



Detection of Disease in Calves using Artificial Intelligence

Ahmad Ali AlZubi¹

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ABSTRACT

Background: Livestock farming is experiencing a digital transformation and is becoming more information-driven. However, this type of data is often kept in separate storage towers, making it incapable of practicing its potential to boost animal welfare. Lumpy Skin Disease (LSD) is a serious threat to the health of cattle worldwide and has caused financial problems for many cattle farming enterprises. It has been shown that combining machine learning (ML) and artificial intelligence (AI) with biosensor data and conventional visual inspections can improve the identification and diagnosis of this serious condition.

Methods: This study presents an extremely precise livestock farming framework that combines data streams from a wide array of disciplines of dairy cattle to see if ever wider/vast data sources enhance the overall projections for diseases and if using the more complicated prediction models can reimburse for less diverse data to some extent. Using images from the farming landscape, this study highlights the utility of convolutional neural networks (CNNs) in the identification of the Lumpy Skin Disease Virus (LSDV) in animals.

Result: An analysis of the relative weight given to individual factors in predicting accuracy shows that disease in dairy cattle results from the intricate interactions between many life domains/parameters, such as housing, nutrition and climate; that prediction performance is enhanced by incorporating a wider range of data sources and that current information can be repurposed to produce useful information for vaccine development. The study highlights the potential of data-driven dairy interventions, focusing on artificial intelligence for disease prediction in cattle, to improve animal welfare and reduce the risk of disease. A Convolutional Neural Network (CNN) based model effectively classified skin conditions with an overall accuracy of 73.89% after 27 training epochs. This study demonstrates CNN's useful applications in the field of veterinary medicine by highlighting its potential for early detection of Lumpy Skin Disease (LSD).

Key words: Animal health, Artificial intelligence, Bovine respiratory disease (BRD), Cattle farming, Deep learning, Machine learning, Neonatal calf diarrhoea (NCD).

INTRODUCTION

Among the most prevalent reasons for death in dairy cows and veal cows, especially beef young stock, are illnesses, mainly "bovine respiratory disease (BRD) and neonatal calf diarrhea (NCD)". The illness categories that afflict dairy and veal calves have comparable but somewhat varying prevalence estimates. Breathing difficulties, coughing and nasal discharge are all signs of BRD. Antibiotic resistance, which is a major worry in veterinary and human medicine, is also a burning issue in the veal as well as dairy industries (Pillen *et al.*, 2016). Furthermore, owing to residues in animal urine and feces, abuse of antibiotics may cause pollution of surface water near farms. Because calf health has such a broad influence on sustainable development, they must establish precise, fast, as well as practical techniques to detect diseased/ailing calves in both the dairy and veal industries. Visual inspection and clinical tests done by farmers and veterinarians are the most common methods for diagnosing illnesses in calves. This approach is associated with many drawbacks such as: (1) Calves that have been diagnosed as unwell have already shown apparent clinical signs and may have been sick for some time. Clinical indications of BRD, for instance, may appear after the beginning of temperature or even before the onset of temperature, while clinical symptoms of NCD appear after most of the related tissue injury to the intestinal submucosa has already happened. (2) Graphic inspection

¹Department of Computer Science, Community College, King Saud University, Riyadh, Saudi Arabia.

Corresponding Author: Ahmad Ali AlZubi, Department of Computer Science, Community College, King Saud University, Riyadh, Saudi Arabia. Email: aalzubi@ksu.edu.sa
Orcid Id: <https://orcid.org/0000-0001-8477-8319>.

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and medical exams are usually ineffective in detecting unwell calves. For instance, in clinical examination research to diagnose BRD in beef calves, the predicted specificity and sensitivity were 62 and 63%, respectively (Sutherland *et al.*, 2018). As a result, numerous diseased calves go unnoticed or need re-treatment leading to missed interference and an unsuitable antimicrobial quantity in the first case, making it hard to cure them quickly. This leads to increased poorer animal welfare and disease propagation, as well as greater negative economic and environmental effects, all of which contribute to the poor sustainable development of calves-based production environments.

Effective approaches for detecting health concerns in particular calves consistently and accurately are required.

The use of “sensing systems” in animal husbandry has become possible as the cost of electronic equipment has decreased and their deployment has increased. In Fig 1, Digital livestock farming is shown. Physiological and behavioral characteristics may now be monitored constantly and for lengthy periods at the individual animal level (Lowe *et al.*, 2019).

Facial recognition for cows

Face recognition in cattle has gotten a lot of attention in recent years because of the ubiquitous and effective usage of biometrics applications (Fig 2). The identification of livestock is crucial for their registration as well as traceability. Cattle handling and movement would be halted if the proper registration process was used. In general, the advantages of cattle traceability include the capacity to identify the ownership and parentage of each animal, as well as the ability to detect the spread of disease, hence ensuring food safety and validating sources, products, exports and procedures (Smith *et al.*, 2020). Unfortunately, in many nations, the conventional method of cattle identification has long been a concern for recognition, registration, tracking, missing or switched livestock and breeding associations. The Wagyu Registry Association registered cattle between the ages of four months and fourteen months for breeding as well as marketing purposes. To provide the cattle with the appropriate degree of security, traditional cow identifying methods like “microchip, ear notching, freeze branding, Radiofrequency Identification, ear tagging, ear tattooing and drawing were utilized”.

Furthermore, animal body marking systems like tattooing and ear notching may be readily detected by the owner or animal insurance agencies and hence are insufficient to offer the reliability of cattle identification. These techniques are unable to give potential answers to imposter-caused animal disappearances, swapping, theft, duplication and fraud (Wang *et al.*, 2018). As a result, how to build and create frameworks for automated and robust animal recognition remains an ongoing research subject in the computer vision field. According to the published literature, there is an online survey of cattle nowadays. The world's 1.3 billion cattle populace is spread as follows: 30% of the overall population is in Asia, 20% in South America, 15% in Africa, 14% in North Central America and 10% in Europe. In addition, according to a cow population census, about 14.121 million cattle are killed for feeding in the United States each year. Every one of these factors highlights the need for a reliable and automated identification system. The diversity and distinctiveness of vocalizations, coat patterns, body movements and morphologies are used as biometrics attributes in the animal biometrics system. The tiger, zebra, penguin, as well as cow muzzle point patterns, are the same as human fingerprints. The goal of this project is to conduct a complete research project on livestock recognition, identification and tracking to develop

a method to avoid livestock raiding as well as theft-related violent disputes in many nations (Windeyer *et al.*, 2017). Furthermore, cattle recognition systems play an important role in vaccine administration, disease outbreak prevention and ownership assignment in production planning. Animal biometrics are used to determine an individual's identification due to its physical, chemical, as well as behavioral features. Biometric technologies are predicted to outperform conventional animal identification methods and they may be used to address the issues of lost, swapped, neglected and duplicated animals, border transfers, fraudulent insurance claims and displacement at slaughterhouses (Cattle Facial Recognition Could Combat Agricultural Fraud, 2020). It's a new kind of animal detection and recognition study based on an animal biometrics trait called composition (Ankitha *et al.*, 2020). For animal identification and livestock management, animal biometrics employs fully automated or semiautomated systems to recognize people or animals based on their intrinsic morphological and behavioral features. In animal biometrics, phenotypic appearance drives the development of increasingly sophisticated cow face recognition (Ankitha *et al.*, 2020).

Animal farming and advanced technologies

Getting ways to enhance performance

In practice, new technology may be utilized to get the best replies to various animal husbandry matters. Getting ideal answers to decrease costs, optimize production, boost efficiency and generate appropriate diet formulas are a few instances. Modern systems may take into account factors like genetics, the environment and management goals to provide relevant as well as contextually optimum answers. Generally, the more information a network gathers and analyses, the more likely it will arrive at correct and optimum answers. Farmers will also benefit from such a system as it is evidence-based or data-driven.

Considerate complex systems

Today, modern technologies allow us to investigate how complicated systems, like natural systems, function. It may aid us in extracting useful data from information and improving our understanding of complicated animal systems. They may aid in the collection of experimental evidence as well as the calculation of useful parameters, such as fractional levels of rumen decomposition or clear-cut rates of mammary cell growth. Modern technologies, on the other hand, are not immune to failure (Ankitha *et al.*, 2020). They are excellent tools for identifying regions lacking scientific information or a system's regulatory assumption may be erroneous.

Identifying complex patterns

Modern technologies excel in understanding a wide range of data formats, including audio, text, video, as well as

photos. Advanced algorithms can forecast patterns cluster, or categorise, within these datasets. Pattern recognition has been used to identify illness and monitor animals in animal production systems using modern data processing and algorithms. For example, big data and machine learning techniques have been developed to analyze animal behavior changes or identify animals (Van Soest *et al.*, 2016). Animal behavior patterns such as ruminating, posture, grazing, as well as gait may now be classified using a variety of sensors. Publications show how 3-axis accelerometers, optical sensors and magnetometers, including depth video cameras, may be used to recognize and predict animal behavior when combined with machine learning algorithms.

They also have further instances of how big data and machine learning might assist in diagnosing animal illnesses sooner than is now achievable. Sadeghi, for instance, captured the vocalizations of both healthy as well as *Clostridium perfringens*-infected broilers. The researchers used an Artificial Neural Network (ANN) model to identify and analyze five clusters of data, which revealed the difference between diseased and healthy birds (Rana *et al.*, 2019; Min, *et al.*, 2024; Na and Na, 2024; Maltare, 2023). They were capable of discriminating between diseased as well as healthy birds with a precision of 67% on 3 days and 100% on 9 days after infection.

Skills in foresight

This contributes to modern technology's capacity to estimate and predict economic consequences like BW (body weight), milk output and egg production. In circumstances when the previous development of the herd BW is known, Alonso employed an SVM classification model to correctly forecast the body weight of individual cattle. When just a few body weight values were available and accurate forecasts for longer periods were necessary, our technique outperformed individual regressions produced for individual animals (Obermeyer *et al.*, 2016).

Recognizing, predicting and preventing diseases using sensors

As previously mentioned, recognizing, predicting and mitigating animal illnesses is a significant cost driven. Sensors, artificial intelligence, big data and ML are instances of recent technology that provide farmers with novel choices. It permits nonstop surveillance of vital AH factors like mobility and quality of air, including food and drink intake, rather than responding to problems after they become apparent or employing the services of physicians (Fauw *et al.*, 2018). An infectious disease pandemic on a huge animal farm, where thousands of animals are housed together, might result in massive losses. The emergence of an infectious illness will be difficult to control unless the farmer intervenes quickly (Lynch *et al.*, 2018).

Sensors, ML and big data

In a large animal farm, where thousands of animals are kept together, an infectious disease pandemic might result in enormous losses. In such a circumstance, unless the farmer intervenes soon, the spread of infectious disease will be impossible to stop. When symptoms first appear, it is sometimes too late to act. If a disease is left untreated, it will quickly spread, resulting in animal mortality, worse clinical outcomes and economic difficulties (Ebrahimie *et al.*, 2018). Sensors, big data, as well as machine learning algorithms have been used to accurately detect the early beginnings of numerous illnesses in pigs as well as sheep depending on sluggish body motions, before the onset of other apparent illness indicators, patients may have delayed reaction times and reduced activity levels. Farmers, on the other hand, may find it difficult to detect such modifications with the naked eye in a big herd with multiple animals. A farmer or animal attendant may not notice a sick animal's unusual feeding patterns, fluid intake, or body movements among a large herd of animals (Ducheyne *et al.*, 2015). Farmers may use big data, machine learning (ML) sensors and to spot anomalous behavior and anticipate disease outbreaks.

Monitoring air quality is one way to diagnose this disease. The quantity of sick birds increases the concentration of VOCs in the air. This shift may be detected far sooner by air sensors than by a farmer or a doctor. Farmers who have been notified may then take immediate action to stop the sickness from spreading further. A strategy like this saves many animals' lives while also preventing financial losses. Similarly, sensors, big data and powerful algorithms can forecast certain illnesses in bigger animals much better than people can. For example, mastitis, an udder illness, causes cows to produce the milk of poor quality and quantity (Brahimi *et al.*, 2019). SSC (Somatic cell counts), as well as EC (electric conductivity) values, are traditionally used to detect mastitis. On the other hand, such manual assessments are often inaccurate, inconsistent and ineffective. Instead, cows' mastitis risk may now be consistently collected, predicted and reduced using computerized sensors and algorithms (Fig 3).

Methods for early illness diagnosis are not new. Researchers already have the technology to achieve this, such as RtPCR. They were, nevertheless, expensive and could not be implemented on a large scale. Machine learning (ML), Sensors and big data, algorithms now provide significant cost savings compared to previous detection methods (Sahar *et al.*, 2020). They can swiftly forecast and prevent dangerous diseases like African Swine Flu for a low cost. More critically, modern technologies can now forecast the development of several infectious illnesses before they become widespread (Table 1).

In other circumstances, based on animal motions, algorithms may forecast illness signs like lameness.

At the preclinical stage, alterations in movement, intensive use of specific body parts, as well as inactivity in other body parts may consistently predict early lameness (Frizzarin *et al.*, 2021). Lameness is the 3rd most frequent condition affecting farmers since it diminishes milk output and raises the risk of harm. Farmers may save significant financial losses by predicting lameness in advance (Bruijn *et al.*, 2010). Such information focuses on handling huge data, sensors and machine learning may be used to assist farmers in anticipating and preventing illnesses in a cost-effective as well as non-invasive way.

MATERIALS AND METHODS

Dataset

The diversity and accuracy of the dataset are important factors that improve the prediction and practical application of the model. A carefully labeled dataset of animal images with lumpy skin disease conditions and normal skin conditions has been assembled for the CNN model and the images are divided into two groups: normal and diseased (Fig 4). Collected along with wildlife professionals, this dataset ensures a thorough representation of images including both Lumpy Skin Disease Virus (LSDV) and non-LSDV cases, with a significant number in each group. The virus that causes LSD is called LSDV and it belongs to the Capripoxvirus genus. It causes skin lumps or nodules. To enable effective model training and evaluation, the dataset which consists of 1,000 photos divided into two groups has been split into a training set (80%) and a validation set (20%).

Image preprocessing and augmentation

For uniformity, images are resized to 256 × 256 pixels and pixel values are normalized by dividing by 255. Images are labeled for health categories after resizing, making it possible to distinguish between LSDV and non-LSDV in training and test datasets. By creating new images from the existing collection, data augmentation increases the diversity of the dataset. This method includes flipping vertically or horizontally, zooming and random shifts and rotations. It also reduces overfitting.

Model selection

The sequential CNN model, which excels at managing big datasets, was selected for the image classification task. Using this trained model allows for efficient recognition of fine details in images.

Training learning process

Apply transfer learning by extracting features from the trained CNN model. To fit the characteristics of the lumpy skin disease dataset, freeze the weights of the first few layers and modify the later layers only when necessary. This method maximizes training efficiency and resource utilization by utilizing the depth of knowledge that the model has learned from a larger dataset. Fig 5 represents a detailed process of the proposed model.

Feature extraction

Fig 6 shows the layers, output shapes and associated parameters of the neural network model architecture. This model uses filter sizes of 32, 64 and 128 and consists of convolutional layers (Conv2D) with different output shapes. To downsample the spatial dimensions, max-pooling layers (MaxPooling2D) are positioned strategically. 'Dropout' layers are added to the training set to avoid overfitting. A hierarchical structure for feature extraction is produced by the connections between the convolutional and max-pooling layers. The model ends with dense layers (Dense) for classification, the last of which generates an output of two units, which is equal to the number of classes in the classification task. This thorough explanation sheds light on the architecture of the network and the range of parameters used during training.

Evaluation matrices

Accuracy

The percentage of instances correctly classified out of all the instances. It offers a broad summary of the algorithm's accuracy.

$$\text{Accuracy \%} = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

Precision

It is the ratio of all predicted positive observations to the number of correctly predicted positive observations.

$$\text{Precision \%} = \frac{TP}{TP + FP} \times 100$$

Recall

The ratio of correctly predicted positive observations to the total number of actual positives is known as recall (sensitivity). When the cost of false negatives is high, it is imperative.

$$\text{Recall \%} = \frac{TP}{TP + FN} \times 100$$

F1- score

The normalized mean of recall and precision is the F1-Score. It offers a balance between recall and precision.

$$\text{F1- score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Recall} + \text{Precision}}$$

Confusion matrix

A table that provides a thorough analysis of the model's performance by showing true positive, true negative, false positive and false negative values.

RESULTS AND DISCUSSION

The model was subjected to iterative optimization processes during the 27th epoch of the training procedure (Fig 7). Each iteration represented the processing of a single batch through the training dataset. Important performance

metrics are presented in this epoch's terminal output. Lower values indicate improved convergence. The reported loss, expressed as 0.3276, measures the difference between actual and predicted values during the training phase. The accuracy metric, with a value of 0.8604, indicates the percentage of correctly classified instances in the entire training dataset. Higher values of this metric

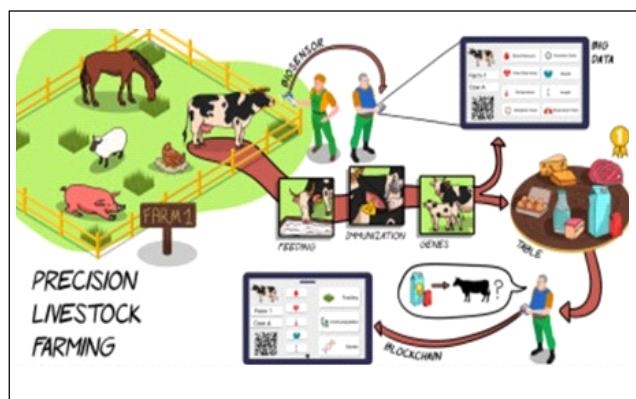


Fig 1: Digital livestock farming (source: ATLAS).

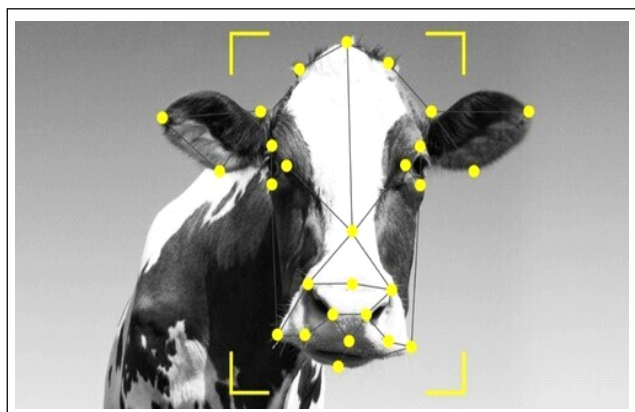


Fig 2: Facial recognition for cows (Source: Innovation News Network).

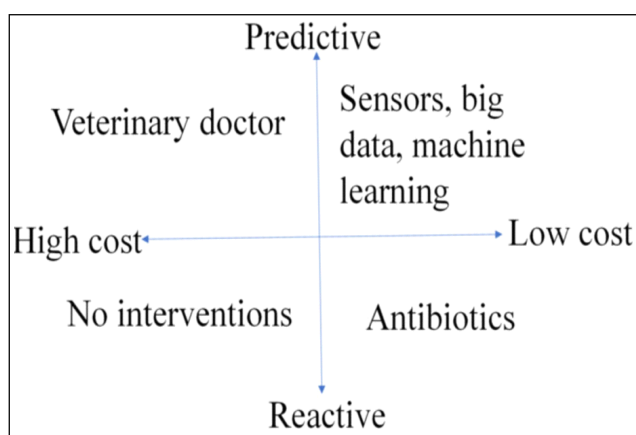


Fig 3: The contrast between the predictive and reactive disease management strategies in animals.

indicate better model performance. In addition, the model's generalization performance on a separate dataset that was not used for training is indicated by the validation loss (0.7896) and accuracy (0.7225) metrics, which provide important information about the adaptation of the model for unobserved data. The metrics that are presented provide a concise evaluation of the model's effectiveness at the end of the 27th training epoch, which allows for more in-depth analysis and possible improvement of its performance characteristics.

The confusion matrix for the healthy and diseased predictions is presented in Fig 8. The model correctly identified 92 truly healthy instances and 94 truly diseased instances. However, it misclassified 47 healthy instances as diseased and 19 diseased instances as healthy.

The performance of the model to differentiate between the Healthy and Diseased categories is compared in the classification report (Table 2). For the Healthy category, recall (0.6622) suggests capturing actual instances, while precision (0.8288) indicates accuracy. Precision and recall are balanced by the F1-score (0.7366). For Diseased, recall (0.8312) emphasizes capturing real cases, while precision (0.6667) shows accuracy. Precision and recall are



Fig 4: Healthy and diseased cow images.

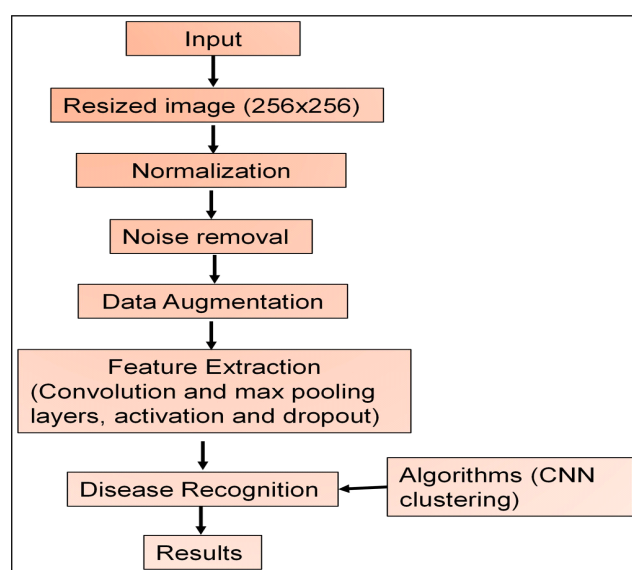


Fig 5: Flow chart of proposed CNN model.

combined by the F1-score (0.7393). The accuracy overall is 73.89%.

For precision, recall and F1-score, macro-average metrics yield 0.7477, 0.7467 and 0.738 when given equal

weight. Weighted-average metrics yield 0.7576, 0.7389 and 0.7382, respectively, after accounting for class imbalances. This brief analysis offers an in-depth understanding of the classification efficacy of the model.

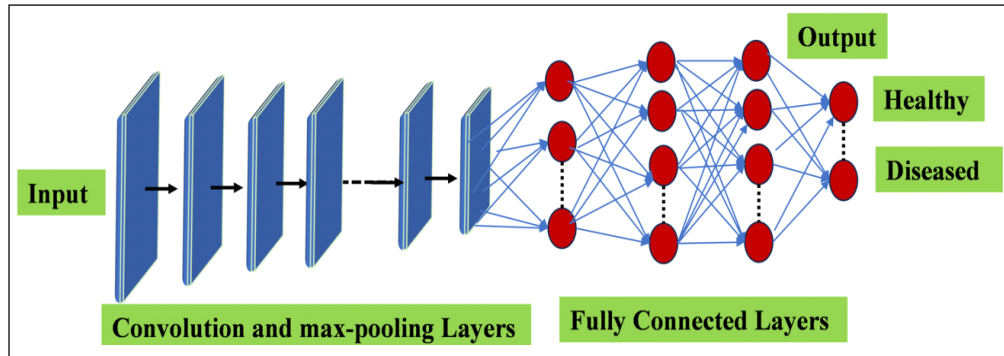


Fig 6: Architecture of CNN model employed for disease detection in calves.

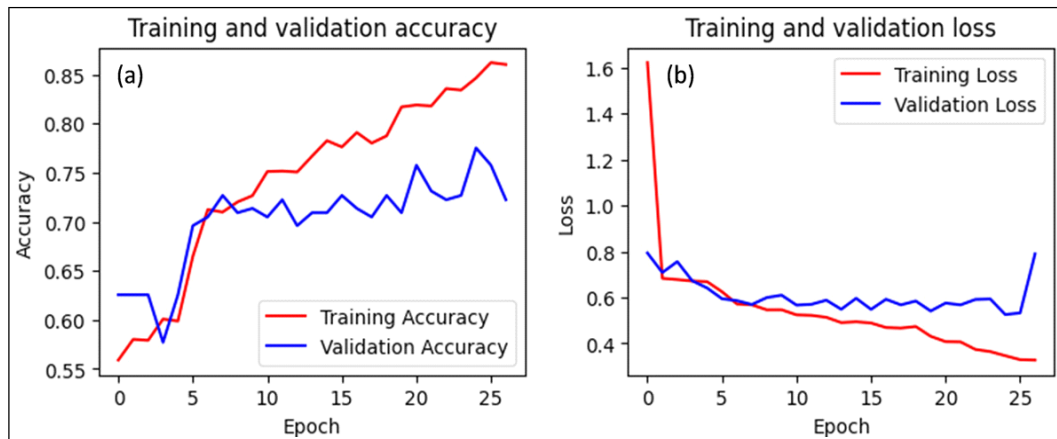


Fig 7: Accuracy and loss as a function of epoch for training and validation data.

Table 1: Modern technology aids animal producers in illness prediction and prevention.

Disease	Parameter detected	Algorithm (s)
Postpartum disease	Protein production, Milk yield, Lactose yield	Random forest algorithm (RFA)
African Swine Flu	Mobility, speed, direction	Optical flow algorithm
Coccidiosis	VOC (Volatile Organic Compounds) in air	Principal Component Analysis (PCA)
Mastitis	Electrical conductivity (EC), Somatic cell count (SSC)	Gradient Boosted Trees (GBT), Bag of Words (BoW)
Lameness	Neck movement, leg movement and image/video data	Fog computing

Table 2: Classification report.

Label	Precision	Recall	F1-score	Support
Healthy	0.8288	0.6622	0.7366	139
Diseased	0.6667	0.8312	0.7393	113
Accuracy			0.7389	252
Macro avg	0.7477	0.7467	0.738	252
Weighted avg	0.7576	0.7389	0.7382	252

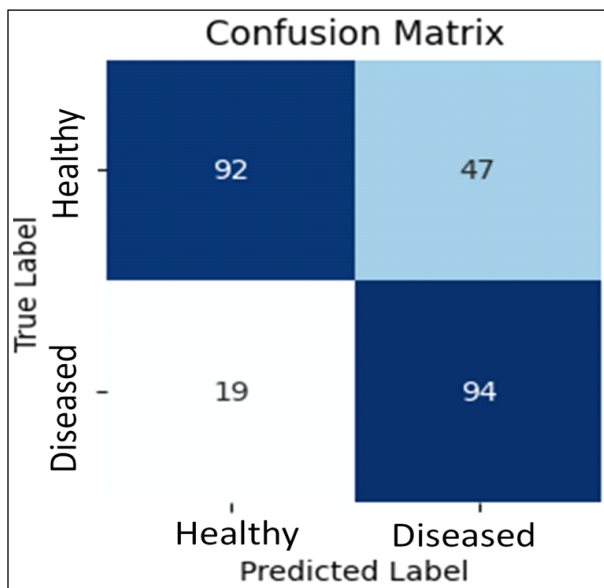


Fig 8: Confusion matrix.

CONCLUSION

As part of Agriculture, sensor technology, big data and machine learning are all being employed increasingly often in contemporary animal husbandry. When nutritionists, veterinarians and producers are unable to go to barns, farms and feed mills owing to transportation constraints, real-time 24/7 insight into animal activity, consumption and output is required. Such insights are provided by sensing technology, which results in data that can be accessed remotely, lowering costs and improving reaction times to customer needs.

The study focuses on the application of machine learning and image processing techniques for the detection of lumpy skin disease in animals. It goes into detail to explain a Convolutional Neural Network (CNN) that is intended for the classification and detection of skin diseases. Digital image processing includes important activities like gathering image datasets, preprocessing, representation, interpretation and detection. It is driven by a predetermined protocol. Data augmentation, image resizing, channel order and normalization are examples of specific operations. Metrics such as recall, accuracy, precision and F1-score are used to evaluate the robustness of the built classifier to determine its effectiveness. In the context of this Lumpy Skin Disease study, precision and recall measures are essential for assessing how well the model predicts each class.

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Author contributions

The author contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all aspects of this work.

Data availability statement

Not applicable.

Declarations

Author declares that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

The author declare that they have no conflict of interest.

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