Sustainable Machine Intelligence Journal

Journal Homepage: sciencesforce.com/smij

Sustain. Mach. Intell. J. Vol. 11 (2025) 1–10

Paper Type: Original Article

Deep Learning-Based Detection of Lumpy Skin Disease in Livestock using CNNs

Walid Abdullah [1], Sudeep Tanwar [2] and Mohamed Abouhawwash [3,4,*]

[1] Faculty of Computers and Informatics, Zagazig University, Zagazig, Sharqia, 44519, Egypt; waleed@zu.edu.eg.

[2] Department of Computer Science and Engineering, Institute of Technology, Nirma University, Ahmedabad, India; sudeep.tanwar@nirmauni.ac.in.

[3] Department of Industrial and Systems Engineering, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia; mohamed.abouhawwash@kfupm.edu.sa.

[4] Interdisciplinary Research Center of Smart Mobility and Logistics (IRC-SML), King Fahd University of Petroleum & Minerals Dhahran 31261, Saudi Arabia.

Received: 29 Sep 2024 **Revised:** 19 Feb 2025 **Accepted:** 18 Mar 2025 **Published:** 20 Mar 2025

Abstract

Lumpy Skin Disease (LSD) is a viral disease affecting cattle, resulting in a large economic loss in the livestock industry. Early and accurate detection is essential to prevent outbreaks and minimize its impact. In this study, we explore the use of deep learning models for automated LSD classification from cattle images. We evaluate five state-of-the-art convolutional neural networks (CNNs) including MobileNetV2, ResNet50V2, DenseNet121, InceptionV3, and Xception using transfer learning. The dataset consists of images categorized as either healthy or infected, with data augmentation applied to improve model generalization. Performance is assessed based on accuracy, precision, recall, and F1-score. Among the tested models, DenseNet121 achieved the highest accuracy of 90.36%, outperforming the other architectures. The results demonstrate the potential of deep learning for rapid and reliable LSD detection, which could aid veterinarians and farmers in early disease identification.

Keywords: Lumpy Skin Disease; Deep Learning; Convolutional Neural Networks; Livestock Disease Detection; Transfer Learning; Precision Livestock Farming.

1 | Introduction

Lumpy Skin Disease (LSD) is a viral disease that severely affects cattle, leading to significant economic losses in the livestock industry. It is caused by the Lumpy Skin Disease Virus (LSDV) and is primarily transmitted through insect vectors such as mosquitoes and ticks [1]. The disease results in fever, skin nodules, reduced milk production, and, in severe cases, death. LSD outbreaks can have devastating effects on dairy and beef farming, particularly in regions with limited veterinary resources [2]. Early detection and intervention are essential to controlling the spread of the disease, reducing economic losses, and ensuring animal welfare. However, traditional diagnostic methods often require skilled professionals and specialized laboratory tests, which may not be accessible in rural and resource-limited areas. And despite advancements in veterinary diagnostics, there is still a significant gap in automated, scalable, and real-time detection methods for LSD [3]. This highlights the need for a rapid, automated, and cost-effective solution for LSD detection. Artificial

Corresponding Author: mohamed.abouhawwash@kfupm.edu.sa

https://doi.org/10.61356/SMIJ.2025.11515

intelligence (AI) has demonstrated success in medical imaging and disease classification [4], but its applications and improvements in livestock disease detection are still needed. This research aims to address this gap by leveraging deep learning models for automated LSD detection using cattle images [5].

Deep learning, particularly convolutional neural networks (CNNs), has achieved remarkable success in image-based disease detection in human healthcare and agriculture. CNNs can learn complex patterns from images, making them well-suited for classifying diseases based on visual symptoms [6]. In veterinary applications, CNNs have been widely applied in the field of animal health monitoring for various tasks, including some disease detection [7, 8], However, the potential of deep learning for LSD detection still needs further exploration. By applying transfer learning with pre-trained CNN architectures, it is possible to leverage existing knowledge from large-scale image datasets and adapt these models for accurate classification of LSD in cattle [9]. This study evaluates five state-of-the-art CNN architectures including MobileNetV2, ResNet50V2, DenseNet121, InceptionV3, and Xception to identify the most effective model for automated LSD detection.

The primary objective of this research is to develop an automated deep learning-based system for classifying LSD in cattle images. Specifically, this study aims to evaluate the performance of different CNN architectures in detecting LSD, compare their accuracy, precision, recall, and F1-score to identify the most suitable model, and analyze the impact of transfer learning and data augmentation on model performance. By addressing these objectives, the study seeks to provide a robust AI-driven solution for LSD detection that can assist veterinarians and farmers in early diagnosis, reducing the reliance on manual examination and laboratory testing.

This research makes several contributions to the field of veterinary disease diagnostics and AI-based livestock management. First, it provides a comparative analysis of multiple CNN architectures for LSD classification, offering insights into the strengths and limitations of each model. Second, it demonstrates the effectiveness of transfer learning in adapting pre-trained models for livestock disease detection, reducing the need for large, labeled datasets. Third, it proposes an AI-driven framework that can be integrated into mobile applications or on-farm diagnostic tools, enabling real-time disease detection in remote and resource-limited areas. Finally, the study highlights the potential of deep learning in enhancing disease surveillance and early intervention in the livestock industry. By bridging the gap between AI research and veterinary practice, this work contributes to the development of intelligent agricultural technologies that improve animal health and productivity.

The rest of this paper is organized as follows: Section 2 provides a detailed review of related work, discussing existing LSD detection methods and the application of deep learning in livestock disease classification. Section 3 describes the dataset, preprocessing techniques and outlines the deep learning methodology, including the selected CNN architectures, transfer learning approaches, and model training process. Section 4 presents experimental analysis, Environmental setup and the evaluation metrics. Section 5 shows the performance of different models and discusses the findings, challenges, and limitations. Section 6 presents the implications of using AI for LSD detection in real-world livestock management. Finally, Section 7 concludes the study by summarizing key contributions, limitations, and potential directions for future research in AI-driven veterinary diagnostics.

2 | Related Work

This section reviews existing studies on AI-based disease detection in livestock, particularly on machine learning applications for LSD detection, and discusses innovations, methodologies, and techniques employed in previous research. By analyzing prior studies, this review identifies research gaps and highlights the contributions of this work in advancing AI-driven diagnostics for cattle health.

Artificial intelligence, particularly deep learning, has been extensively used in veterinary medicine for disease detection [10]. Convolutional Neural Networks (CNNs) have shown remarkable success in analyzing medical and agricultural images [9, 11]. In livestock health monitoring, several deep learning models have been explored for image-based disease detection. The authors in [12] proposed the VGG16 model for cattle disease detection, aiming to enhance diagnostic accuracy and efficiency. The study focused on classifying foot and mouth disease (FMD), infectious bovine keratoconjunctivitis (IBK), and LSD using a fine-tuned VGG16 model, pretrained on ImageNet. The methodology included data collection, preprocessing, and transfer learning to adapt the model for livestock disease classification. The model was evaluated using precision, recall, and F1-score, achieving a test accuracy of 88.14%. The results demonstrated the potential of CNN-based approaches for automated veterinary diagnostics, contributing to improved disease monitoring in the livestock industry. Another model was employed in [13], where a hybrid CNN-SVM approach was proposed for cattle disease identification. The study focused on detecting Foot and Mouth Disease, Bovine Respiratory Disease, Mastitis, Bovine Tuberculosis, and Johne's Disease using a dataset of 5,000 images. The integration of CNN with SVM enhanced diagnostic precision, achieving an accuracy of 94%, outperforming Random Forest (85%) and standalone SVM (87%). Evaluation metrics, including recall and F1-score, indicated that the model consistently exceeded 90% performance across all disease categories. However, the study highlighted that the model's accuracy is significantly affected by image quality, and its implementation in resource-limited environments poses computational challenges.

Researchers also applied pretrained CNN models and custom architectures to analyze images of infected and healthy animals to classify skin lesions in cattle. However, most existing studies focus on small datasets and do not provide comprehensive model comparisons. In [14], authors employed multiple CNN architectures, including deep CNN, Inception-V3, and VGG-16, were utilized for early detection of external cattle diseases such as FMD, LSD, and IBK. The study aimed to enhance disease recognition in husbandry farms through deep learning techniques. The proposed system achieved 95% accuracy, demonstrating its potential in reducing human diagnostic errors and assisting veterinarians and farmers in early disease identification. Another approach was explored in [15], where a CNN-based architecture was proposed for Lumpy Skin Disease detection in dairy cows. The study employed image preprocessing and segmentation techniques to identify affected areas before feature extraction. Four CNN models including DenseNet, MobileNetV2, Xception, and InceptionResNetV2 were evaluated for classification. The results demonstrated that MobileNetV2 achieved the highest performance among all these models with a high accuracy.

In [16], a deep learning-based segmentation and classification approach was proposed for detecting high-risk areas of LSD in cattle. The study utilized a 10-layer CNN trained on the Cattle's Lumpy Skin Disease (CLSD) dataset. Feature extraction was performed using color histograms, as skin color plays a crucial role in identifying affected areas. A deep pre-trained CNN extracted features from segmented regions, and classification was conducted using an Extreme Learning Machine (ELM) classifier. The proposed model achieved an accuracy of 90.12%, showing its effectiveness compared to state-of-the-art techniques in LSD detection. Another machine learning-based approach was proposed in [17] for the early prediction of LSD in cattle using image classification. The study employed Convolutional Neural Networks (CNNs) and evaluated three well-known architectures: VGG16, VGG19, and InceptionV3, achieving accuracies of 87%, 86%, and 85%, respectively. The methodology included image preprocessing, model training, and performance evaluation on a separate test dataset. Additionally, the study examined the impact of different activation functions (ReLU, Sigmoid, Tanh, and Linear) in the fully connected layers, analyzing their role in optimizing model performance.

These studies highlight the rapid advancements in applying deep learning models for LSD detection in cattle. While CNN-based architecture has shown strong classification performance, further improvements are needed. Many existing works rely on pretrained models with limited adaptation to LSD-specific features, and datasets often lack diversity and large-scale representation. Enhancing classification accuracy and model robustness remains a challenge, especially in real-world conditions with varying image quality and environmental factors. To address these gaps, this study aims to develop and evaluate multiple deep learning models, enhance classification accuracy through advanced preprocessing, and utilize a diverse dataset for better generalization. Additionally, it seeks to analyze and compare model performance using key evaluation metrics to establish a reliable framework for LSD diagnosis.

3 | Materials and Methods

This section outlines the approach used to develop and evaluate deep learning models for LSD classification. It describes the dataset composition, preprocessing techniques, model architecture, training strategies. The study leverages transfer learning with various pre-trained CNN architectures to enhance feature extraction and classification accuracy.

3.1 | Dataset Description

The dataset used in this study consists of images of cows categorized into two classes: healthy cows and cows affected by LSD. The dataset was collected from publicly available sources, ensuring diversity in lighting conditions, angles, and cow breeds. Figure 1 provides a sample of the images used in this study, illustrating both healthy and infected cattle. The training set, comprising 80% of the total images, was used to optimize model parameters and learn relevant patterns. The validation set, accounting for 10% of the images, was employed to fine-tune hyperparameters and monitor performance during training, ensuring the model did not overfit the training data. Finally, the testing set, also consisting of 10% of the images, was reserved for evaluating the final model's performance on unseen data.

Figure 1. Images of healthy and infected cattle used in the Dataset.

To improve model robustness and prevent overfitting, preprocessing techniques were applied. Each image was resized to 224 × 224 pixels to match the input size required by pre-trained CNNs. Normalization was performed by scaling pixel values to the [0,1] range [18]. In addition, to increase the variability of training data and enhance model generalization, data augmentation techniques were applied [19]. The augmentation was only applied to the training set, while validation and testing sets remained unchanged to evaluate real-world performance accurately.

3.2 | Deep Learning Models

In this study, several deep learning models were utilized for feature extraction and classification, leveraging transfer learning to enhance performance. The study explored multiple CNN architectures that were pre-trained on the ImageNet dataset [20], allowing them to extract meaningful and discriminative features from the input images. The selected architectures included MobileNetV2, ResNet50V2, DenseNet121, InceptionV3, and Xception, each offering unique structural advantages. MobileNetV2 was chosen for its lightweight design and efficiency, making it suitable for deployment in resource-constrained environments [21]. ResNet50V2, with its deep residual connections, aimed to mitigate vanishing gradient issues and improve feature propagation [22]. DenseNet121 was incorporated due to its densely connected layers, which promote feature reuse and efficient parameter utilization [23]. InceptionV3 leveraged multi-scale feature extraction through inception modules, enhancing its ability to recognize intricate patterns [24]. Finally, Xception, an extension of the Inception architecture, utilized depthwise separable convolutions to improve computational efficiency while maintaining high accuracy [25]. These models were trained and fine-tuned on the LSD dataset, and their performances were systematically evaluated to identify the most effective approach for LSD classification.

Each model was modified by replacing the original classification head with a custom fully connected layer tailored for binary classification. The modification included a Global Average Pooling Layer to reduce the feature dimensions while retaining essential spatial information. This was followed by dense layers with 128 and 64 neurons, both utilizing ReLU activation to introduce non-linearity and improve feature learning. To prevent overfitting, dropout layers with a 40% dropout rate were incorporated [26]. Finally, a sigmoid activation function was applied in the output layer to produce probability scores for binary classification.

3.3 | Model Training and Hyperparameter Tuning

The models were trained using binary cross-entropy loss and optimized with the Adam optimizer using a batch size of 32, ensuring efficient memory utilization while maintaining stable gradient updates [27]. The models were trained for 60 epochs, with early stopping implemented to halt training if the validation loss did not improve for a predefined number of epochs, preventing overfitting [28]. The initial learning rate was set to 0.001, but to improve convergence and avoid overshooting optimal weights, the ReduceLROnPlateau strategy was applied. This technique dynamically reduced the learning rate by a factor of 0.2 when the validation loss plateaued, ensuring more refined weight adjustments in later training stages.

To further enhance performance, fine-tuning was employed on the pre-trained CNN models. Initially, the base models were frozen to leverage their pre-trained features. After the network was sufficiently trained on the dataset, the top 20 layers of the base CNN models were unfrozen, allowing the model to adapt to dataset-specific patterns. This fine-tuning process helped the models capture more domain-specific features related to LSD, leading to improved classification accuracy [29]. The fine-tuned layers were trained with a lower learning rate (1e-5) to prevent drastic weight updates, ensuring that the learned representations were refined without disrupting the pre-trained knowledge.

4 | Experimental Analysis

This section provides a comprehensive analysis of the experimental setup, model implementation, and evaluation metrics used to assess the performance of deep learning models for LSD detection in cattle.

4.1 | Environmental Setup

The experiments were conducted using the Kaggle environment, which provides a high-performance cloud-based computing environment for deep learning tasks. The system specifications included an Intel Xeon CPU, 30GB RAM, and an NVIDIA Tesla P1000 GPU, which ensuring efficient model training and evaluation. The experiments were implemented using Python 3.10.12 programing language, with TensorFlow 2.17.1 and Keras 3.5.0 as the primary deep learning frameworks [30, 31].

4.2 | Implementation Details

Five different CNN architectures were employed: MobileNetV2, ResNet50V2, DenseNet121, InceptionV3, and Xception. Each model was initialized with pre-trained ImageNet weights, leveraging transfer learning for feature extraction. Initially, the base layers of the models were frozen to retain pre-trained features, and only the top classification layers were trained. Later, fine-tuning was applied by unfreezing the top 20 layers to allow the models to learn dataset-specific features. The full implementation details and hyperparameters tuning methods are presented in Table 1.

Table 1. Training and model Hyperparameter settings.

Setting type	Hyperparameter	Setup
Data	Image size	224 * 224
	Training-validation-testing ratios	80: 10:10
	Rescaling factor	1/255
	Augmentation techniques	Rotation, Shear, Zoom, Flip, Shift.
Model	Optimizer	Adam
	Batch size	32
	Epochs	60
	Initial learning rate	0.001
	Learning rate scheduler	ReduceLROnPlateau
	Early stopping	monitor='val_loss', patience=5

4.3 | Evaluation Metrices

To evaluate the performance of the models, multiple evaluation metrics were used. These metrics provide a comprehensive assessment of model effectiveness in distinguishing between LSD-infected and healthy cattle. The key evaluation measures include accuracy, precision, recall, and F1-score. Additionally, confusion matrices were generated to analyze the classification outcomes and identify patterns in misclassification.

- Accuracy quantifies the proportion of correctly classified images relative to the total number of samples. It is mathematically expressed as:

$$Accuercy = (TP + TN)/(TP + TN + FP + FN) \tag{1}$$

Where TP (True Positives) are correctly identified LSD cases, TN (True Negatives) are correctly classified as healthy cases, FP (False Positives) occur when healthy samples are misclassified as LSD-positive, and FN (False Negatives) represent LSD-infected samples incorrectly labeled as healthy.

- Precision measures the reliability of positive predictions by calculating the proportion of correctly identified LSD cases among all instances predicted as positive:

$$Precision = (TP)/(TP + FP) \tag{2}$$

- Recall (Sensitivity) evaluates the model's ability to correctly detect all actual LSD cases. It is defined as:

$$Recall = (TP)/(TP + FN) \tag{3}$$

- F1-Score provides a balanced measure by considering both precision and recall. It is calculated as:

$$F1 - Score = 2 * (Precision * Recall)/(Precision + Recall) \tag{4}$$

$Precision$ Metric is important in minimizing false alarms, it ensures that healthy animals are not mistakenly diagnosed as infected. On the other hand, the high $Recall$ indicates that the model effectively captures LSD cases and reduces the likelihood of undetected infections, which is crucial for disease control and containment. Finally, $F1 - Score$ balances precision and recall, making it especially useful for handling imbalanced datasets while maintaining high sensitivity and specificity.

5 | Results and Discussion

In this study, several deep learning models were employed for LSD detection, including MobileNetV2, ResNet50V2, DenseNet121, InceptionV3, and Xception. These models were trained and tested on a curated dataset of cattle images to distinguish between healthy and infected cases. The models were evaluated using accuracy, precision, recall, and F1-score to assess their classification effectiveness. Table 2 summarizes the classification performance of the five CNN models tested. Additionally, Figure 2 provides a visual representation of these performance metrics. DenseNet121 achieved the highest accuracy (90.36%) and F1-score (90.25%), indicating its superior capability in distinguishing between healthy and infected cattle. MobileNetV2 and ResNet50V2 also performed well, with accuracies of 88.22% and 88.44%, respectively. InceptionV3 had the lowest accuracy (82.87%), suggesting that it was less effective in feature extraction for LSD detection.

Table 2. Model performance comparison.

Model	Accuracy	Precision	Recall	F1-Score
MobileNetV2	0.8822	0.8876	0.8760	0.8800
ResNet50V2	0.8844	0.8851	0.8810	0.8826
DenseNet121	**0.9036**	**0.9031**	**0.9020**	**0.9025**
InceptionV3	0.8287	0.8428	0.8174	0.8219
Xception	0.8715	0.8720	0.8680	0.8696

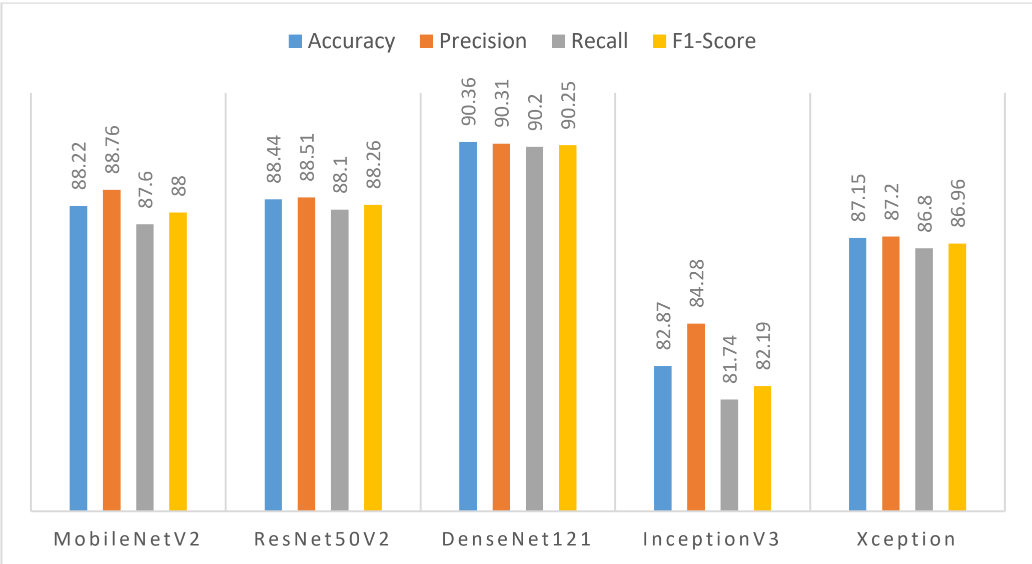
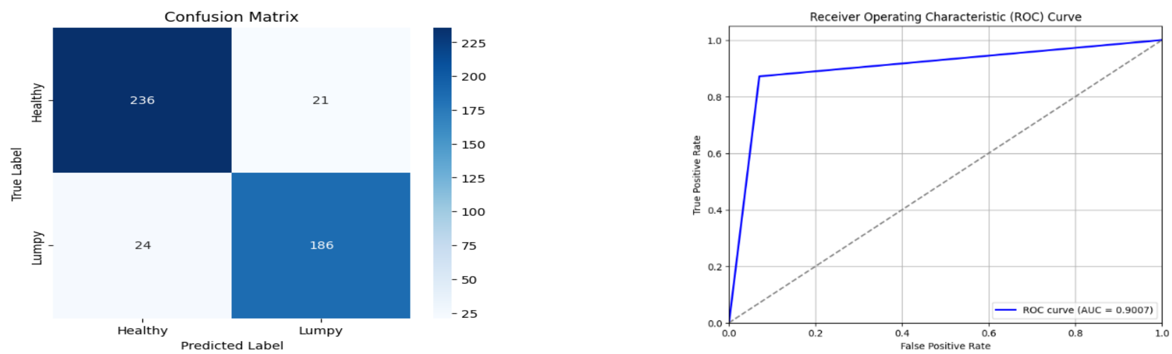


Figure 2. Performance comparison of different CNN models in LSD detection.

The confusion matrix in Figure 3(a) offers deeper insights into DenseNet121 model classification behavior. exhibited the highest true positive and true negative counts, indicating its effectiveness in minimizing misclassifications. Additionally, the Receiver Operating Characteristic (ROC) curves were plotted Figure 3(b), with the Area Under the Curve (AUC) values which indicates the model's ability to distinguish between classes.



(A) (B)

Figure 3. Performance Analysis of the DenseNet Model: (a) Confusion Matrix; (b) ROC Curve.

6 | Implications

The findings of this study have significant implications for the livestock industry, particularly in improving disease management, enhancing productivity, and supporting global food security. LSD is a major threat to cattle health, leading to economic losses due to reduced milk production, poor meat quality, and increased mortality rates [32]. The integration of deep learning models for early and accurate disease detection can help mitigate these losses by enabling rapid intervention, reducing the spread of infection, and minimizing the need for mass culling, which often disrupts supply chains in the livestock sector.

From a food security perspective, ensuring the health of livestock directly impacts the availability and affordability of animal-based food products, including milk and meat. Outbreaks of LSD and other infectious diseases can lead to shortages, price fluctuations, and economic instability in rural communities that depend on livestock farming. AI-driven diagnostic tools can strengthen disease surveillance and early warning systems, preventing large-scale outbreaks and ensuring a stable supply of livestock products, thereby contributing to global food security efforts.

This study also aligns with the United Nations' Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger) and SDG 3 (Good Health and Well-being) [33]. By improving livestock disease detection, this research supports sustainable agricultural practices, ensuring a steady food supply while reducing economic hardships for farmers. Additionally, minimizing disease outbreaks through AI-powered early detection promotes animal welfare and reduces the overuse of antibiotics and other treatments, which aligns with SDG 12 (Responsible Consumption and Production). This not only enhances efficiency but also contributes to the digital transformation of the livestock industry, paving the way for more resilient and data-driven agricultural systems.

7 | Conclusion and Future Work

This study explored the application of deep learning for Lumpy Skin Disease (LSD) detection in cattle by evaluating five advanced CNN architectures: MobileNetV2, ResNet50V2, DenseNet121, InceptionV3, and Xception. The models were assessed using multiple performance metrics, including accuracy, precision, recall, and F1-score, to ensure a comprehensive evaluation of their classification capabilities. Among these deep learning models, DenseNet121 demonstrated the highest classification performance, achieving an accuracy of 90.36%, making it the most suitable model for LSD diagnosis. The results highlight the potential of AI-driven diagnostic tools in improving disease detection accuracy, aiding early intervention, and supporting the livestock industry in disease management. Despite these promising results, several areas warrant further exploration. Future work will focus on enhancing model generalizability by incorporating larger and more diverse datasets, including images from different environmental conditions and cattle breeds. Additionally, lightweight models optimized for real-time deployment on edge devices will be investigated to facilitate on-field disease detection. Further research will also explore integrating explainable AI techniques, ensuring that model predictions are interpretable and trustworthy for veterinarians and farmers.

Acknowledgments

The author is grateful to the editorial and reviewers, as well as the correspondent author, who offered assistance in the form of advice, assessment, and checking during the study period.

Author Contributions

All authors contributed equally to this work.

Funding

This research was conducted without external funding support.

Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

References

[1] Khan, Y.R., et al. (2021). A review: Surveillance of lumpy skin disease (LSD) a growing problem in Asia. Microbial pathogenesis, 158, 105050.

[2] Tran, H.T.T., et al. (2021). Lumpy skin disease outbreaks in Vietnam, 2020. Transboundary and Emerging Diseases, 68(3), 977-980.

[3] Sharma, S., et al. (2024). In Depth Analysis of Recent Models for Lumpy Skin Disease Virus and Stage Detection: A Comparative Study. Paper presented at the International Conference On Emerging Trends In Expert Applications & Security.

[4] Hamet, P. and J. Tremblay. (2017). Artificial intelligence in medicine. metabolism, 69, S36-S40.

[5] Patel, H., et al. (2022). Role of artificial intelligence in livestock and poultry farming. Sinkron: jurnal dan penelitian teknik informatika, 6(4), 2425-2429.

[6] Kayalibay, B., G. Jensen, and P. van der Smagt. (2017). CNN-based segmentation of medical imaging data. arXiv preprint arXiv:1701.03056.

[7] Rohan, A., et al. (2024). Application of deep learning for livestock behaviour recognition: A systematic literature review. Computers and Electronics in Agriculture, 224, 109115.

[8] Fuentes, S., et al. (2022). The livestock farming digital transformation: implementation of new and emerging technologies using artificial intelligence. Animal health research reviews, 23(1), 59-71.

[9] Shin, H.-C., et al. (2016). Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. IEEE transactions on medical imaging, 35(5), 1285-1298.

[10] Appleby, R.B. and P.S. Basran. (2022). Artificial intelligence in veterinary medicine. Journal of the American Veterinary Medical Association, 260(8), 819-824.

[11] Kamilaris, A. and F.X. Prenafeta-Boldú. (2018). A review of the use of convolutional neural networks in agriculture. The Journal of Agricultural Science, 156(3), 312-322.

[12] Shinde, S., et al. (2024). Cattle Disease Detection using VGG16 CNN Architecture. Paper presented at the 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT).

[13] Mehta, S. and S. Choudhary. (2024). Advancements in Veterinary Diagnostics: A CNN-SVM Model for Cattle Disease Identification. Paper presented at the 2024 4th Asian Conference on Innovation in Technology (ASIANCON).

[14] Rony, M., D. Barai, and Z. Hasan. (2021). Cattle external disease classification using deep learning techniques. Paper presented at the 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT).

[15] Saha, D.K. (2024). An extensive investigation of convolutional neural network designs for the diagnosis of lumpy skin disease in dairy cows. Heliyon, 10(14).

[16] Genemo, M. (2023). Detecting high-risk area for lumpy skin disease in cattle using deep learning feature. Advances in Artificial Intelligence Research, 3(1), 27-35.

[17] Gupta, A., et al. (2023). Revolutionizing cattle health: a machine learning approach to efficiently predict lumpy disease in cows. Paper presented at the 2023 4th IEEE Global Conference for Advancement in Technology (GCAT).

[18] Raju, V.G., et al. (2020). Study the influence of normalization/transformation process on the accuracy of supervised classification. Paper presented at the 2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT).

[19] Mikołajczyk, A. and M. Grochowski. (2018). Data augmentation for improving deep learning in image classification problem. Paper presented at the 2018 international interdisciplinary PhD workshop (IIPhDW).

[20] Krizhevsky, A., I. Sutskever, and G.E. Hinton. (2012). Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 25.

[21] Howard, A.G. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861.
[22] He, K., et al. (2016). Deep residual learning for image recognition. Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.
[23] Huang, G., et al. (2017). Densely connected convolutional networks. Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.
[24] zegedy, C., et al. (2017). Inception-v4, inception-resnet and the impact of residual connections on learning. Paper presented at the Proceedings of the AAAI conference on artificial intelligence.
[25] Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.
[26] Nitish, S. (2014). Dropout: a simple way to prevent neural networks from overfitting. J. Mach. Learn. Res., 15, 1.
[27] Jais, I.K.M., A.R. Ismail, and S.Q. Nisa. (2019). Adam optimization algorithm for wide and deep neural network. Knowl. Eng. Data Sci., 2(1), 41-46.
[28] Prechelt, L. (2002). Early stopping-but when? Neural Networks: Tricks of the trade (pp. 55-69): Springer.
[29] Vrbančič, G. and V. Podgorelec. (2020). Transfer learning with adaptive fine-tuning. IEEE Access, 8, 196197-196211.
[30] Abadi, M., et al. (2016). {TensorFlow}: a system for {Large-Scale} machine learning. Paper presented at the 12th USENIX symposium on operating systems design and implementation (OSDI 16).
[31] Gulli, A. and S. Pal. (2017). Deep learning with Keras: Packt Publishing Ltd.
[32] Khan, A., et al. (2022). Lumpy skin disease: a threat to the livestock industry-a review. Agrobiol Rec, 9, 22-36.
[33] Fund, S. (2015). Sustainable development goals. Available at this link: https://www. un. org/sustainabledevelopment/inequality.