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A Deep Learning Tool for Early Detection and Control of Lumpy Skin Disease Using Convolutional Neural Networks

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Abstract: Lumpy skin disease (LSD), a highly contagious viral disease of cattle, continues to pose a significant threat to animal welfare and global economic stability. Early detection and intervention are crucial for mitigating its impact. This research explored the potential of convolutional neural networks (CNNs) for automated LSD classification based on clinical and laboratory data. We compared two prominent CNN architectures, Inception and Xception, in their ability to identify patterns and predict LSD occurrence. Both models were trained on a large dataset of labeled images, effectively learning to distinguish LSD-infected animals from healthy ones. However, Xception emerged as the superior technique, achieving a remarkable 98.8% accuracy compared to Inception's 94%. This 4.8% improvement in accuracy demonstrates the potential of Xception for more precise and reliable LSD detection. These findings suggest that CNNs, particularly Xception, can be valuable tools for early LSD diagnosis, enabling prompt veterinary intervention and reducing disease spread. Integrating this technology into veterinary practices can significantly improve animal health management and disease control efforts, ultimately minimizing LSD's global impact on cattle populations.

Keywords: Convolutional Neural Networks; Inception; Xception; Lumpy Skin Disease; Machine Learning.

1. Introduction

Pakistan's agricultural sector, heavily reliant on crops and livestock, employs 45% of the workforce and contributes 21% to GDP. Livestock alone accounts for 56% of agricultural value addition and 12% of GDP, significantly impacting poverty alleviation and economic growth. Over estimated 30.96 million cattle, 27.44 million sheep, 54.27 million goats, 0.90 million horses, and approximately 1.50 million camels [14]. However, the country faces significant challenges due to the presence of various animal skin diseases. In Pakistan, various skin diseases significantly impact animals, including lumpy skin disease [13], dermatophilosis [18], and goat and sheep pox [17]. These diseases not only cause considerable economic losses but also hinder the growth and productivity of the livestock sector. To address these issues, the Pakistani government and relevant stakeholders are actively implementing control and prevention measures, including vaccination campaigns, improved animal management practices, and awareness programs. By effectively managing and combating animal skin diseases, Pakistan can enhance the health and well-being of its livestock, ensure food security, and unlock the full potential of its livestock sector for sustainable economic development [11].

Lumpy skin disease (LSD) is a highly contagious viral infection of cattle, buffalo, and other ruminants, prevalent in much of Africa and the Middle East. The causative agent, lumpy skin disease virus (LSDV), belongs to the Capripox genus within the Poxviridae family. Transmission primarily occurs through arthropod vectors, such as biting flies and mosquitoes, but direct contact with infected animals, contaminated feed, and water can also play a role. Skin lesions, which can persist for extended periods, are considered the main source of infection, harboring the virus within their crusts [9].

Lumpy Skin Disease (LSD) relies on three primary methods: histopathological examination of infected tissue [3], virus isolation in the lab [7], or PCR testing [15]. However, distinguishing LSD from bovine pseudo-LSD, caused by a different herpes virus, can be tricky based solely on clinical symptoms. This is where PCR shines, offering definitive differentiation between the two diseases thanks to its ability to detect specific viral DNA sequences [2]. Unfortunately, there are no magic cures for LSDV infections. The only available treatment option for infected livestock focuses on supportive care, aiming to manage symptoms and improve overall health. This may involve administering non-steroidal anti-inflammatory drugs (NSAIDs) or antibiotics to combat secondary bacterial infections of the skin. The key to preventing outbreaks, however, lies in vaccination. Effective LSD vaccines exist and have proven successful in controlling the spread of the disease [4].

Therefore, the aim of this proposed research is to develop an automation model for animal lumpy skin disease detection using Convolutional Neural Network, enabling early identification and intervention to mitigate the spread of the disease, this proposed reseach holds the potential to revolutionize animal healthcare, safeguard rural livelihoods, and empower Pakistan's livestock sector to thrive.

2. Materials and Methods

2.1. Research Design

This research leverages an experimental design, a common approach in image processing and machine learning, to develop a prototype for detecting lumpy skin disease in animals. The process involves manipulating data (independent variable) and observing its impact on disease detection (dependent variable). Following three key stages: data collection, method selection, and performance evaluation, this research aims to equip veterinarians with an early detection tool for Lumpy Skin Disease.

2.2. Data Collection

The proposed research built a valuable dataset specifically tailored for Lumpy Skin Disease detection in Pakistan. Over 1000 images were sourced from veterinary clinics, online sources, and even captured directly by the researchers, ensuring quality and diversity. These images, depicting both healthy cattle and infected cattle, formed the foundation for training and testing the machine learning model, laying the groundwork for a powerful tool to combat this devastating disease in Pakistan.

2.3. Dataset Preparation

The research builds an accurate Lumpy Skin Disease (LSD) detection system using CNNs. Images from veterinary clinics and online sources are meticulously labeled and split 80% images for training dataset and 20% images for testing datasets. To ensure compatibility with the models, all images are resized and augmented with rotations, flips, and shifts. This diverse and standardized dataset, coupled with careful shuffling, paves the way for powerful LSD detection models.

2.4. Model Architecture

This research employs two cutting-edge convolutional neural networks (CNNs) for image classification: Inception model [5] and Xception model [8] as shown in figure 1. Inception excels at capturing both global and local image features through its innovative inception modules, which perform parallel convolutions of different filter sizes within a single layer. This balancing act between computational efficiency and accuracy has propelled Inception to the forefront of image classification tasks [16], on the other hand Xception, an evolution of Inception, takes a more extreme approach by replacing traditional convolutional layers with depth wise separable convolutions. This separation of spatial and channel-wise information enhances feature capture while reducing computational demands, making Xception a powerful and efficient model choice [8].

2.5. Evaluation Method

We calculate key metrics like Recall, Accuracy, F-score, and Precision, drawing upon the model's performance in classifying cases as true positive (TP), true negative (TN), false negative (FN), and false positive (FP). By analyzing these metrics, we gain a comprehensive understanding of the model's strengths and weaknesses, guiding us in refining its ability to correctly identify diseased and healthy cattle [6].

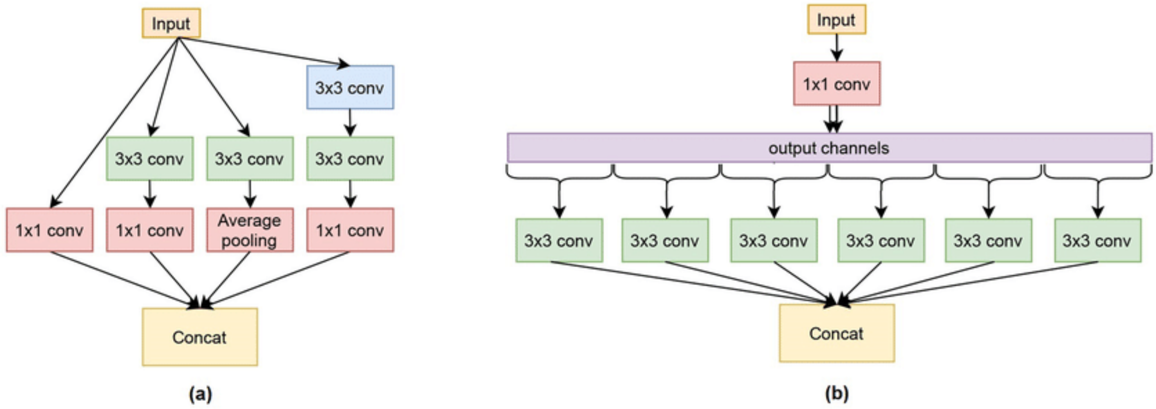


Figure 1. Basic architecture: (a) Inception module, (b) Xception module

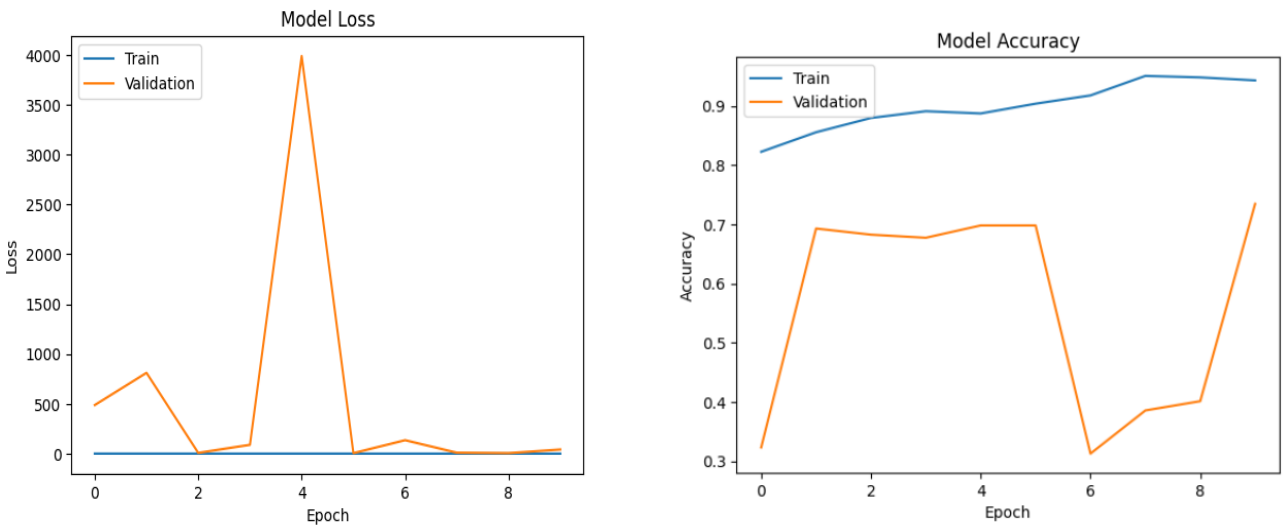
3. Results

3.1. Model Construction

The construction of a Convolutional Neural Network (CNN) models, specifically employing Inception and Xception architectures, for the detection of lumpy skin disease in animals. These models were selected based on their documented performance in image-based tasks. To ensure data quality, meticulous preprocessing was undertaken, including manual cropping, image segmentation, and noise removal, facilitated by Python. The subsequent analysis unveils the effectiveness of the proposed model in detecting lumpy skin disease, with significant implications for the advancement of automated disease diagnostic systems in veterinary medicine [12].

3.2. Inception Model

The Inception model demonstrates a clear overfitting behavior as evidenced by the divergence between training and validation metrics. Initially, both loss and accuracy curves (Figure 1a and Figure 1b, respectively) exhibit promising trends, indicating effective learning. However, a sharp decline in validation accuracy accompanied by a sudden spike in validation loss around epoch 4 signifies the onset of overfitting. The model begins to memorize the training data rather than learning generalizable features. This overfitting is further emphasized by the continued decrease in training loss while validation loss fluctuates wildly. These findings suggest that the Inception model requires additional strategies to mitigate overfitting and improve its generalization capabilities for accurate Lumpy Skin Disease detection.

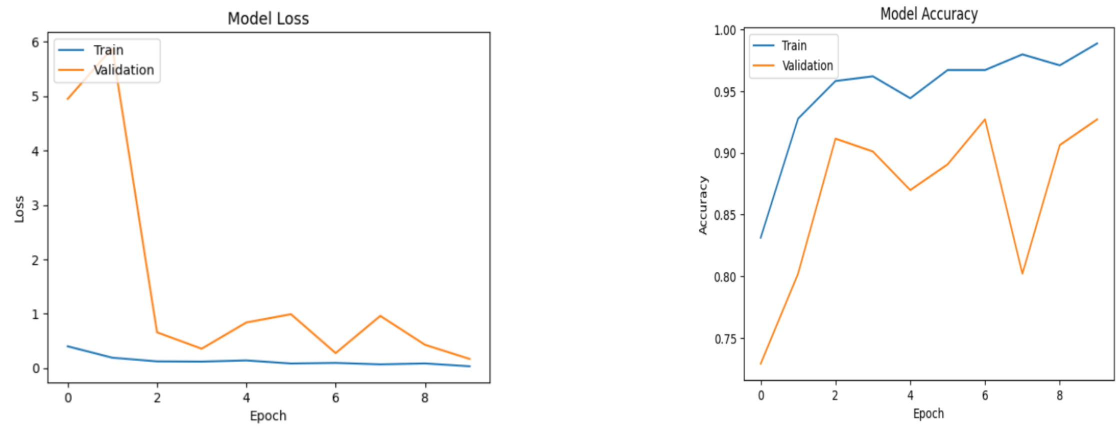


(a) **(b)**

Figure 2. (a) Inception model loss graph. (b) Inception model accuracy graph

3.3. Xception Model

The Xception model demonstrates a robust and stable performance throughout the training process, as evidenced by the behavior of both loss and accuracy curves (Figure 2a and Figure 2b, respectively). Both metrics consistently improve, with a relatively small gap between training and validation sets, indicating effective learning and strong generalization capabilities. This is in contrast to the Inception model, which exhibited significant overfitting. The Xception model's ability to maintain consistent performance suggests its potential as a reliable tool for Lumpy Skin Disease detection.



(a) **(b)**

Figure 3. (a) Xception model loss graph. (b) Xception model accuracy graph

4. Discussion

Our research, focused on early Lumpy Skin Disease detection in livestock, delves into the effectiveness of pre-trained CNN models like Inception and Xception, achieving a remarkable 98.8% accuracy with Xception. While another study also explored building specialized CNN models for disease detection, their focus shifted to tomato leaf diseases, achieving 91.2% accuracy with a custom, lightweight model. Both studies highlight the potential of CNNs for tackling domain-specific challenges, but our use of established models prioritizes efficiency and immediate implementation in veterinary settings [19]. While the custom model's smaller size offers advantages for resource-constrained environments, our pre-trained models benefit from extensive pre-training data, potentially leading to more robust performance and generalizability to unseen scenarios in Lumpy Skin Disease detection. Ultimately, both approaches showcase the versatility of CNNs and pave the way for their application in diverse disease-detection tasks across agriculture and veterinary medicine [1] [21].

Proposed research, focused on livestock disease detection, used Inception and Xception models and achieved impressive accuracy. While another study leveraged deep learning for plant disease detection with DenseNet121 and EfficientNetB0, achieving even higher accuracy. Both studies showcase the power of advanced neural networks in different fields, but our Xception model's superior performance in livestock disease detection holds significant benefits for the agricultural sector in Pakistan [2] [20].

Our research, focused on early Lumpy Skin Disease (LSD) detection in livestock with Inception and Xception models, shares a central theme with another study that crafted a bespoke CNN for tomato plant disease identification. Both studies champion the power of specialized CNNs – ours achieving a remarkable 98.8% accuracy with Xception – in outperforming pre-trained models for their specific tasks. While the tomato plant study achieved even higher accuracy (98.31% to 99.81%), our Xception model excels in the veterinary domain, offering early LSD detection with its robust performance. This dual focus not only highlights the versatility of CNNs but also showcases their potential to revolutionize disease management in diverse fields, from safeguarding livestock health and economic stability in the agricultural sector to improving crop yields through timely intervention. By embracing tailored CNN models like Xception, we pave the way for advancements in automated disease recognition systems, ultimately contributing to a healthier future for both livestock and crops [10] [22].

5. Conclusions

Our investigation into Lumpy Skin Disease detection revealed a clear frontrunner: the Xception model. While both Inception and Xception displayed impressive learning capabilities on our 1024-image dataset.

Table 1. Model Comparison

Sr#	Title 2	Title 3
1	Inception	94%
2	Xception	98.8%1

Xception emerged as the superior classifier, achieving a remarkable 98.8% accuracy compared to Inception's 94% as shown in Table 1. These findings highlight Xception's superior ability to capture the intricate patterns within Lumpy Skin Disease images. Its more efficient learning and higher accuracy make it a potentially invaluable tool for veterinarians, enabling them to confidently diagnose the disease and implement early interventions.

Ethics Approval: The study was conducted according to the Responsible Conduct in Research (RCR) Training Policy (Policy#10.07.001) of the University of Agriculture, Faisalabad. The RCR policy is followed by the instructions of National Institute of Health (NIH Publications No. 8023, revised 1978) regarding animal welfare and housing in research.

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