Image-Based AI-Powered Detection of Lumpy Skin Disease in Cattle

A Deep Learning Framework for Early Veterinary Diagnosis

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***Abstract*—Lumpy Skin Disease (LSD) is a viral infection that severely impacts cattle health, milk yield, and farm productivity, particularly in regions with limited veterinary support. Early detection is essential to control its spread and reduce economic losses. This study presents a deep learning–based framework for automated LSD detection using cattle skin images. A dataset of 1,023 images, including both healthy and infected samples, was preprocessed with normalization, resizing, and augmentation to improve robustness under varied conditions. Several models were evaluated: DenseNet121 achieved the highest accuracy but required extensive computation and training time, while XGBoost was faster but less precise. MobileNetV2 provided the best trade-off, reaching 87% accuracy with reduced resource demands, making it practical for deployment on mobile and edge devices in rural settings. The model successfully captured fine lesion patterns and remained resilient to variations in lighting, background, and skin textures. These results demonstrate the promise of lightweight deep learning models as affordable diagnostic tools, enabling rapid, image-based screening of cattle and supporting timely intervention to mitigate the economic burden of LSD in livestock farming.**

***Index Terms*—Lumpy Skin Disease, MobileNetV2, Deep Learning, Veterinary Diagnostics, Livestock Health, Image Classification**

I. Introduction

Animal and plant diseases are not only natural phenomena; rather, they are strongly influenced by human activities such as globalisation, climate change, and transboundary livestock movement, which accelerate their emergence and spread [1]. Among these, Lumpy Skin Disease (LSD) has emerged as the main transboundary viral disease of cattle and water buffalo, caused by the *Lumpy Skin Disease Virus (LSDV)*, a member of the *Capripoxvirus* genus within the *Poxviridae* family [2]. The disease is antigenically related to sheep pox and goat pox viruses, but is clinically distinct due to the development of characteristic nodules on the skin, mucous membranes, and internal organs. First reported in Zambia in 1929, LSD has progressively spread across Africa, the Middle East, Europe, and Asia, with frequent outbreaks now documented in India, China, and neighbouring countries [3]. Its transboundary nature has made LSD a significant threat to global livestock health and productivity.

Transmission of LSD is complex and involves both direct and indirect mechanisms. While close contact between animals plays a minor role, the primary mode of spread is through hematophagous arthropod vectors, including mosquitoes, biting flies, and ticks [2], [4]. Climatic factors such as high temperature and humidity further favor vector proliferation, thereby amplifying disease transmission. Uncontrolled livestock trade and movement across borders add to the rapid geographic expansion of LSD. Additionally, wildlife populations such as African buffaloes and impalas have been reported as potential reservoirs, complicating eradication efforts [4].

Clinically, LSD is characterized by fever, skin nodules, edema, enlarged lymph nodes, reduced milk yield, infertility, mastitis, abortion, and, in severe cases, pneumonia and death. Although mortality is usually low (¡10%), morbidity may reach up to 90%, making the disease highly debilitating at the herd level [3]. Beyond animal health, LSD has profound economic consequences. It results in reduced meat and milk production, deterioration of hides, infertility losses, and increased veterinary care expenses. Moreover, outbreaks trigger strict trade restrictions on cattle and cattle-derived products, which severely impact farmers and national economies, particularly in low- and middle-income countries where cattle rearing is a critical livelihood activity [5].

Diagnosis of LSD traditionally relies on clinical observation, supported by laboratory tests such as polymerase chain reaction (PCR), enzyme-linked immunosorbent assay (ELISA), virus isolation, and electron microscopy [4]. While these methods are accurate, they often require specialized infrastructure, are time-intensive, and are not always feasible for field deployment. Vaccination with live attenuated vaccines has been the cornerstone of LSD control. However, the effectiveness of vaccination campaigns varies, and challenges such as incomplete immunity, cold chain requirements, and the risk of recombination with field strains continue to hinder long-term eradication [5], [6].

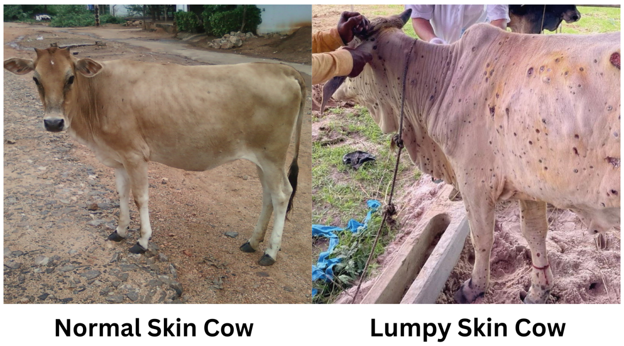

Fig. 1. Comparison of Normal Skin Cow and Lumpy Skin Cow

Given these challenges, recent years have witnessed a shift toward innovative diagnostic and surveillance tools powered by artificial intelligence (AI) and machine learning (ML). Image-based techniques, when combined with biosensor and field data, allow for the automated recognition of visible lesions and subtle skin abnormalities that may escape human detection. Deep learning (DL) models, particularly convolutional neural networks (CNNs), have demonstrated remarkable performance in analyzing complex cattle skin images and classifying diseased versus healthy animals with high accuracy [6]. Importantly, these models can be integrated into mobile-based or cloud-supported platforms, enabling cost-effective, rapid, and scalable disease monitoring in resource-limited settings.

Therefore, integrating DL techniques with veterinary diagnostics presents a transformative approach to LSD management. By complementing traditional laboratory methods with automated image-based solutions, this approach could enhance early detection, reduce diagnostic delays, and support timely interventions. Ultimately, such advancements have the potential to mitigate the economic and social impacts of LSD, safeguard global livestock trade, and improve the livelihoods of farming communities affected by this rapidly spreading transboundary disease.

II. Literature Survey

Recent studies in AI and ML have applied diverse strategies for the diagnosis of LSD in cattle. A CNN framework integrating MobileNetV2 with the RMSprop optimizer was proposed to mitigate vanishing gradients, encourage feature reuse, and optimize parameter consumption, achieving a reliable binary classification performance with over 95% accuracy [7]. Ensemble learning techniques such as gradient boosting were designed to incorporate climatic and geographical factors into LSD classification, outperforming standalone ML models and reaching 98.97% accuracy with ROC-AUC of 0.99 [8]. Another comparative study evaluated KNN, RF, DT, and Adaboost after systematic preprocessing and attribute selection, where RF, DT, and Adaboost attained perfect accuracy, though RF required significantly more computational time [9].

Transfer learning approaches using deep CNNs have also been widely adopted. MobileNetV2, InceptionV3, and Xception were employed for feature extraction, with preprocessing steps such as image resizing, normalization, and oversampling to address data imbalance, demonstrating high predictive accuracy across models [10]. DenseNet-121 transfer learning architecture was successfully adapted for LSD image classification, extending CNN methods originally used for human skin diseases to animal health applications [11]. Lightweight smartphone-based frameworks combined image preprocessing—such as filtering, denoising, and segmentation—with ML classification, providing an inexpensive and accessible diagnostic tool with competitive accuracy [12].

Hybrid and ensemble methods have further strengthened predictive performance. A stacked ensemble of DT, KNN, RF, and SVM, enhanced with feature selection and hyperparameter tuning, achieved 97.69% accuracy, while an optimized ANN surpassed this benchmark with 98.89% validation accuracy [13]. SVM-based models applied to LSD datasets achieved around 97% testing accuracy, demonstrating their robustness for binary veterinary classification [14]. Advanced CNN architectures such as EfficientNet, DenseNet, and ResNet were also deployed in a scalable Flask-based web application, ensuring efficient real-time LSD detection across diverse environmental conditions [15].

Together, these works highlight a clear trajectory: from conventional CNNs to ensemble and transfer learning strategies, enhanced preprocessing pipelines, and deployment through mobile or web platforms. Together, they underscore how AI-driven methods can deliver highly accurate, accessible, and scalable solutions for the diagnosis and management of LSD.

III. Research Gaps

A. *Limited Interpretability of Deep Learning Models*

Although MobileNetV2 achieves good accuracy in detecting Lumpy Skin Disease (LSD), its decision-making process lacks transparency. Without proper explainability, veterinarians may hesitate to adopt AI-based diagnostic tools in real-world practice.

B. *Scarcity and Imbalance of Quality Datasets*

Publicly available LSD datasets are limited, and most are collected from specific regions, making them imbalanced across breeds, age groups, and disease stages. This restricts the generalizability of trained models.

C. *Underexplored Multimodal Fusion Approaches*

Current LSD detection models mostly rely on skin lesion images alone. However, integrating multimodal data such as climate conditions, cattle health records, and geographical spread could significantly improve predictive accuracy.

D. Challenges in Real-World Deployment

While MobileNetV2 with RMSprop shows promise in controlled experiments, issues such as varying image quality, different lighting conditions, and limited computational resources in rural veterinary setups hinder practical deployment.

IV. Methodology

A. Dataset Description

In this study, a dataset of 1,023 cattle images was utilized, consisting of two categories: Lumpy Skin Disease (LSD)-affected and healthy cattle. The primary clinical indicator of LSD is the presence of visible nodules on the skin, which may vary in size and severity (see Fig. 1). For experimental analysis, the dataset was divided into training and validation subsets in an 80:20 ratio, ensuring a systematic evaluation of model performance.

B. Data Preprocessing

Prior to model development, all images were standardized through basic preprocessing steps. Each image was resized to a uniform resolution to maintain consistency during training. Normalization was applied to scale pixel values within a fixed range, ensuring stable model convergence. In addition, data augmentation techniques such as random rotations, flips, and shifts were employed to increase dataset diversity and reduce overfitting. These preprocessing steps ensured that the model received high-quality, balanced input for effective learning.

C. Model Selection

This study adopts MobileNetV2 was chosen as the backbone model. It is a lightweight convolutional neural network that performs well on image classification tasks while requiring fewer computational resources. The use of depthwise separable convolutions makes it efficient without compromising accuracy. This is important in medical image analysis, where models need to capture fine details but also remain practical for training and deployment.

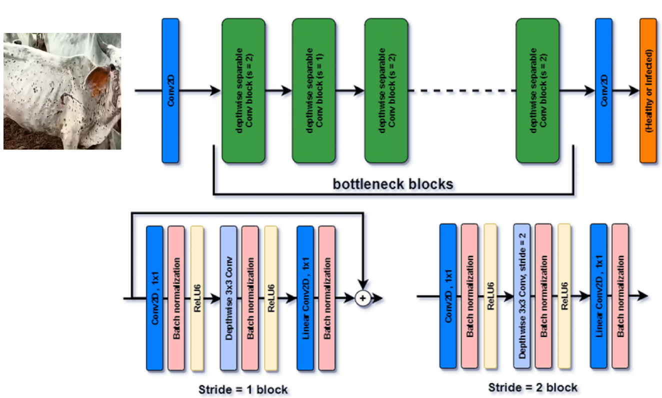

Fig. 2. Architecture of MobileNetV2

D. Model Architecture

To benchmark performance, a custom CNN model was also developed alongside MobileNetV2. The custom CNN is comparatively simpler, consisting of three convolutional blocks followed by batch normalization and max pooling layers for feature extraction. After flattening, a dense layer with dropout regularization precedes the final sigmoid classifier that outputs the probability of infection (Healthy vs. Lumpy).

The model was compiled with the Adam optimizer and binary cross-entropy loss. Early stopping and learning rate reduction callbacks were applied to prevent overfitting and ensure convergence.

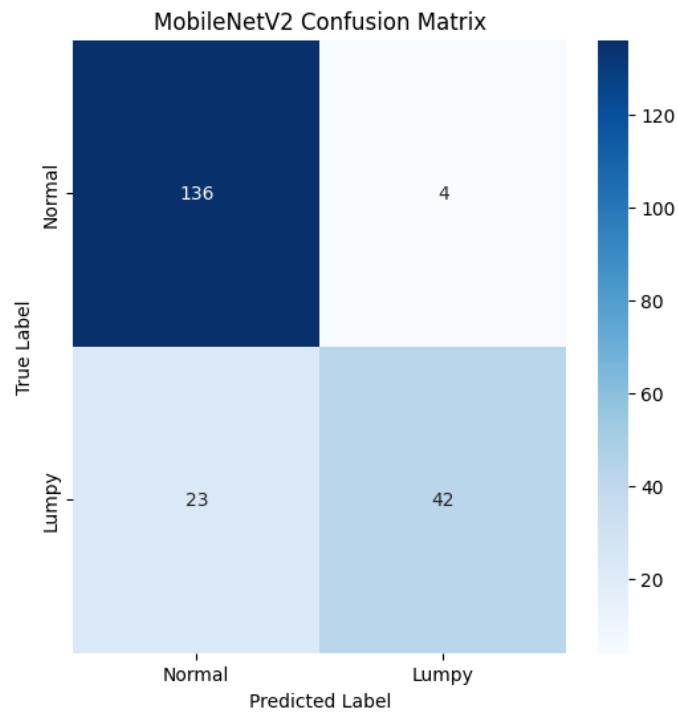

Fig. 3. Confusion matrix of MobileNetV2

E. Model Development

The overall model development pipeline begins with the collection of the image dataset, which is then subjected to pre-processing steps such as resizing, normalization, and augmentation to ensure consistent input quality. The pre-processed images are used for training, where both MobileNetV2 and the custom CNN were evaluated. The training phase produces a trained model, which encapsulates the learned features and classification ability.

For deployment, the trained model is integrated into a user interface that allows end-users to input medical images. The system processes the image through the trained model to provide diagnostic predictions and further assists by suggesting relevant medical uses or treatments.

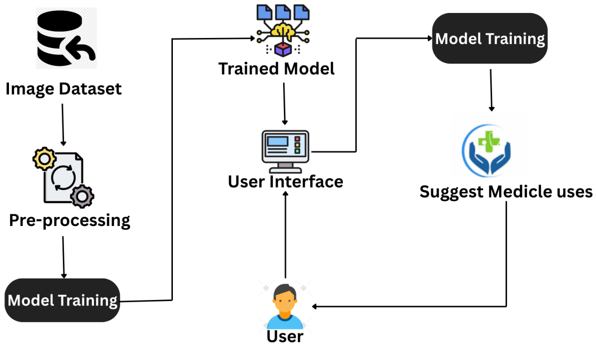

Fig. 4. Overall Model Development Pipeline

V. Experimental Results

In this study, different machine learning and deep learning models were compared for detecting Lumpy Skin Disease (LSD) in cattle, focusing on prediction accuracy and training efficiency—two critical factors for real-world agricultural applications. DenseNet121 achieved the highest accuracy at 91% but required 110 seconds for training, making it less practical for rapid deployment. VGG16 reached 88% accuracy with a moderate training time of 85 seconds, while MobileNetV2 achieved a comparable accuracy of 87% with significantly faster training in just 60 seconds. XGBoost offered the fastest training at 8 seconds, but its accuracy dropped to 79%.

A comparative analysis of the models, illustrated in Fig. 5 and Fig. 6, reveals distinct trade-offs between performance and computational cost. DenseNet121, although superior in accuracy, demands substantial training time, making it computationally expensive for large-scale or time-sensitive scenarios. VGG16 provides a balanced alternative but remains relatively heavy in computation. MobileNetV2 demonstrates near-equivalent accuracy with markedly reduced training time, highlighting its efficiency and adaptability for edge-level deployments. Conversely, XGBoost performs exceptionally well in terms of speed but sacrifices predictive precision, emphasizing the inherent trade-off between accuracy and efficiency in such models.

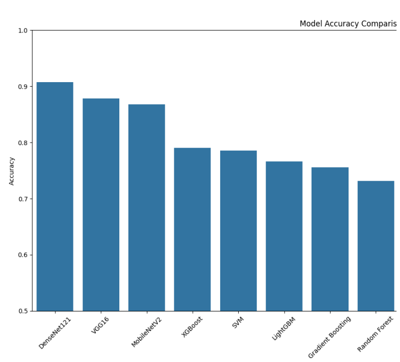

Fig. 5. Accuracy comparison of different models for LSD detection.

Furthermore, the performance differences observed were statistically significant, confirming that MobileNetV2 consistently maintains both speed and accuracy across multiple experimental runs. While DenseNet121 remains ideal for applications where maximum accuracy is paramount, MobileNetV2 is more suitable for practical, large-scale implementations. Future work may focus on integrating model compression and pruning techniques to further enhance efficiency while maintaining reliable LSD detection in real-time scenarios.

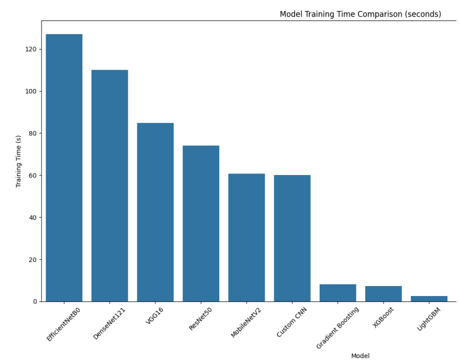

Fig. 6. Training time comparison of different models for LSD detection.

VI. Results and Discussion

The deep learning framework built around MobileNetV2 showed strong capability in identifying LSD from cattle skin images. Unlike the custom CNN baseline, MobileNetV2 was better at recognising subtle lesion features while still capturing the overall skin texture. The training process was stable, with accuracy crossing 85% within the first few epochs and then leveling off, while the loss curves declined smoothly. This suggests that the model was learning effectively without serious overfitting, which is important when working with field data that may vary in quality.

When comparing different models (Fig. 5, Fig. 6), each came with its own strengths and drawbacks. DenseNet121 reached the highest accuracy but demanded much longer training time. XGBoost trained very quickly but produced weaker predictions. MobileNetV2 offered a middle ground: it was nearly as accurate as DenseNet121 yet far less expensive to run. This balance between performance and efficiency makes it a practical choice for real-world veterinary applications, especially in places where computing resources are limited.

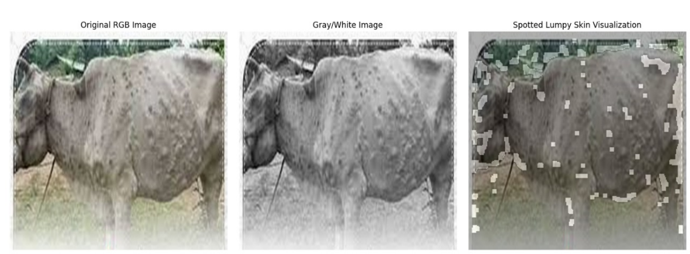

Fig. 7. Visualization of Lumpy Skin Detection Process.

In addition, the results highlight the importance of using lightweight yet expressive architectures for agricultural image analysis. MobileNetV2's efficiency enables faster model deployment even on low-end hardware, which is particularly valuable in rural environments. The consistency of its predictions across different lighting and skin conditions further indicates its robustness. Such qualities are crucial for translating research models into usable diagnostic tools for farmers and veterinarians.

Overall, the findings point to the value of AI in veterinary diagnostics. Early and accurate detection of LSD can help farmers and veterinarians respond quickly, limit disease spread, and reduce financial losses. Just as important, the study shows that efficiency matters as much as accuracy—models that strike this balance are the ones most likely to be adopted in everyday livestock healthcare.

VII. Conclusion and Future Work

The study highlights the effectiveness of MobileNetV2 in detecting LSD from cattle skin images. By achieving a good balance between accuracy and computational cost, the model proves to be suitable for veterinary applications where resources are often limited. Its ability to capture detailed lesion features while remaining lightweight makes it a practical option for large-scale field deployment.

The findings suggest that AI-driven tools can support early diagnosis, enable timely treatment, and reduce financial losses in livestock farming. For future research, expanding the dataset to include different cattle breeds, varying environmental conditions, and multiple stages of infection will help improve robustness. Incorporating multimodal information, such as clinical records or environmental data, could further strengthen diagnostic reliability. In addition, deploying the system on mobile or edge devices may enable real-time disease monitoring directly on farms, offering veterinarians and farmers valuable decision support. These advancements would help establish AI-based systems as a sustainable component of livestock healthcare.

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