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A decision support system for herd health management for dairy farms

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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

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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:

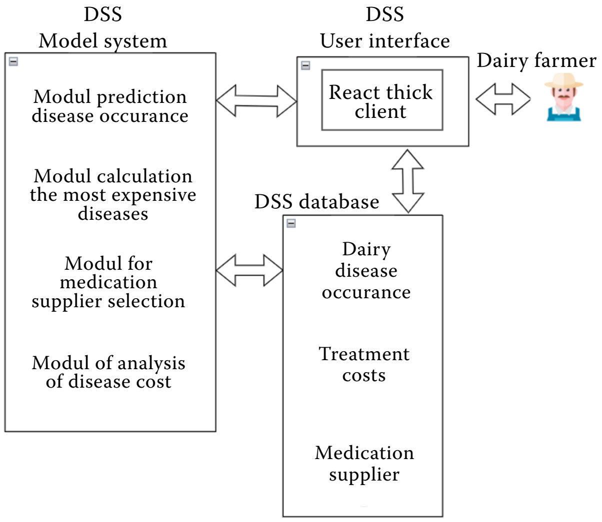

Figure 1. Architecture for dairy health management decision support system (DSS)

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

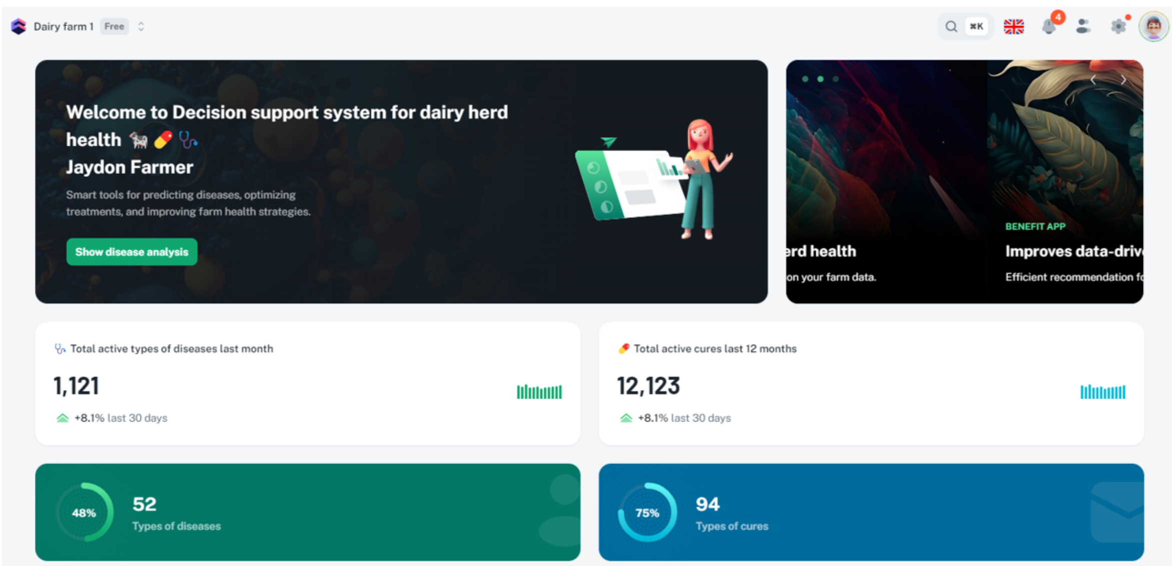

Figure 2. Dashboard screen of the decision support system (DSS) web application

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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).

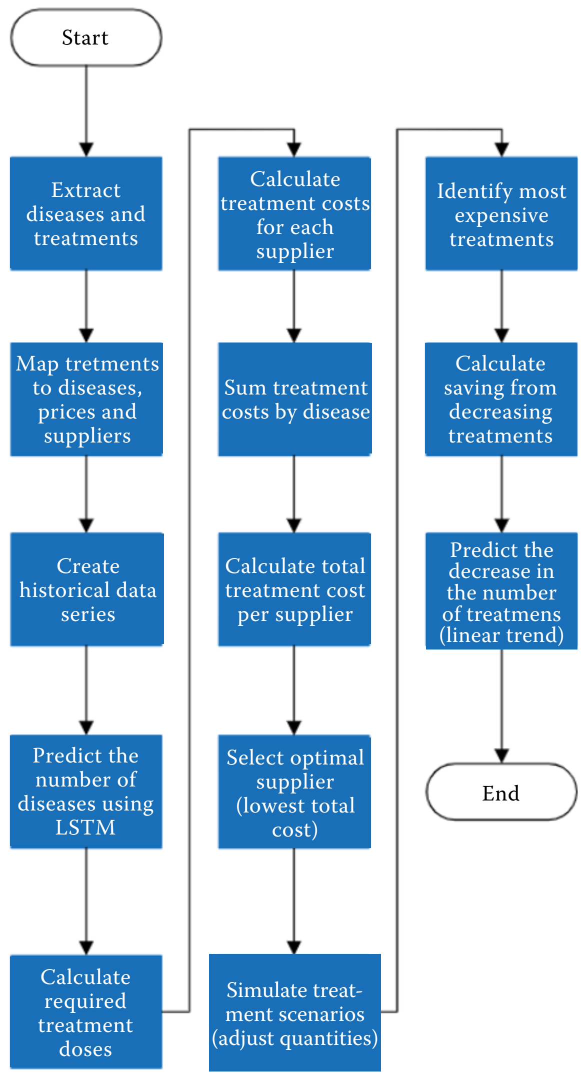

Figure 4. Diagram of all modules calculation in the decision support system (DSS) web application for dairy disease records

LSTM = long short-term memory

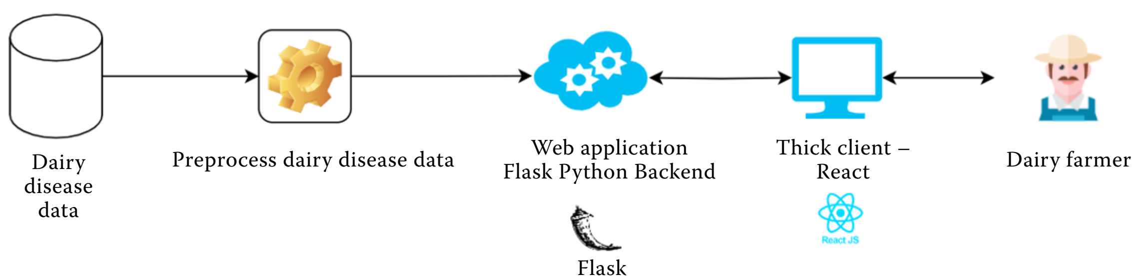

Figure 3. Schematic diagram of the data flow in the decision support system (DSS) web application for diary diseases

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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;

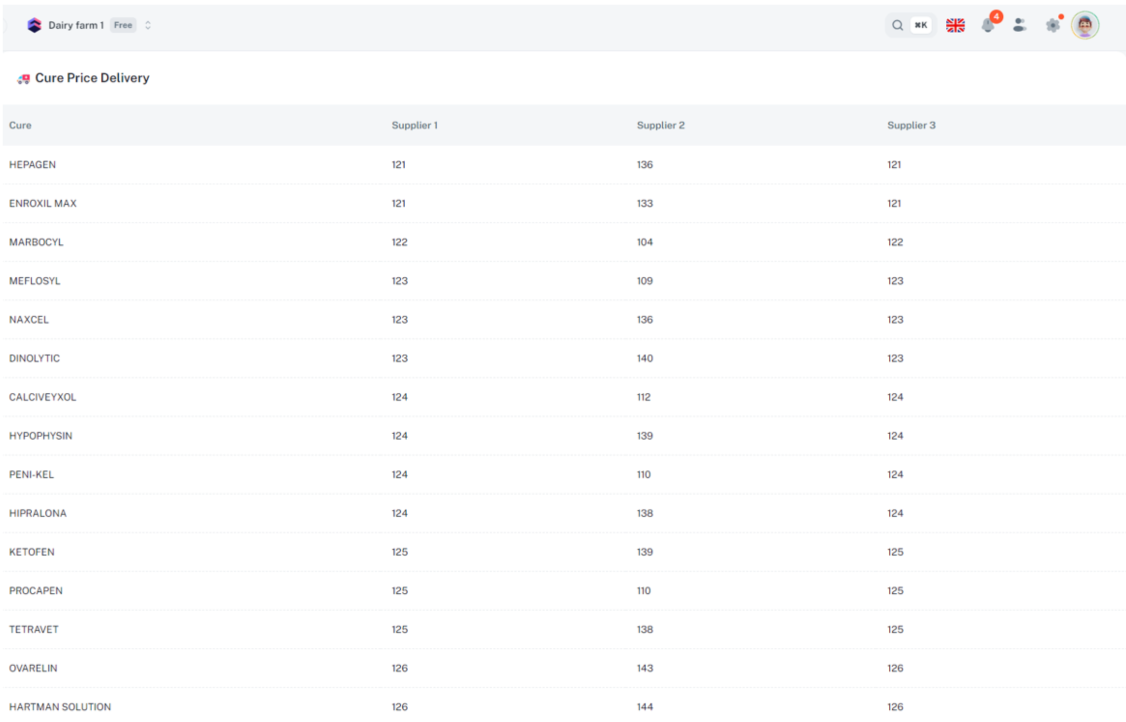
y^k_{t+1} – the predicted number of events of disease k in the period t + 1;

$y^k_t, y^k_{(t-1)}, ..., y^k_1$ – 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 $y_t^k, y_{t-1}^k, ..., y_1^k$ supposed the following formula whose parameters are

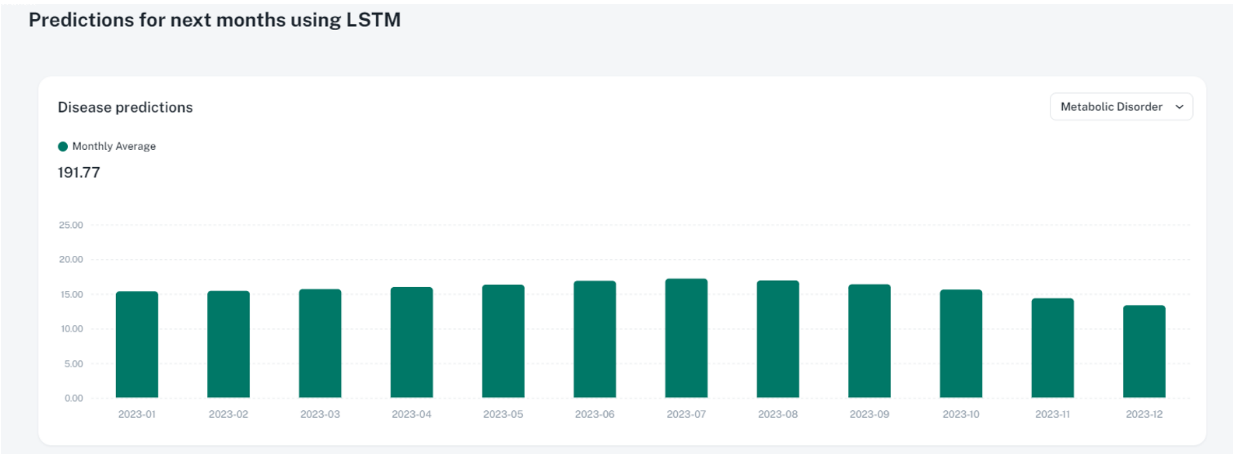
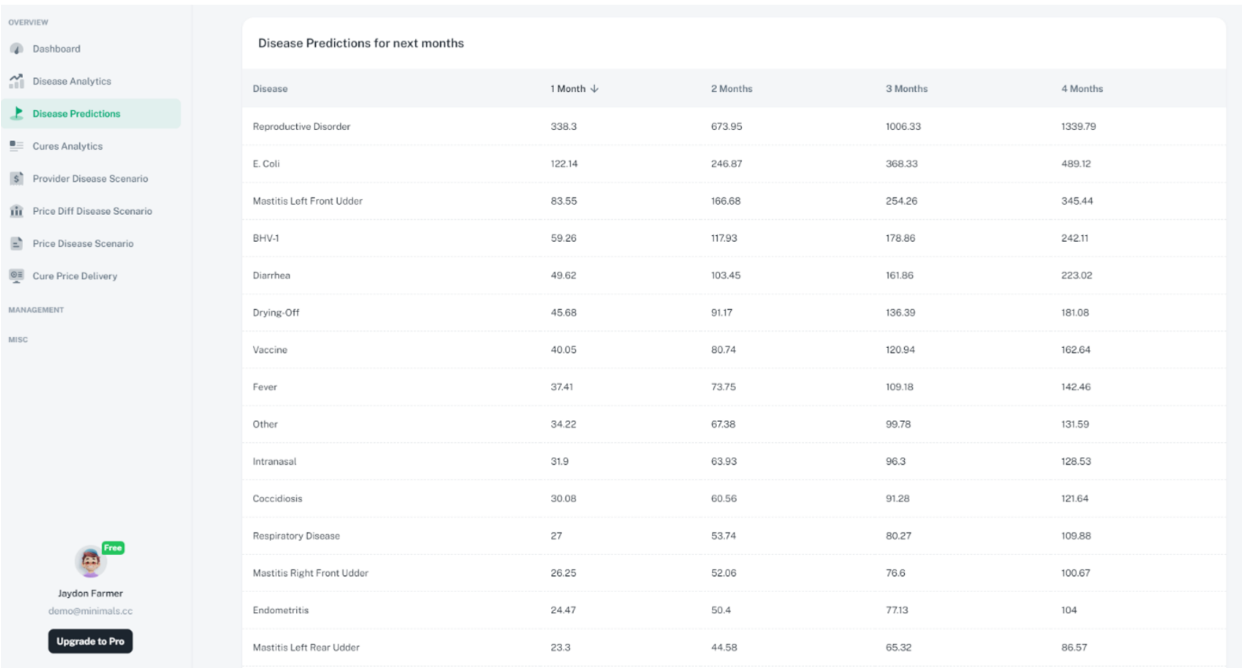


Figure 6. Disease prediction using an long short-term memory (LSTM) neural network – metabolic disorders



Disease Predictions for next months

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;

$j = 1, 2, ..., t$ – 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, $t - 1$, ... , 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 $m \in \{1, ..., M\}$ from the current supplier $s = 1$ in period $t + 1$ is calculated as follows:

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

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:

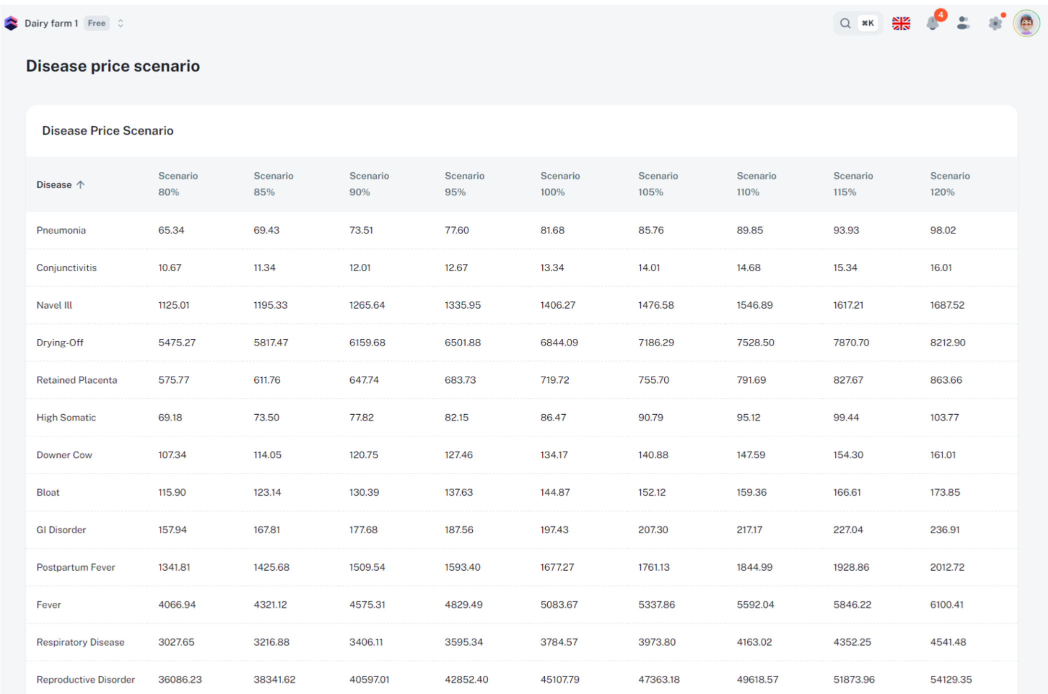
$$l^*: \Delta C_s^{l^*} = \max_k \Delta C_j^k \tag{10}$$

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


Dairy farm 1 Free

Disease price scenario

Disease Price Scenario

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.

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,

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

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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).

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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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