—summary data of occurrences of dairy cow disease over 5 years.

Diseases	Min Occurrence	Max Occurrence	Sum of All Occurrences	Mean Occurrence	SD	F1	F2
Abscess	0	1.0	1.0	0.000	0.021	0.958	0.000
Acidosis	0	1.0	3.0	0.001	0.037	0.917	0.001
Tympani	0	3.0	4.0	0.002	0.068	0.917	0.001
Bleeding	0	2.0	5.0	0.002	0.057	0.875	0.002
Dermatitis	0	2.0	6.0	0.003	0.061	0.875	0.002
Pneumonia	0	2.0	7.0	0.003	0.071	0.958	0.002
Udder Edema	0	1.0	7.0	0.003	0.057	0.875	0.003
Pain	0	1.0	11.0	0.005	0.071	0.833	0.005
Nerve Damage	0	2.0	14.0	0.006	0.091	0.708	0.006
Jaw Edema	0	2.0	15.0	0.007	0.098	0.875	0.006
Postpartum Sepsis	0	4.0	17.0	0.008	0.130	0.875	0.005
Damaged Teat	0	2.0	21.0	0.010	0.103	0.708	0.009
Torn During Birth	0	3.0	25.0	0.012	0.127	0.667	0.010
Digestive Troubles	0	4.0	28.0	0.013	0.160	0.833	0.008
Abomasal Dilatation	0	3.0	32.0	0.015	0.157	0.625	0.010
Peritonitis	0	2	35	0.016	0.156	0.792	0.012
Mastitis	0	5	39	0.018	0.238	0.708	0.008
Eye Injury	0	3	51	0.024	0.190	0.458	0.018
High somatic in milk	0	6	70	0.032	0.359	0.875	0.011
Postpartum hypocalcemia	0	4	97	0.045	0.331	0.333	0.020
Phlegmon	0	4	159	0.073	0.346	0.208	0.052
Respiration	0	4	162	0.075	0.350	0.375	0.052
Laminitis	0	4	226	0.104	0.415	0.083	0.074
Retained placenta	0	3	287	0.132	0.403	0.042	0.111
Limb Edema	0	3	330	0.152	0.456	0.042	0.116
Diarrhea	0	7	372	0.172	0.604	0.417	0.102
High temperature after calving	0	5	541	0.250	0.604	0.000	0.180
Uterus	0	14	582	0.269	1.111	0.167	0.096
High temperature	0	5	821	0.379	0.798	0.000	0.235
Endometritis	0	15	834	0.385	1.369	0.208	0.111
Necrobacillosis	0	6	996	0.460	0.877	0.000	0.287
Metabolic problems	0	6	1047	0.483	0.927	0.000	0.278
Mastitis RB	0	16	2643	1.220	2.007	0.000	0.482
Mastitis RF	0	19	2806	1.295	2.211	0.000	0.493
Mastitis LB	0	18	3103	1.432	2.363	0.042	0.499
Mastitis LF	0	23	6851	3.162	3.488	0.000	0.800

Diseases—names of dairy diseases; Min Occurrence—minimal daily occurrence of dairy disease; Max Occurrence—minimal daily occurrence of dairy disease; Sum of all Occurrences—sum of all occurrences of dairy disease per the whole time period; Mean Occurrence—mean value of occurrences of dairy disease per the whole time period; SD—standard deviation of dairy occurrences per the whole time period; F1—the relative number of quarters *i* during which the disease occurs (described below); F2—a relative number of occurrence of disease per a total number of monitored days (described below).

well as sustainable production and consumption patterns [2] and water and sanitation management [3], in line with sustainable development goals (SDGs) 10, 12 and 6, respectively. In turn, increasing dairy intake reduces healthcare costs [4] and inequalities in food security and nutrition [5]. The need for sustainable livestock production in response to challenges is using a farm animal algorithm in order to address the population increase and avoid food problems in the future [6].

Milk production and reproduction are influenced by a multitude of factors that complement each other [7,8] and can be useful in diagnosing various problems and diseases. In dairy cattle, a wide range of diseases occur, from reproductive tract issues to problems with the mammary gland [9,10] and limbs [11], and even metabolic diseases [12] affecting the general resilience of dairy cows [13]. Most of these diseases have significant economic implications due to reduced milk yield and, for example, the necessity for early culling of dairy cows. Dairy cow diseases considerably decrease farm productivity [14]. In addition to adversely affecting animal welfare by causing pain and discomfort [15], dairy cow diseases such as digital dermatitis decrease milk yield [16] and lead to fertility problems [17]. Making matters worse, diseases like mastitis can affect milk quality and safety, posing risks to human health [18]. Due to increased veterinary costs and loss of livestock, these diseases financially strain dairy farms, which incur high economic losses [19]. Minimizing such economic losses may require a one-health approach to dairy production [20], including research on disease prevention and modelling.

Modelling and predicting dairy cow diseases using precision livestock farming approaches [21] and/or enhancing cattle production and management through convolutional neural networks [22] provides dairy farmers with valuable information for effective herd health management through strategies specifically designed to tackle each disease individually [23,24]. Projecting disease occurrences enables dairy farmers to improve animal health [25]. As a result, dairy farmers not only observe a positive impact on animal health [26] but also increase their profitability [27], primarily by decreasing costs with antibiotics [28].

Predictive models for dairy cow diseases were developed based on several research directions. Dairy diseases can be detected with wearable precision dairy technologies [29,30] and processed at the disease with machine learning [31]. In practice, machine learning algorithms were applied to project lameness [32] and combined with sensor data to predict mastitis [33]. However, machine learning-based approaches require developing a specific model for each disease. Conversely, other models can predict diseases at the herd level by regularly collecting herd summary data and applying parametric and nonparametric approaches to forecast herd health conditions, but not at the disease level [34]. Therefore, developing a model for simultaneously predicting several diseases may demand alternative approaches, such as Markov chains.

Markov chains have already been applied for cow behavior analysis and calving time prediction [35]. A Markov chain model with two states, shedding and non-shedding, was developed to analyze Listeria monocytogenes fecal shedding in dairy cattle [36]. Furthermore, Hidden Markov models were used to project healthy or diseased states based on monthly somatic cell scores of dairy cows with or without clinical mastitis [37] and to detect lameness in image records of cow movements [38]. However, as in the machine learning studies described above, low data availability limits the consistency of these models [39]. Nevertheless, a Markov chain model was integrated with a daily dynamic programming model to assess the effect of reproductive performance on dairy cattle herd value [40].

The present study aims at leveraging Markov chains to effectively model and predict the progression and occurrence of dairy cow diseases during lactation towards improving decision-making [41–43], and farm management about herd health and cutting costs [44].

The data outlined in Table 1 highlight the low occurrence of most diseases in this dairy farm.

2.2. Statistical Methods

To assess differences in dairy cow disease occurrences during the study period, we performed the nonparametric Kruskal–Wallis test using time series data for each disease. Based on the results from this test, we identified significant quarterly differences in variables for each disease (the significance level for this study is set to 5%).

2.3. Criteria for Model Selection

Initially, we analyzed the data to identify frequent diseases. For such diseases, we applied the Markov Chain model; otherwise, we used the Elementary probability model.

For each disease $i = 1, 2, \ldots, D$, quarter $q = 1, 2, \ldots, Q$, and day $t = 1, 2, \ldots, N$, two markers are calculated, namely $O1(i,q)$ and $O2(i)$.

The marker $O1(i,q)$ is equal to zero when disease i does not occur in quarter q; otherwise, the marker is equal to one. The marker $O1(i,q)$ is calculated according to the following formula:

$$O1(i,q) = sgn\left(\sum_{t \in \mathcal{Q}_q} d(i,t)\right) \tag{1}$$

where $d(i,t)$ is the number of occurrences of dairy disease i on day t, the set $\mathcal{Q}_q$ consists of all days in quarter q.

The marker $O2(i)$ expresses the number of days disease i occurs throughout the monitoring period. This marker is calculated according to the following formula:

$$O2(i) = \sum_{t \in \mathcal{N}} sgn(d(i,t)) \tag{2}$$

where $d(i,t)$ is the number of occurrences of dairy disease i on day t and $\mathcal{N}$ represents the set of all monitoring days.

The decision to use the Elementary probability model or the Markov Chain model is made based on the relative number of quarters i and on the relative number of days i during which the disease occurs. Two indexes are calculated $F1(i)$ and $F2(i)$ as follows:

$$F1(i) = \frac{\sum_{k=1}^{n} O1(i,k)}{Q} \tag{3}$$

where Q is number of monitored quarters.

$$F2(i) = \frac{O2(i)}{N} \tag{4}$$

where N is total number of monitored days.

The following rule for model selection is applied:

$$\begin{array}{c} If\ F1(i) > 0.5\ and\ F2(i) > 0.01,\ then\ the\ Markov\ Chain\ model\ is\ used; \\ otherwise\ (if\ F1(i) \le 0.5\ or\ F2(i) \le 0.01),\ the\ Elementary\ Probability\ model\ is\ used. \end{array} \tag{5}$$

2.4. Description of the Model

2.4.1. Classical Probabilistic Model

The classical probability model is chosen if a rare disease occurrence is assumed based on the Formula (5). Two states are then considered: 0—the disease does not occur, and

1—the disease occurs. The probability $\hat{p}(i,1)$ of the occurrence of the disease i is calculated as a relative frequency using the following formula:

$$\hat{p}(i,1) = \frac{\sum_{t=1}^{N-T} d(i,t)}{N-T} \tag{6}$$

where $d(i,t)$ is the number of occurrences of dairy disease i on day t, N is the total number of days, and T is the number of the last days used to test the prediction (Figures 1 and 2).

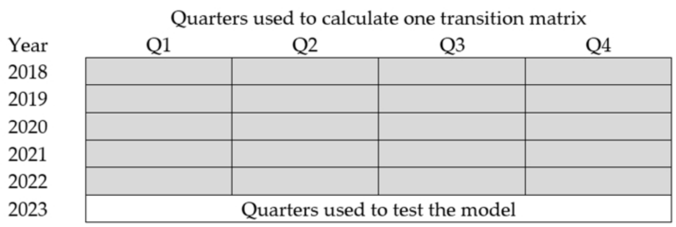

Figure 1. Quarters used across multiple years to calculate a single transition matrix for the HMC, with the final set of quarters in 2023 used for model testing.

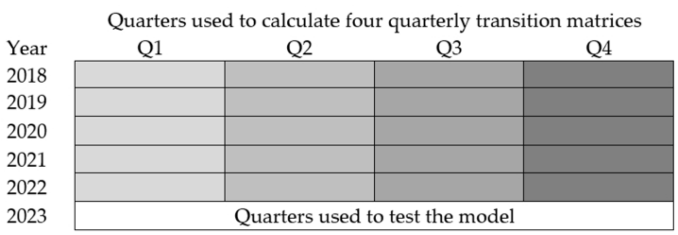

Figure 2. Grouping of quarters across years used to calculate four quarterly transition matrices for the NHMC, with the final set of quarters in 2023 used for model testing.

Accordingly, the probability $\hat{p}(i,0)$ of non-occurrence of disease i is calculated using the following formula:

$$\hat{p}(i,0) = 1 - \hat{p}(i,1) \tag{7}$$

The accuracy of this model is tested by comparing its results with real data using Chebyshev distance, which is particularly suitable for highlighting the maximum deviation between predicted and actual values, thereby providing a clear measure of the model's worst-case error performance.

2.4.2. Discrete Markov Chain Model

A Markov chain is a stochastic process that models the probability of transition from one state to another, where the next state depends only on the current state and not on the sequence of events that preceded it (the "memoryless" property). If the Discrete Markov chain model was selected in the previous phase to predict disease occurrence based on Formula (5), discrete Homogeneous (HMC) or Non-homogeneous (NHMC) Markov chain model accuracy is tested using Chebyshev distance. For this purpose, the Markov chain states are defined first, and then either the Transition matrix is calculated for the HMC model or the four Transition matrices are calculated for the NHMC model and each season. After the predictions, the accuracy of the model is calculated using Chebyshev distance to compare the results with real data.

To clarify the differences between the models, a Homogeneous Markov Chain (HMC) assumes that the transition probabilities remain constant over quarters, which simplifies the modeling process when disease occurrence patterns are relatively stable throughout the year. On the other hand, a Non-homogeneous Markov Chain (NHMC) allows transition probabilities to vary over quarters, capturing temporal or seasonal variations in disease dynamics. This flexibility in the NHMC model is crucial for scenarios where disease progression is influenced by seasonal factors, making it a more suitable choice when the data suggest periodic changes in disease occurrence.

Step 1—Definition of the states of the Markov chain model

The states of the Markov chain model are defined as the number of dairy cows affected by the disease per day. All states form the set $\{0, 1, 2, \ldots, M\}$, where M is the number of dairy cows, 0 means that no dairy cow is affected by the disease per day, and M means that all dairy cows are affected by the disease per day. However, only a smaller number $k \leq M$ of cows is affected usually. Therefore, the real set of states of disease i is

$$\begin{aligned} \mathcal{S}(i) &= \{s_0, s_1, \ldots, s_{K-1}, s_K\} \\ &= \left\{0,\ 1, \ldots, \max_{t=1,\ldots,N-T}(d(i,t)) - 1, \max_{t=1,\ldots,N-T}(d(i,t))\right\} \end{aligned} \tag{8}$$

where $d(i,t)$ is the number of occurrences of dairy cow disease i on day t.

If the probability of states referring to the highest number of disease occurrences per day is very low, the following subset $\mathcal{S}_R(i)$ of the set of states $\mathcal{S}(i)$ of the Markov chain model is used:

$$\mathcal{S}_R(i) \subseteq \mathcal{S}(i) \tag{9}$$

where $0, 1, \ldots, R$ are elements of $\mathcal{S}_R(i)$, $R \leq K$, and state R aggregates all other $\{s_R, s_{R+1}, \ldots, s_K\}$ states.

Step 2—Homogenous Markov Chain

Assuming the homogeneity of the process during the monitoring period, we first determine the Transition matrices for all possible numbers of states R (Figure 1). For each disease i, the transition probabilities are calculated using the following formula:

$$P_R(i) = \begin{pmatrix} p_R(i,1,1) & p_R(i,1,2) & \ldots & p_R(i,1,R) \\ p_R(i,2,1) & \ddots & & \vdots \\ \vdots & & & \\ p_R(i,R,1) & \ldots & & p_R(i,R,R) \end{pmatrix} \tag{10}$$
$$\text{where } p_R(i,a,b) = \frac{\sum_{t=1}^{N-T} c_{ab}(i,t)}{\sum_{b \in \mathcal{S}_R(i)} \sum_{t=1}^{N-T} c_{ab}(i,t)}$$

where $p_R(i,a,b), a, b = 1, 2, \ldots, R$, is the probability of the transition from state a sick dairy cows to state b sick dairy cows, N is the count of all days, T is the length of the predicted period, and $c_{ab}(i,t)$ is equal to either 1 if the transition from state a to state b occurs in time t or 0 otherwise.

At the end, the transition matrix is calculated for all reasonable R for which $\lfloor K/2 \rfloor \leq R \leq K$ because a smaller number of states would not describe the numbers of sick cows well enough.

State probabilities for each disease $i = 1, \ldots, N$ are predicted as follows:

$$\hat{p}_R^T(i) = p_{init} \cdot P_R^T(i) = p_{init} \cdot P_R(i) \cdot P_R(i) \cdot \ldots \cdot P_R(i) \tag{11}$$

where $\hat{p}_R^T(i) = (\hat{p}_R(i,0), \hat{p}_R(i,1), \ldots, \hat{p}_R(i,R))$ is the predicted distribution of states probabilities in predicted period T, p_{init} is vector of initial state probabilities with dimension R with all zeros, except the state describing the last count of occurrences of disease i, where its value is 1, $P_R^T(i) = P_R(i) \cdot P_R(i) \cdot \ldots \cdot P_R(i)$ is the transition matrix from time $N - T + 1$ to N, i.e., T-th power of matrix $P_R(i)$, and T is the length of the predicted period.

The best value R^* is selected based on Chebyshev distance minimization to identify the best predictive accuracy:

$$R^* = \arg \min_{R=\lfloor K/2 \rfloor,\ldots,K} \left\{ \max_{j=1,\ldots,R} \left(\left| \hat{p}_r^T(i,j) - \frac{\sum_{t=N-T+1}^{N} c_j(i,t)}{T} \right| \right) \right\} \tag{12}$$

where $\hat{p}_r^T(i,j)$ is a j-th element of the vector $\hat{p}_R^T(i)$, i.e., predicted probability of state j, and $c_j(i,t)$ is equal to either 1 if j dairy cows were sick with disease i in time t or 0 otherwise.

Based on predicted state probabilities the mean value of disease occurrences per day can be calculated as:

$$\hat{m}(i) = \hat{p}_R^T(i) \cdot (0, 1, 2, \ldots, R^*)' \tag{13}$$

The mean value of disease occurrences per day, $\hat{m}(i)$, is calculated as the scalar product of two vectors: the vector of predicted state probabilities $\hat{p}_R^T(i)$ and the transposed vector of possible disease occurrence states $(0, 1, 2, \ldots, R^*)'$.

Step 3—Non-Homogenous Markov Chain

If the quarter data show a non-homogeneous process, all four quarterly transition matrices must be calculated, that is, one for each predicted quarter (Figure 2).

These four transition matrices are then tested using Formulas (10)–(12) regarding the split time span.

2.5. Calculation of the Prediction Model for Dairy Cow Diseases

Figure 3 shows a flow diagram of the individual steps taken in the process of predicting the number of sick cows in a specific period.

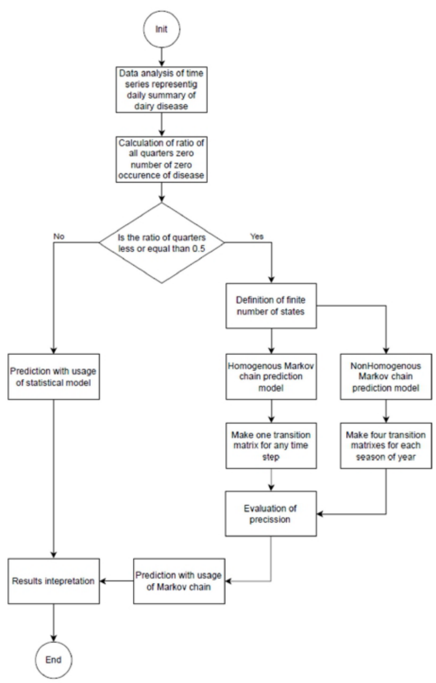

Figure 3. Flow diagram of the calculation of the prediction model for dairy cow diseases.

Markov chain model was implemented, calculated, and tested using Python programming language.

3. Results

In this study, we used three mathematical models, namely Elementary Probability and discrete HMC and NHMC models, to predict the probability distribution of dairy cow diseases in the next one and two months.

3.1. Rare Diseases

The results of the prediction of disease occurrences in the next month, assuming that $F1(i) \leq 0.5$ *or* $F2(i) \leq 0.01$, are presented in Table 2. The predicted probabilities of disease occurrences are computed using the Elementary probability model expressed by Formulas (6) and (7).

Table 2. Basic probability model for predicting rare diseases that do not meet the selection criteria.

Diseases	Total Sum of Disease Occurrence	$\hat{p}(i,0)$	$\hat{p}(i,1)$
Abscess	1	1	0.000
Acidosis	3	0.999	0.001
Tympani	4	0.998	0.002
Bleeding	5	0.998	0.002
Dermatitis	6	0.997	0.003
Pneumonia	7	0.997	0.003
Udder Edema	7	0.997	0.003
Pain	11	0.996	0.004
Nerve Damage	14	0.994	0.006
Jaw Edema	15	0.993	0.007
Postpartum Sepsis	17	0.992	0.008
Damaged Teat	21	0.99	0.010
Torn During Birth	25	0.988	0.012
Digestive Troubles	28	0.987	0.013
Abomasal Dilatation	32	0.985	0.015
Peritonitis	35	0.984	0.016
Mastitis	39	0.982	0.018
High somatic	70	0.968	0.032

Diseases—names of dairy diseases; Total sum of disease occurrence; $\hat{p}(i,0)$—a predicted probability of non-occurrence of disease *i*; $\hat{p}(i,1)$—a predicted probability of an occurrence of disease *i*.

3.2. Prevalent Diseases

The HMC model was first applied to predict the state probabilities in the next one (model HMC30) and two (model HMC60) months. The results of the prediction of disease occurrences in the next months, assuming that $F1(i) > 0.5$ *and* $F2(i) > 0.01$, are presented in Table 3.

For the next month, the mean Chebyshev distance was 0.132, and the median value was 0.104. For the next two months, the predictive performance of the Markov chain model reached a mean Chebyshev distance of 0.189, with a median value of 0.2. The maximum deviations of Chebyshev distance were observed when predicting the occurrence of 'Necrobacillosis' and 'Mastitis LF' using the HMC model.

As shown in Appendix A, the mean value of the first state (healthy herd) across all records was approximately 0.761 for one month and 0.761 for two months. These values highlight the healthy state of the dairy herd.

The NHMC model was then applied to predict the probability distribution for the next one and two months. The NHMC results are presented in Table 4. Transition matrices were calculated separately for each quarter. The mean Chebyshev distance was 0.12, and the median value was 0.088 for one month of prediction. The predictive performance of the NHMC model for the next two months reached a mean Chebyshev distance of 0.101, with a median value of 0.074. As shown in Appendix A, the mean value of the first state was approximately 0.731 for the next month and 0.732 for the next two months, across all records. These results demonstrate the healthy state of the dairy herd.

Table 3. Basic probability model for predicting prevalent diseases that meet the selection criteria.

Diseases	Min Number of States	Max Number of States	HMC30 Opt. Number of States R^*	HMC30 Chebyshev Distance	HMC30 Mean Value of Dairy Disease Occurrences	HMC60 Opt. Number of States R^*	HMC60 Chebyshev Distance	HMC60 Mean Value of Dairy Disease Occurrences
Eye Injury	2	4	3	0.019	0.023	4	0.250	0.025
Postpartum hypocalcemia	2	5	5	0.021	0.046	4	0.250	0.045
Phlegmon	2	5	4	0.052	0.073	4	0.250	0.074
Respiration	2	5	5	0.032	0.076	4	0.250	0.076
Laminitis	2	5	4	0.019	0.103	4	0.250	0.098
Retained placenta	2	4	3	0.025	0.131	3	0.333	0.129
Limb Edema	2	4	4	0.031	0.153	3	0.333	0.151
Diarrhea	2	8	8	0.104	0.177	5	0.200	0.167
High temperature after calving	2	6	4	0.149	0.248	4	0.250	0.252
Uterus	2	15	9	0.092	0.257	9	0.111	0.263
High temperature	2	6	6	0.168	0.381	4	0.250	0.357
Endometritis	2	16	9	0.134	0.378	9	0.111	0.371
Necrobacillosis	2	7	5	0.452	0.439	5	0.200	0.435
Metabolic problems	2	7	5	0.050	0.482	5	0.200	0.467
Mastitis RB	2	17	10	0.222	1.196	10	0.100	1.214
Mastitis RF	2	20	17	0.193	1.293	16	0.063	1.301
Mastitis LB	2	19	11	0.121	1.386	11	0.091	1.4
Mastitis LF	2	24	22	0.472	3.154	13	0.077	3.105
Reproduction problems	2	70	36	0.145	10.892	36	0.028	10.895

Diseases—names of dairy diseases; Min number of states—minimal number of states of Markov chain; Max number of states—maximum number of states of Markov chain; HMC30 Opt. number of states R^*—Optimal number of states calculated for Homogenous Markov chain model for next 30 days; HMC30 Opt. number of states Chebyshev distance—Chebyshev distance for an Optimal number of states calculated for Homogenous Markov chain model for next 30 days; HMC30 Mean value of dairy disease occurrences—Mean value calculated for next 30 days of dairy disease occurrence; HMC60 Opt. number of states R^*—Optimal number of states calculated for Homogenous Markov chain model for next 60 days; HMC60 Opt. number of states Chebyshev distance—Chebyshev distance for an Optimal number of states calculated for Homogenous Markov chain model for next 60 days; HMC60 Mean value of dairy disease occurrences—Mean value calculated for next 60 days of dairy disease occurrence.

Table 4. Results of non-homogenous Markov chains.

Diseases	Min Number of States	Max Number of States	NHMC30 Opt. Number of States R^*	NHMC30 Chebyshev Distance	NHMC30 Mean Value of Dairy Disease Occurrences	NHMC60 Opt. Number of States R^*	NHMC60 Chebyshev Distance	NHMC60 Mean Value of Dairy Disease Occurrences
Eye Injury	2	4	4	0.053	0.117	4	0.055	0.121
Postpartum hypocalcemia	2	5	4	0.100	0.281	4	0.103	0.289
Phlegmon	2	5	5	0.144	0.389	5	0.056	0.385
Respiration	2	5	4	0.045	0.157	4	0.065	0.163
Laminitis	2	5	4	0.027	0.143	5	0.034	0.183
Retained placenta	2	4	3	0.025	0.138	4	0.013	0.199
Limb Edema	2	4	3	0.041	0.176	3	0.074	0.182
Diarrhea	2	8	5	0.175	0.397	5	0.054	0.383
High temperature after calving	2	6	4	0.147	0.248	4	0.137	0.258
Uterus	2	15	9	0.083	0.47	9	0.036	0.477
High temperature	2	6	6	0.176	0.469	4	0.171	0.41
Endometritis	2	16	9	0.128	1.105	9	0.042	1.134
Necrobacillosis	2	7	7	0.410	0.756	7	0.269	0.744
Metabolic problems	2	7	6	0.070	0.398	7	0.156	0.626
Mastitis RB	2	17	14	0.188	2.606	10	0.104	1.399
Mastitis RF	2	20	11	0.221	1.946	11	0.086	2.003
Mastitis LB	2	19	11	0.104	1.404	11	0.130	1.447

Table 4. *Cont.*

Diseases	Min Number of States	Max Number of States	NHMC30 Opt. Number of States R^*	NHMC30 Chebyshev Distance	NHMC30 Mean Value of Dairy Disease Occurrences	NHMC60 Opt. Number of States R^*	NHMC60 Chebyshev Distance	NHMC60 Mean Value of Dairy Disease Occurrences
Mastitis LF	2	24	14	0.460	3.599	14	0.263	3.744
Reproduction problems	2	70	40	0.144	12.566	40	0.071	12.55

Diseases—names of dairy diseases; Min number of states—minimal number of states of Markov chain; Max number of states—maximum number of states of Markov chain; NHMC30 Opt. number of states R^*—Optimal number of states calculated for Non-Homogenous Markov chain model for next 30 days; NHMC30 Opt. number of states Chebyshev distance—Chebyshev distance for an Optimal number of states calculated for Non-Homogenous Markov chain model for next 30 days; NHMC30 Mean value of dairy disease occurrences—Mean value calculated for next 30 days of dairy disease occurrence; NHMC60 Opt. number of states R^*—Optimal number of states calculated for Non-Homogenous Markov chain model for next 60 days; NHMC60 Opt. number of states Chebyshev distance—Chebyshev distance for an Optimal number of states calculated for Non-Homogenous Markov chain model for next 60 days; NHMC60 Mean value of dairy disease occurrences—Mean value calculated for next 60 days of dairy disease occurrence.

The results enabled us to compare two approaches, namely the HMC and the NHMC models, to assess their accuracy using Chebyshev distance. For one and two months, the predictive accuracy of the HMC model was 0.132 and 0.189, respectively. In turn, for the same intervals, the predictive accuracy of the NHMC model was 0.144 and 0.101, respectively. Thus, HMC is more accurate than NHMC. For all diseases, the mean probability of the non-occurrence of the disease was higher than 79%.

3.3. Analysis of the Results

In this section, we analyze the results from the predictive model for diseases Metabolic problems, Mastitis RB and Reproduction problems, respectively.

3.4. Metabolic Problems

The mean value of the expected number of occurrences per day is 0.482, according to the HMC model. Even the histogram (Figure 4) of the probability of the number of metabolic problems shows that the state of no disease occurs on more than 72% of the days and the result accuracy of the HMC model has 0.05 measured by the Chebyshev distance.

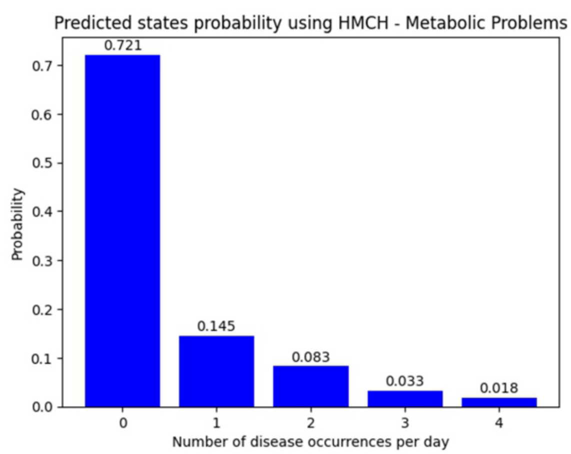

Figure 4. Predicted probability distribution of metabolic problems—homogenous Markov chain model for next 30 days.

3.5. Mastitis RB

The expected mean value of Mastitis RB disease occurrences per day is 1.196. According to the histogram (Figure 5) of probabilities of the number of sick dairy cows shown in Figure 5, the state of no disease occurs in less than 52% of the days rounded on decimals.

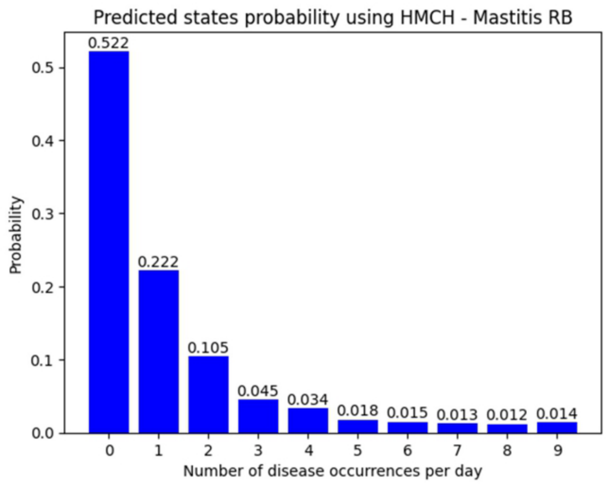

Figure 5. Predicted state probability using HMCH of Mastitis RB for next 30 days.

3.6. Reproduction Problems

The expected number of these diseases was 10.892 per day predicted by the homogenous Markov chain model for the next 30 days with an accuracy of 0.145 measured by Chebyshev distance. According to the histogram shown in Figure 6 of the probabilities of the number of dairy disease occurrences per day, the state of no disease occurs in less than 46% of the days. These results highlight the need to prepare for a relatively high number of 10 sick dairy cows per day.

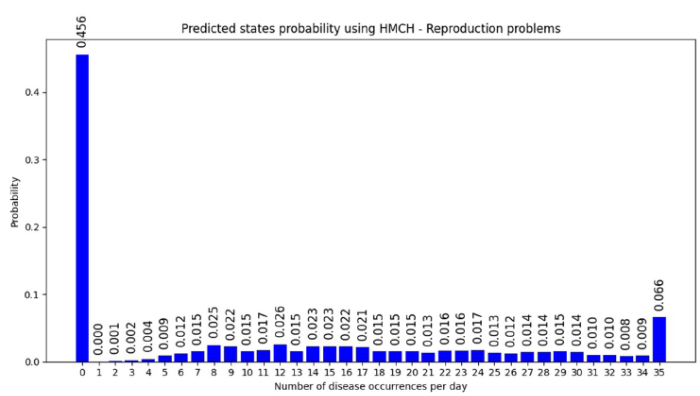

Figure 6. Predicted state probability using HMCH of Reproduction problems for next 30 days.

4. Discussion

To effectively model and predict the progression and occurrence of dairy cow diseases during lactation, we selected Markov chain models because the number of dairy cows with a disease in a forecasted period depends on the number of cows with this disease in the previous period [45]. Based on our data analysis and on the accuracy of the results, we further selected HMC rather than NHMC. The HMC model can be used to support the decision-making process in estimating the number of individual diseases, monitoring the development of herd health status and determining the appropriate intensity of veterinary services in dairy farms.

Our HMC model is applicable as a prediction tool for dairy cow diseases in a wide range of dairy farms, regardless of their technological level [46]. As a predictive component, this model may also be integrated into a decision support system to improve our ability to predict and manage the health conditions of dairy herds [47], in addition to supporting effective decision-making by predicting potential health outcomes. Leveraging advanced statistical methods for short-term forecasting, this new methodological approach can significantly enhance decision support by capturing various data structures in different volumes and qualities. In addition, this model can be applied to herds of different sizes worldwide to evaluate entire herds from a specific number of animals. Thus, our model enables proactive dairy health management strategies.

During its use, the Markov chain must be updated, which entails updating the values of the matrix of transition probabilities either immediately with each forecast query or after a predetermined period. Because the former approach has the disadvantage of overestimating even instantaneous fluctuations, the latter seems more appropriate. However, this approach requires moving the time window. To this end, the recommended length of forecasts is one-fifth of the length of the time series, but predictions over longer periods are also feasible, up to a quarter.

The accuracy of our HMC and NHMC models in predicting the number of diseases of dairy cows did not significantly differ from that of a similar study using an NHMC model in different time periods [48]. However, nonhomogeneous Markov chain prediction [49] using appropriate intervals is a feasible alternative for further research and experiments with disease time series aimed at detecting sub-trends.

Practical Use

Our model may be used as a Markov Chain Decision Process (MCDP) to project individual diseases, thereby assessing veterinarian needs in dairy farms. Based on two different actions, our model enables us to measure differences in two mean values and to increase health state probability. As a prediction tool for dairy cow diseases, this framework is applicable to a wide range of dairy farms, including low-tech farms [46]. Unlike precision livestock farming (PLF) applications, which often require substantial investment in technological infrastructure and real-time sensor data, our model provides a statistically robust alternative that remains accessible and effective for farms with limited resources or lower levels of technological advancement. This makes it particularly suitable for low-tech or smaller-scale operations, where the implementation of PLF systems may be cost-prohibitive. As a predictive component, its incorporation into a Dairy Disease Decision Support System (DSS) may enhance dairy herd health prediction and management [47], effectively supporting decision-making by forecasting potential health outcomes and, therefore, enabling proactive management strategies. This novel approach to statistically leverage data to predict short-term trends supports decision-making processes.

5. Conclusions

Our Markov chain model is a promising tool for predicting the occurrence of dairy cow diseases in the next month. With practical adaptations, this model can be efficiently implemented in dairy farms for farmers to gather useful information for farm health management. One of the key advantages of the Markov chain model is its ability to provide accurate predictions even with limited or incomplete data, making it highly applicable in real-world farming conditions. This model can be incorporated into decision support systems for disease prognosis and strategy design in dairy farms to cut costs with antibiotics for individual diseases, monitor the quality of veterinary services and develop dairy health programs based on disease occurrence. Based on the achieved results, extending the design and development of new applications will be an objective for further research.

Author Contributions: Conceptualization, J.S. and L.S.; methodology, J.S. and H.B.; software, J.S. and H.B.; validation, H.B., L.S., J.S. and R.H.; formal analysis, J.S., H.B., J.D. and L.S.; investigation, J.S., J.D., H.B., L.S. and R.H.; resources, L.S. and J.S.; data curation, J.S., J.D., H.B., P.B., R.H. and T.H.; writing—original draft preparation, J.D. and L.S.; writing—review and editing, J.D. and L.S.; visualization, J.S. and P.B.; supervision, H.B. and L.S.; project administration, J.D. and L.S.; funding acquisition, J.D., L.S. and J.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Ministry of Agriculture of the Czech Republic (projects NAZV QK22010270).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Predicted probability distributions of states with homogeneous and non-homogeneous Markov chains.

Diseases	HMC 30 Optimal Number of States	HMC 30 Predicted Distribution	HMC 60 Optimal Number of States	HMC 60 Predicted Distribution	NHMC 30 Optimal Number of States	NHMC 30 Predicted Distribution	NHMC 60 Optimal Number of States	NHMC 60 Predicted Distribution
Eye Injury	3	[0.981 0.015 0.004]	4	[0.981 0.015 0.002 0.002]	4	[0.947 0.019 0.004 0.03]	4	[0.945 0.02 0.004 0.031]
Postpartum hypocalcemia	5	[0.979 0.004 0.01 0.006 0.001]	4	[0.979 0.004 0.01 0.007]	4	[0.9 0.007 0.005 0.088]	4	[0.897 0.007 0.006 0.09]
Laminitis	4	[0.926 0.05 0.019 0.005]	4	[0.928 0.05 0.018 0.004]	4	[0.906 0.057 0.025 0.012]	5	[0.901 0.055 0.022 0.004 0.018]
Retained placenta	3	[0.889 0.091 0.02]	3	[0.89 0.091 0.019]	3	[0.885 0.092 0.023]	4	[0.869 0.087 0.02 0.024]
Limb Edema	4	[0.884 0.082 0.031 0.003]	3	[0.883 0.083 0.034]	3	[0.865 0.094 0.041]	3	[0.859 0.1 0.041]
Diarrhea	8	[0.896 0.059 0.03 0.008 0.004 0.001 0.001 0.001]	5	[0.899 0.057 0.029 0.008 0.007]	5	[0.825 0.072 0.037 0.013 0.053]	5	[0.837 0.063 0.033 0.014 0.053]
High temperature after calving	4	[0.818 0.127 0.044 0.011]	4	[0.816 0.128 0.044 0.012]	4	[0.82 0.123 0.046 0.011]	4	[0.813 0.128 0.047 0.012]
Uterus	9	[0.905 0.041 0.018 0.007 0.01 0.005 0.007 0.004 0.003]	9	[0.905 0.041 0.017 0.007 0.01 0.005 0.007 0.004 0.004]	9	[0.875 0.05 0.017 0.004 0.011 0.002 0.002 0.004 0.035]	9	[0.875 0.051 0.014 0.004 0.012 0.002 0.002 0.004 0.036]
High temperature	6	[0.765 0.132 0.073 0.02 0.007 0.003]	4	[0.77 0.132 0.069 0.029]	6	[0.735 0.124 0.099 0.026 0.011 0.005]	4	[0.754 0.121 0.086 0.039]
Phlegmon	4	[0.948 0.034 0.015 0.003]	4	[0.949 0.032 0.015 0.004]	5	[0.856 0.049 0.02 0 0.075]	5	[0.861 0.043 0.021 0 0.075]
Respiration	5	[0.948 0.032 0.017 0.002 0.001]	4	[0.947 0.033 0.017 0.003]	4	[0.921 0.03 0.02 0.029]	4	[0.918 0.031 0.021 0.03]

Table A1. *Cont.*

Diseases	HMC 30 Optimal Number of States	HMC 30 Predicted Distribution	HMC 60 Optimal Number of States	HMC 60 Predicted Distribution	NHMC 30 Optimal Number of States	NHMC 30 Predicted Distribution	NHMC 60 Optimal Number of States	NHMC 60 Predicted Distribution
Endometritis	9	[0.891 0.032 0.016 0.011 0.014 0.015 0.007 0.004 0.01]	9	[0.891 0.033 0.016 0.011 0.014 0.015 0.007 0.004 0.009]	9	[0.791 0.039 0.023 0.009 0.009 0.014 0.011 0.011 0.093]	9	[0.788 0.041 0.022 0.009 0.007 0.015 0.007 0.011 0.1]
Necrobacillosis	5	[0.719 0.173 0.073 0.02 0.015]	5	[0.721 0.172 0.073 0.019 0.015]	7	[0.677 0.164 0.067 0.022 0.013 0.002 0.055]	7	[0.686 0.159 0.065 0.019 0.013 0.002 0.056]
Metabolic problems	5	[0.721 0.145 0.083 0.033 0.018]	5	[0.726 0.143 0.084 0.032 0.015]	6	[0.776 0.117 0.063 0.027 0.011 0.006]	7	[0.756 0.103 0.061 0.021 0.008 0 0.051]
Mastitis RB	10	[0.522 0.222 0.105 0.045 0.034 0.018 0.015 0.013 0.012 0.014]	10	[0.52 0.222 0.104 0.045 0.035 0.018 0.015 0.014 0.012 0.015]	14	[0.488 0.154 0.09 0.046 0.02 0.019 0.019 0.023 0.02 0.007 0.006 0.001 0.001 0.106]	10	[0.543 0.171 0.096 0.054 0.023 0.023 0.022 0.027 0.023 0.018]
Mastitis RF	17	[0.507 0.221 0.112 0.057 0.036 0.017 0.013 0.008 0.007 0.006 0.003 0.004 0.001 0.002 0.001 0.002 0.003]	16	[0.506 0.219 0.112 0.057 0.036 0.018 0.014 0.008 0.008 0.007 0.003 0.004 0.001 0.002 0.001 0.004]	11	[0.479 0.191 0.107 0.047 0.025 0.015 0.019 0.008 0.008 0.019 0.082]	11	[0.48 0.182 0.106 0.049 0.024 0.016 0.021 0.008 0.008 0.02 0.086]
Mastitis LB	11	[0.503 0.213 0.1 0.05 0.046 0.021 0.017 0.013 0.011 0.007 0.019]	11	[0.504 0.211 0.099 0.05 0.046 0.021 0.017 0.013 0.012 0.007 0.02]	11	[0.504 0.229 0.101 0.035 0.04 0.012 0.016 0.015 0.013 0.007 0.028]	11	[0.508 0.22 0.099 0.035 0.04 0.013 0.017 0.016 0.014 0.007 0.031]
Mastitis LF	22	[0.195 0.212 0.153 0.121 0.077 0.056 0.042 0.033 0.025 0.019 0.018 0.012 0.009 0.01 0.005 0.006 0.003 0.001 0.002 0 0.001 0]	13	[0.194 0.209 0.151 0.123 0.078 0.057 0.043 0.033 0.025 0.019 0.018 0.012 0.038]	14	[0.206 0.206 0.138 0.109 0.061 0.049 0.038 0.028 0.019 0.019 0.016 0.019 0.011 0.081]	14	[0.204 0.191 0.13 0.115 0.064 0.052 0.04 0.03 0.02 0.02 0.016 0.02 0.012 0.086]
Reproduction problems	36	[0.456 0 0.001 0.002 0.004 0.009 0.012 0.015 0.025 0.022 0.015 0.017 0.026 0.015 0.023 0.023 0.022 0.021 0.015 0.015 0.015 0.013 0.016 0.016 0.017 0.013 0.012 0.014 0.014 0.015 0.014 0.01 0.01 0.008 0.009 0.066]	36	[0.456 0 0.001 0.002 0.004 0.009 0.012 0.015 0.026 0.022 0.014 0.018 0.026 0.015 0.022 0.023 0.022 0.021 0.016 0.014 0.015 0.013 0.016 0.016 0.017 0.012 0.012 0.014 0.013 0.016 0.014 0.01 0.01 0.009 0.009 0.066]	40	[0.425 0 0.002 0.002 0.004 0.007 0.018 0.015 0.009 0.023 0.021 0.034 0.036 0.01 0.017 0.021 0.015 0.018 0.014 0.012 0.007 0.015 0.014 0.016 0.016 0.014 0.011 0.016 0.01 0.011 0.011 0.009 0.009 0.013 0.005 0.007 0.005 0.011 0.005 0.092]	40	[0.425 0 0.002 0.002 0.004 0.007 0.019 0.016 0.01 0.024 0.019 0.035 0.035 0.01 0.013 0.021 0.015 0.019 0.015 0.011 0.008 0.016 0.013 0.017 0.017 0.013 0.009 0.017 0.009 0.012 0.011 0.008 0.008 0.014 0.006 0.008 0.006 0.011 0.004 0.091]

Diseases—names of dairy diseases; HMC30 Opt. number of states R^*—Optimal number of states calculated for Homogenous Markov chain model for next 30 days; HMC 30 Predicted Distribution—predicted probability distribution of optimal states for Homogenous Markov chain model for next 30 days; HMC 60 Opt. number of states R^*—Optimal number of states calculated for Homogenous Markov chain model for next 60 days; HMC 60 Predicted Distribution—predicted probability distribution of optimal states for Homogenous Markov chain model for next 60 days; NHMC 30 Opt. number of states R^*—Optimal number of states calculated for Non-Homogenous Markov chain model for next 30 days; NHMC 30 Predicted Distribution—predicted probability distribution of optimal states for Non-Homogenous Markov chain model for next 30 days; NHMC 60 Opt. number of states R^*—Optimal number of states calculated for Non-Homogenous Markov chain model for next 60 days; NHMC 60 Predicted Distribution—predicted probability distribution of optimal states for Non-Homogenous Markov chain model for next 60 days.

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https://doi.org/10.17221/178/2024-CJAS

A decision support system for herd health management for dairy farms

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Citation: Saro J., Šubrt T., Brožová H., Hlavatý R., Rydval J., Ducháček J., Stádník L. (2024): A decision support system for herd health management for dairy farms. Czech J. Anim. Sci., 69: 502–515.

Abstract: Industrial dairy farms boast highly advanced health monitoring and disease diagnosis systems. But without easily accessible, user-friendly web platforms for real-time decision-making, most dairy farmers cannot proactively manage herd health management and optimize treatments based on disease prediction and prevention. To bridge this gap, we have developed a web application of a Decision support system (DSS) for dairy health management based on machine learning. The system architecture combines a Flask backend with a React frontend and scalable cloud data storage and includes preprocessing, data integration, predictive modelling, and cost analysis. DSS forecasts herd diseases with an accuracy 6.66 mean absolute error and 2.35 median absolute deviation across predictions. Its core predictive capabilities rely on long short-term memory (LSTM) neural networks to forecast disease progression from historical records and on a linear trend model to project cuts in treatment costs. The system calculates medication dosages and cost per disease, streamlines supplier selection, and simulates various treatment scenarios, thereby identifying high-cost diseases with potential savings. In other words, this DSS application processes disease and treatment data by incorporating veterinary records into advanced data analytics and neural networks, thereby predicting diseases, optimizing disease prevention and treatment strategies, and reducing costs. As such, this DSS application provides dairy farmers with a tool for strategic decision-making, veterinary treatment planning, and cost-effective disease management towards improving animal welfare and increasing milk yield.

Keywords: dairy cows; disease monitoring; neural networks, predictive analysis; treatment optimisation; web applications

Managing dairy herd health reduces economic losses by improving animal welfare (von Keyserlingk and Weary 2017) and prevents diseases such as lameness and clinical mastitis (Kasna et al. 2023). Poor dairy cow health can significantly decrease reproduction (Vacek et al. 2007), milk yield and farm revenue (Bruijnis et al. 2013) while simultaneously increasing veterinary costs (Kossaibati and

Supported by the the National Agency for Agricultural Research of the Ministry of Agriculture of the Czech Republic grant project QJ1510136 "Optimization of protein nutrition of monogastric animals based on white lupin (Lupinus albus) seed varieties".

https://doi.org/10.17221/178/2024-CJAS

Esslemont 1997). These issues may be mitigated through regular resilience and health monitoring and preventive measures (LeBlanc et al. 2006) aimed at enhancing the herd performance (Ritter et al. 2021) using sustainable and precision livestock farming approaches. Therefore, modern farm dairy management requires sophisticated health monitoring and disease diagnosis systems for treatment optimisation (Das et al. 2023).

In this context, decision support systems (DSS) have emerged as crucial tools for disease monitoring and diagnosis (Balhara et al. 2021), even providing actionable insights derived from real-time data analysis (Saro et al. 2024). Based on historical health records, in turn, DSSs also enable dairy farmers to optimise treatment protocols by reducing the antibiotic use (Alawneh et al. 2018) and to improve animal welfare by identifying the most effective husbandry systems (Ursinus et al. 2009). In dairy cow health management, DSSs further help farmers and veterinarians alike to make informed decisions by leveraging advances in data science, machine learning (Slob et al. 2021), and web technologies. Case in point, incorporating sensor (Simoni et al. 2024) and machine learning algorithms (Dervic et al. 2024) into DSSs facilitates animal health management, including the detection of early signs of mastitis, lameness, and other common ailments.

Beyond early disease onset detection, major advances in predictive analytics (Ferris et al. 2020) have spurred the development of dairy farming DSSs capable of forecasting disease outbreaks and health issues by integrating emerging artificial intelligence (AI) technology (Vlaicu et al. 2024). Neural networks (Ufitikirezi et al. 2024) and other predictive models have demonstrated the ability to project health trends (Hunter et al. 2021) and to predict common disorders (Zhou et al. 2022) and disease risk (Lasser et al. 2021) in dairy cows based on past data. Providing real-time updates, web-based DSSs have made these tools more accessible to farmers by combining cloud computing with mobile applications (Dhifaoui et al. 2024).

Notwithstanding these advances, predictive DSSs are implemented almost exclusively in industrial-scale operations because they require substantial infrastructure, such as continuous data streams from sensors and external sources, in addition to sophisticated integration tools (Alwadi et al. 2024). Most DSSs focus on monitoring key metrics, ranging from milk production to feed intake rather than predicting health outcomes and incorporating AI or machine learning for disease prediction (Baldin et al. 2021). Effectively integrating predictive DSS into daily farming routines requires web-based, user-friendly interfaces and adaptable models.

Considering the above, we developed a DSS prototype integrating dairy cow disease monitoring, treatment management, predictive analytics, and trend analysis into a comprehensive web application for dairy cow health management. The system aims at (*i*) enhancing disease detection by leveraging real-time data and machine learning, (*ii*) optimising treatments by providing data-driven recommendations, and (*iii*) predicting health trends by deploying predictive models to forecast health issues and disease outbreaks. This web-based interface makes predictive DSS accessible to farmers and veterinarians whilst providing real-time updates and predictive trends.

MATERIAL AND METHODS

Data collection and description

To develop and test this DSS, veterinary records of dairy farm from western Bohemia collected for 5 years were used. These records were sourced from farm management software, veterinary reports, and manual entries provided by the farm staff.

Each record contained the following key data points (Table 1). The data were divided into historical training data (for model building) and real-time data (for DSS testing).

The main part of the dataset includes records of 52 infectious and non-infectious diseases outlined in Table 2.

Data preprocessing

Prior to submitting data into the DSS, the raw dataset was pre-processed to ensure consistency and quality as follows: (*i*) Data cleaning: incomplete records (e.g. missing treatment or cost information) and duplicate entries were identified and removed from the dataset. (*ii*) Transformation: data were transformed into a time series, associating each disease incidence with a time index for outbreak prediction.

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Table 1. Summary of the attributes used in the dairy farm disease log, tracking disease incidence, treatments, and associated costs

Data	Attribute	Description
Occurrence date	occurrence_date	The date the disease was detected in the animal.
Disease	disease	The disease affecting the animal (e.g. mastitis).
Disease diagnosis code	disease_diagnosis_code	A specific code representing the diagnosis of the disease.
Treatment medication	treatment_medication	The name of the medication used to treat the disease (e.g. "NOROSTREP").
Dosage	dosage	The amount of medication given to the animal during the treatment.
Total dosage	total_dosage	The total amount of medication given over the treatment period.
Medication supplier	medication_supplier	The supplier who provided the medication.
Medication cost	medication_cost	The cost of the medication per dosage or unit.
Treatment cost	treatment_cost	The total cost of the treatment, including medication and other expenses.
Farm location	farm_location	The physical location or farm where the animal is being treated.
Animal type	animal_type	The species or type of animal receiving the treatment (e.g, cow, calf).
Animal ID	animal_id	A unique identifier for the animal (e.g. ear tag number).

attribute = variable name in the dataset for each field; data = name of each field related to a farm record; description = explanation of the contents of each field, covering disease incidence, treatment details, costs, location, and animal identifiers

Table 2. Monitored infectious and non-infectious diseases of dairy cows recorded on the study farm

Disease	Mean per month	STD per month	Min occurrence per month	Max occurrence per month	Median occurrence per month
Escherichia coli	132	32.50	49	200	125
Bovine Herpes virus (BHV-1)	63.50	16.50	36	100	60
Intranasal	31.50	7.53	20	55	30.50
Vaccine	73.70	38.10	19	135	89
Abscess	0.97	2.83	0	14	0
Acidosis	0.05	0.29	0	2	0
Minor injuries	0.17	0.64	0	4	0
Dermatitis	0.20	0.86	0	6	0
Abomasal displacement	0.52	1.35	0	7	0
Uterine disease	8.37	10.60	0	40	1.50
Endometritis	9.63	11.60	0	43	3
Phlegmon	2.35	3.70	0	14	0
Coccidiosis	31.40	11.20	18	62	38
Colic	0.02	0.13	0	1	0
Blood in milk	0.12	0.42	0	2	0
Haemorrhage	0.17	0.56	0	3	0
Mastitis	0.37	1.31	0	8	0
Mastitis left front teat	110	70.60	19	339	92
Mastitis left rear teat	48.60	59.70	0	247	22.50
Mastitis right front teat	44.50	55.50	0	291	25.50
Mastitis right rear teat	41	47.40	0	181	23.50
Metabolic disorder	13.60	10.60	0	40	11.50
Foot rot	13.80	8.69	2	41	12
Nerve injury	0.23	0.85	0	6	0

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Table 2. to be continued

Disease	Mean per month	STD per month	Min occurrence per month	Max occurrence per month	Median occurrence per month
Other	15.50	48.40	0	374	4.50
Limb oedema	13.50	14.60	0	74	8.50
Udder oedema	0.07	0.31	0	2	0
Jaw swelling	1.37	3.73	0	25	0
Hoof disease	3.20	3.91	0	17	1.50
Peritonitis	0.58	2.11	0	13	0
Hypothermia	0.05	0.39	0	3	0
Postpartum sepsis	0.23	1.57	0	12	0
Eye injury	0.88	1.76	0	8	0
Teat injury	0.25	0.97	0	6	0
Postpartum uterine torn	0.37	1.12	0	5	0
Superficial injury	0.28	1.08	0	5	0
Prevention	1.58	11.20	0	87	0
Diarrhoea	47.60	31.30	0	149	40.50
Umbilical hernia	0.10	0.54	0	3	0
Reproductive disorder	355	52.80	216	471	357
Respiratory disease	27.60	30.20	1	130	17
Fever	21.50	19.60	0	80	15
Postpartum fever	7.10	4.32	0	19	6.50
Gastrointestinal disorder	0.90	2.78	0	15	0
Tympany	0.75	2.21	0	12	0
Downer cow	1.62	2.73	0	13	0
High somatic cell count	1.17	5.72	0	40	0
Retained placenta	3.67	3.18	0	13	2.50
Drying-off	44.7	8.31	30	69	46
Navel inflammation	7.33	6.12	0	32	7.50
Conjunctivitis	0.15	0.66	0	3	0
Pneumonia	0.63	2.78	0	18	0

disease = name of the disease analysed; max incidence per month = highest monthly number of disease events; mean per month = average monthly incidence; median incidence per month = middle value of monthly disease events; min incidence per month = lowest monthly number of disease events; STD per month = variation in the incidence of the disease from the average of disease incidence

Decision support system (DSS)

The DSS implemented in this study integrates both data-driven and model-driven approaches. It utilises historical veterinary data to predict disease outbreaks and assist farmers in making proactive health management decisions for their herds. The user interface of the system was designed with simplicity in mind, ensuring accessibility for users with varying levels of technical expertise, while still offering powerful analytical tools through machine learning models, such as LSTM networks.

RESULTS

Design of the decision support system for herd health

The DSS prototype developed in this study was implemented using Flask, a Python web framework, leveraging several libraries for data processing and machine learning. This DSS processes veterinary records from a farm, primarily focused on treatments. Providing functionalities for managing data on treatments, the system predicts trends using

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long short-term memory (LSTM) neural networks and analysing linear trends (Figure 1).

Architecture of the decision support system for herd health

The DSS was designed to optimize animal treatment by leveraging modern web technologies with machine learning. The DSS architecture integrates machine learning with farm management systems to support decision-making on disease treatment and cost management. Its architecture consists of the following components:

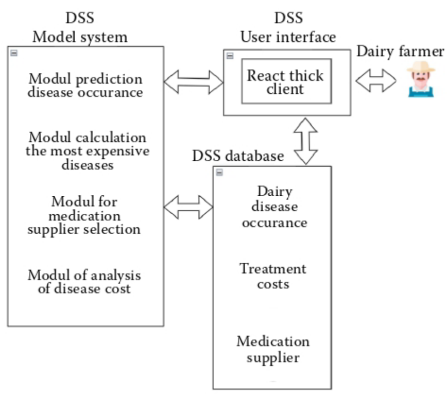

Figure 1. Architecture for dairy health management decision support system (DSS)

Backend. Implemented using Flask, this component handles data processing and model training and runs predictions.

Frontend. Built using React, a JavaScript library; this component provides dairy farmers with a user-friendly interface to upload data, view statistical trends, access predictions, and receive recommendations. Together with the backend, the frontend integrates pre-processed data into an Azure web application, where Flask manages backend operations, and React serves as the thick client for user interactions.

Data storage system. Microsoft Azure's cloud storage provides a robust and scalable infrastructure for storing, processing and managing large datasets, ensuring scalability.

Machine learning. Trained on the historical disease data to predict diseases and to calculate optimal treatment costs, the core predictive models of this DSS are built using LSTM neural networks for time-series forecasting.

As shown in Figure 2, the DSS dashboard provides real-time insights into health monitoring, disease predictions, medication costs, and supplier comparisons, all through a user-friendly interface designed for efficient herd health management.

Data flow in the decision support system for herd health

Designed to optimise disease treatments and treatment costs at the herd level from a dairy farm, the

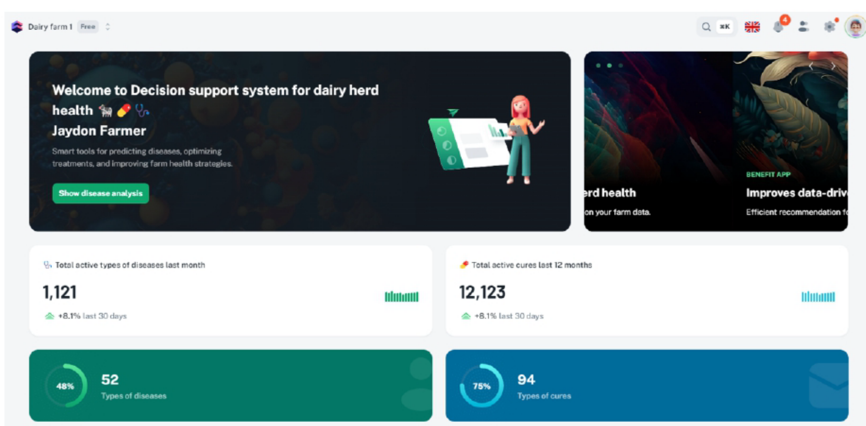

Figure 2. Dashboard screen of the decision support system (DSS) web application

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DSS begins by extracting raw data on diseases and associated treatments from records of the dairy farm to create a comprehensive map, including price and supplier information on each treatment. Raw data undergo preprocessing steps, such as cleaning and normalisation, to ensure that they are suitable for DSS processing. Using Flask for backend operations, the pre-processed data are then integrated into a Microsoft Azure web application and compiled into historical time series data for both diseases and treatments, providing the basis for predictive modelling. The backend system communicates with a thick client developed using React to create an interactive and dynamic user interface for dairy farmer, enabling to input and analyse data, view trends, and interact with the system (Figure 3).

At the core of the DSS lie the modules which analyse the processed data to provide actionable insights, predictions and recommendations. The DSS employs machine learning through LSTM neural networks. Using LSTM neural networks, the DSS predicts diseases for upcoming periods and calculates linear trends over specific intervals. These data are a basis for calculations of treatment doses required for predicted disease levels. For each disease, treatment costs are subsequently computed per suppliers, enabling the DSS to identify the most cost-effective ones among the current and potential suppliers by adding total treatment expenses across all diseases. Optimal suppliers are then selected based on minimal total cost, ensuring cost-effective treatment provisioning.

Creating different scenarios is allowed to assess cost impacts under different conditions. This process involves identifying high-cost treatments to target potential savings and calculating cost reductions from decreasing a high-incidence disease through preventive measures and alternative medications. A linear trend model is applied to project the number of treatments reduced over time, contributing to long-term budgeting and strategic planning. Ultimately, the DSS integrates predictive modelling, cost analysis, and scenario simulations, providing efficient and economical treatment strategies for disease management (Figure 4).

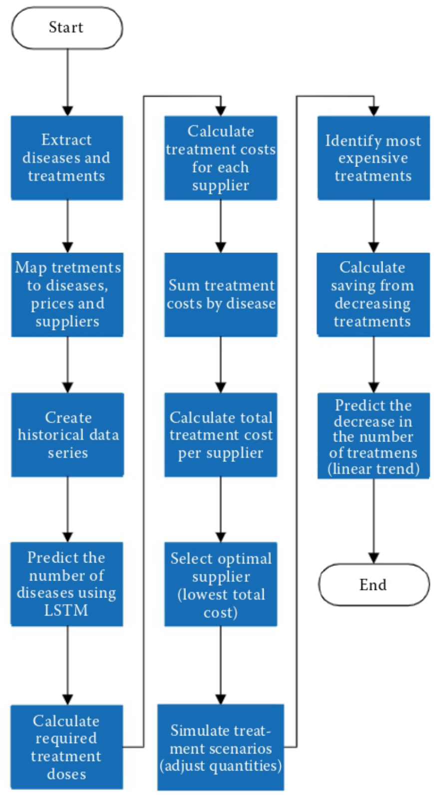

Figure 4. Diagram of all modules calculation in the decision support system (DSS) web application for dairy disease records

LSTM = long short-term memory

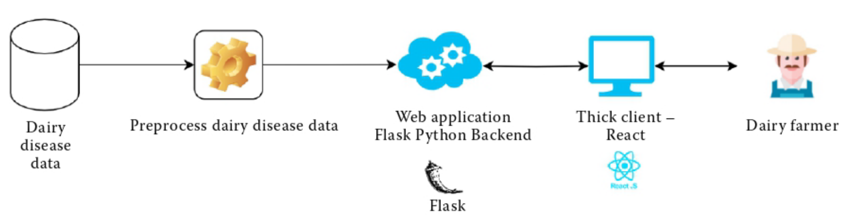

Figure 3. Schematic diagram of the data flow in the decision support system (DSS) web application for diary diseases

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Mathematical models in the decision support system for herd health

In this section, we define the key variables used in the mathematical models of the DSS for herd health, including diseases, medications, time periods, and suppliers, which form the basis for optimising treatment strategies and procurement processes.

Disease $k = 1, ..., K$; where K is the total number of diseases.

Medication $m = 1, ..., M$; where M is the total number of used medications.

Time periods $t = 1, ..., T$; where T is the total number of past time periods.

Suppliers $s = 1, ..., S$; where S is the total number of suppliers, and the current supplier has index 1.

Figure 5 displays a screenshot of the web application showcasing the medication price delivery feature. The interface provides users with real-time pricing information from various suppliers, allowing for comparison and selection of the most cost-effective options. The layout is designed to streamline the decision-making process regarding medication procurement.

Disease prediction using a neural network. The disease prediction is a core task of the DSS for herd health management. For each disease k, the LSTM neural network predicts the number of disease events for the period $t + 1$ based on past data:

$$y^k_{(t+1)} = f(y^k_t, y^k_{(t-1)}, ..., y^k_1) \quad (1)$$

where:

$f(y^k_t, y^k_{(t-1)}, ..., y^k_1)$ – the LSTM neural network function that maps past data to the prediction. LSTM neural network was implemented using the TensorFlow/Keras Python library;

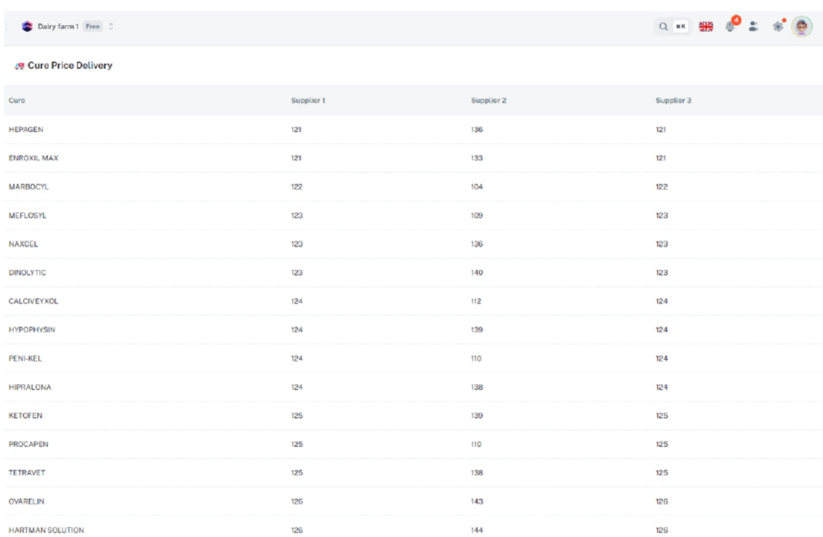
y^k_{t+1} – the predicted number of events of disease k in the period $t + 1$;

$y^k_t, y^k_{(t-1)}, ..., y^k_1$ – past data on disease k at time t, t–1...,1;

t – the current time period $t + 1$ the next predicted time period;

k – index representing a specific disease.

In the implemented LSTM model for disease prediction, the training parameters are as follows: the model uses a batch size of 1 and is trained for 1 epoch. The optimiser used is Adam, which is commonly employed for time series forecasting tasks due to its efficiency and adaptability. The learning rate is set to the default value used by Adam, which is 0.001. The training data is divided into a training



Cure	Supplier 1	Supplier 2	Supplier 3
HEPAGEN	121	136	121
ENROXIL MAX	121	133	121
MARBOCYL	122	104	122
MEFLOSYL	123	109	123
NAXCEL	123	136	123
DINOLYTIC	123	140	123
CALCIVEYXOL	124	112	124
HYPOPHYSIN	124	139	124
PENI-KEL	124	110	124
HIPRALONA	124	138	124
KETOFEN	125	139	125
PROCAPEN	125	110	125
TETRAVET	125	138	125
OVARELIN	126	143	126
HARTMAN SOLUTION	126	144	126

Figure 5. Medication price delivery – screenshot of the web application

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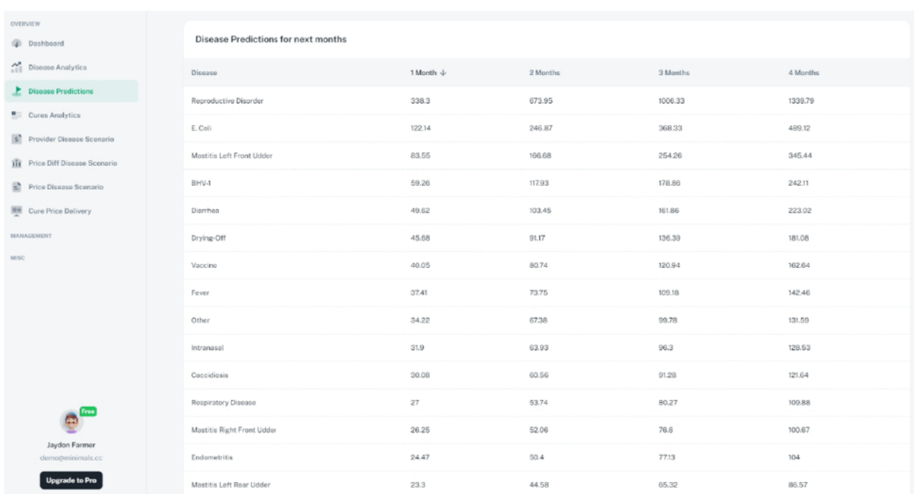
set and a testing set, with the latter used for validating the predictive performance of the model. Data preprocessing involves scaling the time series data using MinMaxScaler (a Python library that scales each feature to a specified range) to normalise the values to normalise the values between 0 and 1, followed by the creation of sequences for training. The performance of the model is evaluated using the mean absolute error (MAE), and predictions are generated for a forecast length of 20% of the dataset.

Using this formula, the model predicts disease incidence based on patterns in historical data. The screen in Figure 6 displays the disease prediction results, showing metabolic disorders.

Figure 7 shows disease predictions for the upcoming months, utilising an LSTM neural network. The model forecasts the expected incidence of various diseases, providing a month-by-month outlook. This visual representation helps in understanding potential disease trends and planning preventive measures accordingly.

Linear trend of disease incidence development. To show the direction of the development of disease incidence, the linear trend for data $y_t^k, y_{t-1}^k, \ldots, y_1^k$ supposed the following formula whose parameters are

Figure 6. Disease prediction using an long short-term memory (LSTM) neural network – metabolic disorders



Disease	1 Month	2 Months	3 Months	4 Months
Reproductive Disorder	338.3	673.95	1006.33	1339.79
E. Coli	122.14	246.87	368.33	489.12
Mastitis Left Front Udder	83.55	166.68	254.26	345.44
BHV-1	59.26	117.93	178.86	242.11
Diarrhea	49.62	103.45	161.86	223.02
Drying-Off	45.68	91.17	136.39	181.08
Vaccine	40.05	80.74	120.94	162.64
Fever	37.41	73.75	109.18	142.46
Other	34.22	67.38	99.78	131.59
Intranasal	31.9	63.93	96.3	128.53
Coccidiosis	30.08	60.56	91.28	121.64
Respiratory Disease	27	53.74	80.27	109.88
Mastitis Right Front Udder	26.25	52.06	76.6	100.67
Endometritis	24.47	50.4	77.13	104
Mastitis Left Rear Udder	23.3	44.58	65.32	86.57

Figure 7. Disease predictions for the following months

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estimated by the least squares method. The model was computed using the scikit-learn library:

$$y_j^k = \alpha^k + \beta^k \times j \quad (2)$$

where:
y_j^k – the (predicted) incidence of disease k for the period j;
α^k – the intercept term for disease k, representing the starting or baseline level of the disease;
β^k – the slope, indicating the rate of change in disease k over time; a positive β^k suggests an increasing trend, while a negative β^k suggests a decreasing trend;
$j = 1, 2, \ldots, t$ – time indices.

Calculation of medication doses for predicted disease incidence in period. The predicted dose of medication for treating disease k in the herd in period is calculated as a proportional function of the medication doses:

$$d_{(m,t+1)}^k = r_m^k \times y_{(t+1)}^k \quad (3)$$

where:
$d_{(m,t+1)}^k$ – the dose of medication m required for disease k in the period $t + 1$;
r_m^k – the proportion of medication m needed to treat disease k;
y_{t+1}^k – the predicted number of events of disease in the period $t + 1$ Equation (1);
m – a type of medication;
k – a specific disease.

This calculation determines the dosage of each medication m required to treat the predicted events of disease k.

Dose prediction using a linear trend. Assuming the linear trend of the development of disease k through treatment for the next period, the model predicts the trend of that development according to the following formula whose parameters are estimated by the least squares method:

$$d_{(m,t)}^k = \gamma^k + \delta^k \times t \quad (4)$$

where:
$d_{m,t}^k$ – number of treatments of disease k for the period t;
γ^k – intercept term for disease k, representing the starting or baseline level of the disease;
δ^k – slope, indicating the rate of change in disease k over time; a positive δ^k suggests an increasing trend, while a negative δ^k suggests a decreasing trend,
t – time period $t, t - 1, \ldots, 1$.

Scenario simulation with predicted values. For creating scenarios, when we assume a decrease or an increase in the disease incidence by the step of 5%, we use the following formula:

$$y(x)_{(t+1)}^k = y_{(t+1)}^k \times (1 + x) \quad (5)$$

where:
$y(x)_{(t+1)}^k$ – prediction for the number of events of disease k under the scenario x%;
$y(x)_{(t+1)}^k = y_{(t+1)}^k$ – predicted number of events of disease k Equation (1);
$x \in \{-0.2, -0.15, -0.1, -0.05, 0, 0.05, 0.1, 0.15, 0.2\}$ – % change applied to the prediction.

This formula models eight new scenarios by adjusting the predicted disease incidence.

Calculation of expected medication costs. The total cost of treating disease k with all necessary medication $m \in \{1, \ldots, M\}$ from the current supplier $s = 1$ in period $t + 1$ is calculated as follows:

$$C_s^k = \sum_{m \in \{1,\ldots,M\}} (d_{(m,t+1)}^k \times p_{m,s}) \quad (6)$$

where:
C_s^k – the expected total cost of treating disease k with all medication from supplier s;
$d_{(m,t+1)}$ – the dose of medication m required for disease k (3);
$p_{m,s}$ – the price of medication m from supplier s,
m – medication;
s – the current supplier.

This calculation aggregates the costs of all medications needed to treat disease k with products from supplier s and can be used for each supplier.

Calculation of total expected medication costs. The total cost of all diseases treated with medications from the current supplier $s = 1$ in the period $t + 1$ is calculated by summing the costs of all diseases:

$$CT_s = \sum_{k=1}^{K} C_s^k \quad (7)$$

where:
CT_s – the total cost of treating all diseases with medication from supplier s;

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C_s^k – the cost of treating disease with medication from supplier s (4);
k – disease;
$s = 1$ – the current supplier.

This calculation can be used for each supplier.

The most expensive diseases and savings from decreased incidence. The most expensive disease k^* for supplier s is the disease with the highest cost:

$$k^*: C_s^{(k*)} = \max_k C_s^k \tag{8}$$

where:
C_s^k – the cost of treating disease with medication from supplier s(4);
k – disease;
k^* – the disease with the maximum treatment cost;
$s = 1$ – the current supplier.

The savings from decreasing the incidence of disease k are calculated as the difference between the cost of current and reduced disease incidence:

$$\Delta C_s^k = C_s^k \times x \tag{9}$$

where:
ΔC_s^k – cost savings from reducing the incidence of disease k;
C_s^k – the original cost of treating disease k with medication from supplier j;
$x \in \{-0.2, -0.15, -0.1, -0.05, 0, 0.05, 0.1, 0.15, 0.2\}$ – the % change applied to the prediction.

The disease with the highest potential savings from its decreased incidence is identified by maximising the cost difference:

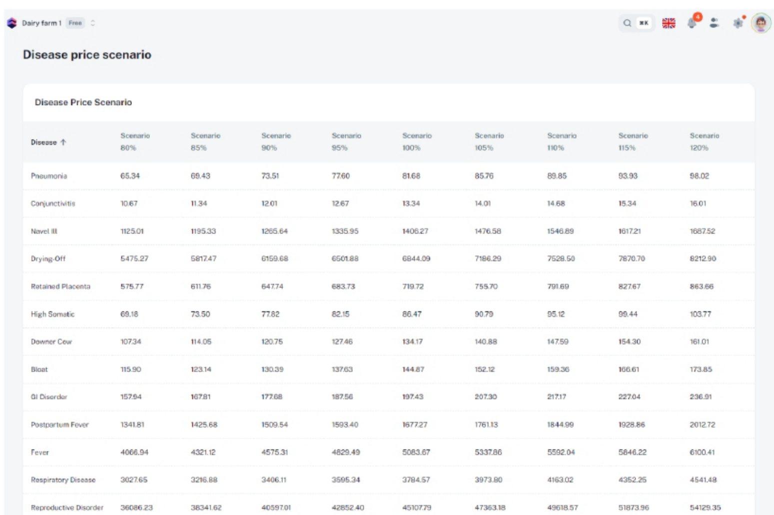
$$l^*: \Delta C_s^{l^*} = \max_k \Delta C_j^k \tag{10}$$

where:
l^* – the disease with the maximum potential savings;
ΔC_j^k – the cost cut resulting from reducing the incidence of disease k with medication from supplier s.

This expression identifies the disease l^* with the highest potential for cost savings by maximising the difference in costs after reducing the incidence of l^*.

Figure 8 illustrates the disease price scenario, depicting the projected costs associated with various diseases. The chart or table showcases different scenarios, factoring the variables such as disease prevalence and medication costs. This visualisation aids in comparing the financial impact of managing different diseases, helping users to optimise their resource allocation and reduce overall expenses. The disease price scenario is illustrated in Figure 8, highlighting projected costs for various diseases based on prevalence and medication expenses, aiding in financial comparison and resource optimisation.

Cost savings by disease are shown in Figure 9, demonstrating how targeted interventions or optimised



Disease	Scenario 80%	Scenario 85%	Scenario 90%	Scenario 95%	Scenario 100%	Scenario 105%	Scenario 110%	Scenario 115%	Scenario 120%
Pneumonia	65.34	69.43	73.51	77.60	81.68	85.76	89.85	93.93	98.02
Conjunctivitis	10.67	11.34	12.01	12.67	13.34	14.01	14.68	15.34	16.01
Navel Ill	1125.01	1195.33	1265.64	1335.95	1406.27	1476.58	1546.89	1617.21	1687.52
Drying-Off	5475.27	5817.47	6159.68	6501.88	6844.09	7186.29	7528.50	7870.70	8212.90
Retained Placenta	575.77	611.76	647.74	683.73	719.72	755.70	791.69	827.67	863.66
High Somatic	69.18	73.50	77.82	82.15	86.47	90.79	95.12	99.44	103.77
Downer Cow	107.34	114.05	120.75	127.46	134.17	140.88	147.59	154.30	161.01
Bloat	115.90	123.14	130.39	137.63	144.87	152.12	159.36	166.61	173.85
GI Disorder	157.94	167.81	177.68	187.56	197.43	207.30	217.17	227.04	236.91
Postpartum Fever	1341.81	1425.68	1509.54	1593.40	1677.27	1761.13	1844.99	1928.86	2012.72
Fever	4066.94	4321.12	4575.31	4829.49	5083.67	5337.86	5592.04	5846.22	6100.41
Respiratory Disease	3027.65	3216.88	3406.11	3595.34	3784.57	3973.80	4163.02	4352.25	4541.48
Reproductive Disorder	36086.23	38341.62	40597.01	42852.40	45107.79	47363.18	49618.57	51873.96	54129.35

Figure 8. Disease price scenario

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treatments lead to significant financial benefits and support effective cost management.

Calculation of expected medication costs for the cheapest supplier. Using the formula (7) the total treatment cost is calculated for each supplier. The best supplier s^* is then selected minimising the total cost:

$$s^{*}: CT_{s*} = \min_{s} CT_{s} \tag{11}$$

where:
s^* – the supplier with maximum potential savings;
CT_s – the total cost of treating supplier s (4);
s – supplier.

Disease difference price scenario

Disease Difference Price Scenario

Disease ↑	Scenario 20%	Scenario 15%	Scenario 10%	Scenario 5%	Scenario 0%	Scenario 5%	Scenario 10%	Scenario 15%	Scenario 20%
Pneumonia	-16.34	-12.25	-8.17	-4.08		4.08	8.17	12.25	16.34
Conjunctivitis	-2.67	-2.00	-1.33	-0.67		0.67	1.34	2.00	2.67
Navel Ill	-281.26	-210.94	-140.63	-70.32		70.31	140.62	210.94	281.25
Drying-Off	-1368.82	-1026.62	-684.41	-342.21		342.20	684.41	1026.61	1368.81
Retained Placenta	-143.95	-107.96	-71.98	-35.99		35.98	71.97	107.95	143.94
High Somatic	-17.29	-12.97	-8.65	-4.32		4.32	8.65	12.97	17.30
Downer Cow	-26.83	-20.12	-13.42	-6.71		6.71	13.42	20.13	26.84
Bloat	-28.97	-21.73	-14.48	-7.24		7.25	14.49	21.74	28.98
GI Disorder	-39.49	-29.62	-19.75	-9.87		9.87	19.74	29.61	39.48
Postpartum Fever	-335.46	-251.59	-167.73	-83.87		83.86	167.72	251.59	335.45
Fever	-1016.73	-762.55	-508.36	-254.18		254.19	508.37	762.55	1016.74
Respiratory Disease	-756.92	-567.69	-378.46	-189.23		189.23	378.45	567.68	756.91
Reproductive Disorder	-9021.56	-6766.17	-4510.78	-2255.39		2255.39	4510.78	6766.17	9021.56

Figure 9. Cost savings by disease

Provider Price Scenario

Percentage ↑	Provider 1	Provider 2	Provider 3	Difference Provider 1	Difference Provider 2	Difference Provider 3
80	-29866.88	-30816.31	-29866.88	119467.50	123265.24	119467.50
85	-22400.16	-23112.23	-22400.16	126934.22	130969.32	126934.22
90	-14933.44	-15408.15	-14933.44	134400.94	138673.39	134400.94
95	-7466.72	-7704.08	-7466.72	141867.66	146377.47	141867.66
100	0.00	0.00	0.00	149334.38	154081.55	149334.38
105	7466.72	7704.08	7466.72	156801.10	161785.62	156801.10
110	14933.44	15408.15	14933.44	164267.82	169489.70	164267.82
115	22400.16	23112.23	22400.16	171734.54	177193.78	171734.54
120	29866.88	30816.31	29866.88	179201.25	184897.86	179201.25

View all ›

Figure 10. Provider cost scenarios by disease

Provider cost scenarios by disease are shown in Figure 10, comparing expenses from different suppliers. This helps evaluate cost variations and identify the most economical options for managing various diseases.

DSS accuracy

The accuracy of the neural network in Table 3 was assessed using the mean absolute error (MAE) for predicting various dairy cow diseases at the herd level. Across all predictions, MAE was 6.66,

https://doi.org/10.17221/178/2024-CJAS

Table 3. Accuracy of disease prediction using the long short-term memory (LSTM) neural network

Disease	MAE per month	MAD per month
Escherichia coli	21.51	17.44
BHV-1	11.68	11.88
Intranasal	6.37	4.02
Vaccine	11.38	5.54
Abscess	2.82	3.93
Acidosis	0.01	0
Minor injuries	0.84	1.19
Dermatitis	0.70	1.54
Abomasal displacement	0.54	0.31
Uterine disease	4.70	2.97
Endometritis	7.01	4.56
Phlegmon	2.01	0.43
Coccidiosis	10.33	3
Colic	0.02	0
Blood in milk	0.14	0
Haemorrhage	0.18	0.01
Mastitis	1.55	2.35
Mastitis left front teat	51.16	21.83
Mastitis left rear teat	17.34	9.26
Mastitis right front teat	14.44	6.31
Mastitis right rear teat	10.18	6.76
Metabolic disorder	7.47	6.63
Foot rot	6.90	3.80
Nerve injury	0.22	0.23
Other	9.02	6.87
Limb oedema	10.36	6.73
Udder oedema	0.04	0
Jaw swelling	2.57	2.25
Hoof disease	3.12	3.57
Peritonitis	1.78	1.06
Hypothermia	0.06	0
Postpartum sepsis	0.35	0.47
Eye injury	2.16	2.29
Teat injury	0.42	0.38
Postpartum uterine torn	0.40	0.37
Superficial injury	0.40	0.02
Prevention	1.10	0
Diarrhoea	29.99	22.94
Umbilical hernia	0.06	0
Reproductive disorder	32.84	31.51
Respiratory disease	20.02	27.95
Fever	17.65	11.21
Postpartum fever	3.11	2.54
Gastrointestinal disorder	1.26	0.09
Tympany	0.88	0.25
Downer cow	1.41	0.52
High somatic cell count	0.36	0
Retained placenta	2.64	1.85
Drying-off	7.77	2.70
Navel inflammation	6	3.57
Conjunctivitis	0.08	0
Pneumonia	1.03	0.97

BHV-1 = bovine herpes virus; disease = name of the disease predicted; MAD = mean absolute deviation, the average deviation from the mean monthly incidence, showing variability; MAE = mean absolute error, the average error in monthly disease predictions; .

indicating the overall average difference between predicted and actual values. The median absolute deviation (MAD) was 4.69, suggesting that most predictions had a lower deviation than the mean. These results demonstrate that our neural network effectively predicts the disease incidence although some predictions show higher deviations, most likely due to the complexity of specific disease patterns.

DISCUSSION

We have developed a DSS web application with an integrated LSTM neural network for herd-level disease prediction and veterinary treatment planning. The key capabilities of this system include uploading and managing Excel files containing veterinary treatment records, extracting medication and diagnosis lists, performing statistical analysis of treatment data, predicting disease incidence, and calculating linear trends for disease data over various periods. The endpoints support operations, such as file management, treatment and disease management, statistical analysis, disease predictions, and trend analysis, providing comprehensive support for herd-level veterinary record management and decision-making on a dairy farm. Our DSS prototype optimises cost management using predictive data, helping farmers to plan expenses and select suppliers, which is essential for farms with limited resources. This approach bridges the knowledge gap between animal health and economics (af Sandeberg et al. 2023).

https://doi.org/10.17221/178/2024-CJAS

Leveraging time-series data for forecasting, this system empowers dairy farmers with an easily accessible tool for proactive and cost-efficient management of herd health in contrast to previous systems focused on individual animals, such as those utilising artificial neural networks (ANN) for mastitis detection or recurrent neural networks (RNN) for reproductive cycle prediction. For instance, ANN-based systems have proved effective in detecting mastitis using sensor data (Sun et al. 2010), but our LSTM model optimises treatment strategies and costs at the herd level, providing broader scalability and greater economic benefits for dairy operations. LSTM models are especially effective for time-series predictions, including forecasting disease outbreaks (e.g. influenza) in public health, which can also be applied to predict disease trends in dairy herds (Amendolara et al. 2023). This approach supports resource optimization, reduces medication usage, and improves overall herd health outcomes by anticipating future disease patterns and enabling better preparation for potential outbreaks.

Despite these advantages, some limitations remain. Our system relies on the availability and quality of the historical data, which may affect its predictive accuracy. Moreover, environmental factors, such as weather conditions and farm-specific practices, may affect disease incidence, but they are not yet incorporated into the model. Future iterations of this DSS prototype should improve the system by integrating such data and expanding its predictive capabilities to a wider range of diseases.

Although the DSS developed in this study offers strategic decision support on a herd level (Cabrera 2021), this assistant is provided without requiring a big data warehouse solution for storage management. This herd-wide approach is advantageous not only in providing a comprehensive view of disease prevalence across a farm but also in supporting farms with limited budgets (Steeneveld and Hogeveen 2015). Those farms often lack access to sensor technology commonly used in precision livestock farming. By implementing machine learning algorithms like LSTM, the system enables dairy farmers to predict diseases relatively accurately by sharing herd health management insights with no need for a high financial investment in on-animal sensors (Steeneveld et al. 2017).

The applicability of this system is further reinforced by its adaptability across various livestock species, such as pigs and poultry in providing appropriate time-series data for disease incidence and medication costs. Additionally, our application incorporates a new UX design aimed at simplicity. Thanks to this design, users without advanced technical skills can intuitively navigate the application, which is crucial for DSS web applications, as shown in the development of DSS Dairy Brain (Ferris et al. 2020). Ease of use and intuitive navigation are critical for fostering the adoption of DSS tools by dairy farmers, regardless of their level of technical expertise (Baldin et al. 2021).

CONCLUSION

The DSS prototype developed in this study to manage dairy disease data may enhance farm management practices. By offering robust data management, detailed statistical analysis, accurate predictive analytics, and insightful trend analysis, the system supports informed decision-making. These capabilities may improve animal health and overall farm productivity, showcasing the potential of DSS in modern dairy farming.

Conflict of interest

The authors declare no conflict of interest.

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Received: October 29, 2024
Accepted: December 6, 2024
Published online: December 23, 2024

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Discussion

Research question 1: A Decision Support System Based on Disease Scoring Enables Dairy Farmers to Proactively Improve Herd Health

Developing a DSS based on disease scoring was a major step towards promoting proactive herd health management in dairy farming. This system effectively categorises and scores diseases by severity, offering a nuanced understanding of herd health dynamics. The key innovation lies in classifying production diseases into six primary dairy disease categories used in dairy farming, enabling data-driven farm management. This DSS successfully identifies disease trends and supports targeted interventions. However, its reliance on historical records underscores the need for continuous data updates. And while this DSS proves effective in Czech farms, its broader implementation may require adapting to varying farm management practices globally.

Research question 2: Discrete Homogeneous and Non-Homogeneous Markov Chains Enhance Predictive Modelling for Dairy Cow Diseases

The use of Markov chains in predictive modelling for dairy cow diseases offers a promising method for anticipating disease occurrences. This approach addresses limitations in traditional machine learning models by effectively handling unavailable and incomplete farm data. Differentiating homogeneous from non-homogeneous Markov chains enhances the adaptability of the model to varying disease progression patterns. Case in point, applying Chebyshev distance minimisation ensures accurate model selection. Expanding this predictive framework to other farm management systems may enhance its practical utility and scalability. Furthermore, this model can be used on dairy farms regardless of their technological level, in contrast to solutions leveraging machine learning or deep learning, which cannot be applied to traditional, smallholder Czech farms lacking high or advanced technical equipment. Therefore, this model has a high potential for application in dairy farms in the Czech Republic and other nations, whether developed or developing countries.

Research question 3: A Web-Based Decision Support System for Dairy Herd Health Management

Utilising Long Short-Term Memory (LSTM) neural networks, this web-based DSS forecasts disease trends while optimising treatment costs through linear trend models. Its cloud-based architecture, featuring a Flask backend and React frontend supports scalability and real-time data processing. A notable feature is its ability to simulate treatment scenarios and recommend cost-effective suppliers, thus streamlining decision-making. However, successful deployment depends on consistent data input and effective user engagement. Expanding its accessibility through mobile interfaces and multilingual support could further enhance its impact across diverse farming environments. In any event, this study demonstrates that integrating predictive modelling and descriptive analysis into a web-based DSS may significantly advance herd health management.

Comparison with current research

Comparing the DSS for disease scoring described in this study with other DSSs focused on dairy cow health highlights its uniqueness and comprehensive approach. Our DSS offers a broader range of applications, while most existing DSS solutions, such as Dairy Brain , focus on processing real-time sensor data or specialised systems, including the Mastitis Decision Support Tool (Alawneh et al., 2018), and address specific health issues. In addition, our DSS evaluates 125 diseases in six categories based on severity and production impact through a scoring system and supports personalised treatment and disease prevention strategies, unlike most existing DSSs, which often rely on simple predictive algorithms or narrowly targeted diagnostic models. Moreover, our system integrates treatment cost analysis, which is still relatively underrepresented in DSSs for dairy farming. Although the system does not operate in real-time, it does use historical data to predict disease occurrence and optimise treatment costs. This multi-functional capability makes it a practical tool applicable to farms of various sizes and focuses, bringing added value to both academic and practical agricultural contexts.

Further comparisons can be found in several recent studies. For example, an integrated decision-support system (IDSS; Baldin et al. 2021) utilises continuous data streams from a farm and beyond to support decision-making whilst shedding light on adoption challenges, such as perceived value and data management. Another web application based on standardised data collection provides decision-making support in the dairy value chain (Louta et al., 2023b). These systems highlight different approaches to animal health management that could inspire further developments of our DSS model.

Predicting dairy herd diseases is crucial for modern livestock health management. Various approaches to modelling health states have emerged in the scientific literature. Among them, Markov chains have been some of the most commonly used tools for their ability to simulate transitions between different health states based on historical data. Our study has demonstrated the advantages of using both homogeneous and non-homogeneous Markov models, underscoring the critical role of disease categorisation and optimisation of transition probabilities in increasing predictive accuracy. However, a notable limitation of Markov chains lies in their assumption of memorylessness, meaning that future states depend solely on the current state and not on the sequence of preceding events. This simplification may overlook complex temporal dependencies present in real-world disease progression.

Our study has extended this approach by introducing adaptive algorithms that adjust to changing herd conditions. Other studies have modelled not only health outcomes but also the economic impacts of various reproductive programs (Giordano et al., 2012). This interdisciplinary perspective shows that Markov models can simulate complex interactions between animal health and farm economic performance. A significant application of Markov chains is observed in absorbing models, particularly in those designed to predict irreversible processes (Maw et al., 2021). Such a method is particularly relevant for monitoring processes with a definitive endpoint, such as calving or severe diseases. But in contrast to these approaches, our study combines different types of Markov chains and introduces advanced adaptation algorithms. This multidisciplinary approach expands prediction possibilities for health management and economic decision-making optimisation at the farm level. Future research should integrate machine learning methods and neural networks to enhance prediction complexity and accuracy.

Our web-based DSS for dairy farming integrates predictive modelling and cost analysis, going beyond state-of-the-art farm management tools by offering a holistic health management platform. Several key differences and advances stand out when comparing other DSS models applied in the agricultural sector this system. The DCDDS (Rong & Li, 2008) functions as a multi-model expert system, primarily diagnosing dairy cow diseases based on user-submitted symptoms. While effective for disease-specific diagnostics, DCDDS lacks predictive analytics and economic modelling, with a narrower functionality than that of our web-based DSS. Similarly, other researchers (Vouraki et al., 2020) have developed systems aimed at enabling sheep and goat farmers to create annual management plans and simulate future scenarios, thus supporting management planning. But while this tool excels in environmental sustainability and profitability planning, its application remains specific to small ruminants, lacking comprehensive disease prediction features critical for dairy herd management.

Overall, currently available DSS models demonstrate strengths in specific agricultural domains—ranging from economic optimisation to disease-specific diagnostics. However, none of them combine predictive health modelling, economic planning, and comprehensive farm management in a single platform. The proposed web-based DSS bridges these gaps, providing an integrated solution tailored to the complex and dynamic needs of dairy farm management.

Research Limitations

The primary limitation of this research lies in its reliance on historical data, which may not fully represent future disease patterns. Additionally, the applicability of the scoring system may be limited by farm-specific practices and environmental conditions. Another significant challenge is the limited availability of farm data in the Czech agricultural environment, as many farms either do not maintain detailed health records or are reluctant to share such data. Furthermore, the level of detail in disease tracking varies across farms, requiring a customized scoring approach tailored to individual farm practices. Lastly, the effectiveness of the system depends on a long-term data collection process because disease occurrence can be seasonal, requiring long monitoring periods for accurate predictions and model calibration.

The model assumes consistent data availability, which can be challenging on farms with irregular data recording. Furthermore, prediction accuracy is constrained by the quality and completeness of historical datasets. Expanding the application of the model to more farms with greater data availability could improve its predictive accuracy and robustness. This broader implementation would improve model calibration, yielding more precise disease trend analysis and enhanced generalisations across different farm environments.

Technical requirements, such as Internet connection, and potential resistance from farmers with limited digital literacy may limit the integration of web-based DSSs. Data privacy concerns also pose barriers to its broader adoption. And not all farms have the funds to invest in such a system, especially smallholder or resource-limited farms. The initial costs of system implementation, maintenance, and data management infrastructure may be prohibitive for many farms, limiting the widespread adoption of web-based DSS solutions. Expanding access through cost-effective versions or subsidised programs will help mitigate this problem.

Future research directions

Research question 1

Future research should focus on expanding the disease scoring system by integrating real-time sensor data and automating the processing of health records. Utilising advanced machine learning models could increase the accuracy of diagnostics and health risk predictions. Additional efforts should be directed towards developing adaptive models adjustable to the specific conditions of individual farms, enhancing their applicability in real-world environments.

Research question 2

Research should explore the development of models based on Markov chains by combining them with other artificial intelligence techniques, such as deep neural networks. This integration could capture more complex patterns in animal health data. Another research direction involves applying these models in regions with limited technological infrastructure, where optimised algorithms with low computational requirements could support effective prediction and decision-making at the farm level.

Research question 3

Future research should focus on improving the current DSS by adding predictive capabilities and integrating a broader range of factors that influence herd health, such as environmental conditions, farming practices, and genetic predispositions. To this end, further data must be collected and analysed, not only historical disease records but also weather information and specific farming practices. Doing so should improve disease prediction accuracy and expand the application of this system to a wider range of diseases. Further research should also integrate other types of machine learning models to improve the prediction of complex interactions between various factors that affect herd health. Another important line of research could also be the application of this system to other livestock species, such as pigs and poultry, and its expansion with new tools for economic analysis and cost prediction related to disease treatment and prevention.

Conclusion

The three key studies of this dissertation, "A Decision Support System Based on Disease Scoring Enables Dairy Farmers to Proactively Improve Herd Health", "Discrete Homogeneous and Non-Homogeneous Markov Chains Enhance Predictive Modelling for Dairy Cow Diseases," and “A Decision Support System for Herd Health Management for Dairy Farms” indexed in Scopus and Web of Science, validate the development and application of advanced DSSs for dairy herds. The results of this research demonstrate that the dissertation objectives were achieved, through the development of innovative DSS tools for enhanced dairy farm health management.

Fulfilment of Dissertation Objectives

The first objective was to design and implement a novel disease scoring system. By categorising diseases such as lameness, mastitis, reproductive disorders and gastrointestinal diseases, among other conditions, the system provides users with a clear and nuanced understanding of disease severity and frequency in a herd. As such, this scoring system enables dairy farmers to monitor herd health more effectively, offering precise, data-driven insights for early intervention and targeted treatment. And by translating complex health data into an actionable format, this system equips farmers with the tools they need to react swiftly to emerging health issues, thereby reducing disease occurrence and minimising the overall impact on herd productivity. Such a system ensures that farmers can allocate resources more effectively, optimise veterinary care, and improve overall herd health and farm profitability. As shown by its application in real-world settings, this scoring system is a practical and value tool for improving the operational management of dairy herds.

The second objective of this research was to develop predictive models using HMCs and NHMCs to estimate the likelihood of disease occurrences. This approach addressed the variability of disease data across farms with different technological capacities and infrastructure. Using historical disease records and Chebyshev distance minimisation, the model can accurately forecast disease trends, with a predicted error rate lower than 15% for most diseases. This level of accuracy supports evidence-based decision-making, enabling farmers to anticipate health risks and take preventive measures before diseases spread or escalate. This predictive model can also optimise antibiotic use, reducing unnecessary treatments and promoting more sustainable farming practices. Thanks to its flexibility, this model is adaptable to farms with varying technological levels as a practical solution for both high- and low-tech farming environments. This DSS component is crucial not only for predicting disease outbreaks but also for guiding strategic decisions regarding treatment, resource allocation, and long-term herd health management.

The third objective was to develop a user-friendly, web-based platform integrating predictive modelling, descriptive analysis, and cost analysis and providing dairy farmers with a comprehensive tool for real-time herd health management. Designed with a scalable, cloud-based architecture using a Flask backend and React frontend, this platform enables seamless data integration, preprocessing, and predictive analysis. The core predictive engine relies on LSTM neural networks specifically chosen for their ability to model and forecast disease progression over time. Evidenced by a mean absolute error of 6.66 and a median absolute deviation of 2.35, the high level of accuracy of this system ensures that farmers receive reliable information on disease trends. In addition to predictive modelling, the platform incorporates a linear trend model to estimate treatment costs, optimise medication dosages, and streamline supplier selection. Its ability to simulate various treatment scenarios enables farmers to identify high-cost diseases and explore potential savings, which is why this tool is an essential asset for cost-effective herd management. By providing accessible, real-time data insights, this platform empowers farmers to make strategic decisions that enhance animal welfare, increase farm productivity, and ensure the sustainability of their operations. As such, the DSS provides reliable and accurate tools for predicting and assessing the health status of dairy herds.

Contributions to Science and Practice

Collectively, these contributions mark significant advancements in the field of dairy farm management. The DSS models developed in this dissertation offer a streamlined, cost-effective alternative to existing high-tech solutions, making advanced disease monitoring and predictive analytics accessible to a wide range of farmers, regardless of their technological infrastructure. The disease scoring system enables farmers to proactively manage herd health by identifying and addressing health issues early, while the predictive modelling tools provide reliable forecasts. These forecasts guide decision-making and optimise resource use in dairy farms. The web-based platform further enhances the practical application of these tools, offering an integrated solution for real-time disease monitoring, treatment planning, and cost management.

This research also contributes to the broader scientific understanding of disease management in dairy farming. By integrating advanced data analytics, machine learning techniques, and mathematical modelling, this dissertation demonstrates the potential for DSS to revolutionise herd health management, improving both the efficiency of farm operations and the well-being of animals. The findings of this research suggest that such systems can lead to significant cost savings, improved herd productivity, and more sustainable farming practices.

Future Research Directions

The development of disease scoring systems and predictive modelling techniques shows significant potential for expansion. Future research could explore additional predictive models or refine current algorithms to enhance accuracy. Emerging technologies, such as more advanced data transmission networks, may also be integrated to enhance real-time data processing and broaden the applications of DSS frameworks. In this context, this research lays the foundation for continued improvements in digital management tools for dairy cow diseases, which may further benefit herd health and farm sustainability on a global scale.

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Appendix No. 1 – Additional Publications and Other Activities of the Author

Over-all Scoring System of Dairy Production Diseases

Jan Saro[a], Luděk Stádník[b] and Helena Brožová[c]

Abstract

Cow metrics and over-all scoring systems are powerful and useful source of comparative criteria information for dairy farms. Dairy herd health is crucial factor, which has consequences for dairy longevity, milk yield and other important prosperity aspects. In this study was developed a new scoring approach for the comparison among dairy farms using a new metric that is able to measure and compare herd health in summary among farms or group of cows within dairy herd.

The scoring methodic of a novel scoring system is inspired by analogical approach in human medical health research area APGAR measurement for newborn children. The developed method takes a list of all dairy diseases from the disease treatment record. From the whole list is calculated summary score of all cows per specified unit of the time. The diseases were classified to three levels of severities from 1 with the lowest, 2 with medium severity and 3 with the highest severity of disease. First attempt of this study was implemented on Czech farm from the time window almost of 5 years.

It was shown in the study that summary score is powerful source of information which is possible use for decision support systems for usage of descriptive analysis of animal health on dairy farm. Consequently, the score is comparable by farm management on the level of dairy herd as well as among several farms to evaluate dairy herd health.

Keywords

dairy cows, decision support system, farm management, herd health, scoring-over-all system, production disease, descriptive analysis

JEL Classification

C44, Q12

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List of Publications

Saro, J., Subrt, T., Brozova, H., Hlavaty, R., Rydval, J., Duchacek, J., & Stadnik, L. (2024). A decision support system for herd health management for dairy farms. Czech Journal of Animal Science, 69(12), 502-515.

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Saro, Jan, Ludek Stadnik, Petra Blahova, Simona Huguet, Helena Brozova, and Jaromír Duchacek. 2024. "A Decision Support System Based on Disease Scoring Enables Dairy Farmers to Proactively Improve Herd Health." *Czech Journal of Animal Science* 69 (5): 165–77. https://doi.org/10.17221/53/2024-CJAS.

Blahova, P., Saro, J., Rydval, J., & Brozova, H. (2024). Evaluating Cognitive Biases and DSS Utilization in Strategic Management: A Socio-Technical Perspective. In Proceedings of the 10th International Conference on Socio-Technical Perspectives in IS (STPIS'24), August 16-17, 2024, Jönköping, Sweden.

Saro, J. (2024). Breaking the Wall of Dairy Farmer AI Assistant. Presented at the 9th annual Falling Walls Lab Czech Republic, National Library of Technology, Prague, September 12, 2024.

Czech Academy of Sciences, UTIA. (February 2024). Presentation of a Predictive Dairy Disease Model Using Markov Chains. Seminar at the Institute of Information Theory and Automation, Czech Academy of Sciences, Prague, Friday session.