

Survey on Detecting Lumpy Skin Disease using Deep Learning

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Abstract -Lumpy Skin Disease is a viral illness in cattle that causes fever, skin nodules, swollen lymph nodes, and significant economic losses due to reduced productivity. Traditional detection methods, such as clinical inspection or lab tests, can be slow and often impractical in rural areas. This survey examines recent deep learning approaches for detecting LSD from cattle skin images. We compare architectures, preprocessing techniques, dataset choices, evaluation metrics, and deployment issues. Finally, we discuss existing limitations and suggest future directions to make LSD detection more reliable, generalizable, and usable in real-world settings.

Keywords: Intrusion Detection System, NIDS, Machine learning, Convolutional Neural Network, Host-based Intrusion Detection System.

1.INTRODUCTION

Lumpy Skin Disease (LSD) is caused by the LSD Virus (LSDV) and primarily affects cattle, leading to visible symptoms such as nodular lesions, fever, swelling of lymph nodes, and drop in milk yield. Outbreaks impose serious costs on farmers and livestock industries. Traditional diagnostic methods are resource intensive and often delayed. Deep learning techniques, particularly image classification models using pretrained networks and transfer learning, offer the promise of automating LSD detection based on skin images. This survey reviews recent studies in this area, highlights what works well, and identifies where improvements are possible.

In recent years, deep learning has emerged as a powerful tool for automating the detection of LSD from cattle skin images. Convolutional Neural Networks (CNNs) and advanced architectures such as VGG, ResNet, DenseNet, and EfficientNet have been effectively utilized for visual classification tasks. By employing transfer learning, these models can analyze visual features of infected cattle and distinguish them from healthy ones with high accuracy, even when limited data are available. This approach enables real-time disease diagnosis, reduces human error, and supports veterinarians and farmers in taking timely preventive actions.

2. Existing Work

Raj et al. proposed an automated diagnosis system integrating deep learning feature fusion to enhance classification accuracy and provide more stability and balanced results. The system is effective for real-time LSD detection in cattle because it combines multiple feature extraction techniques to increase the model's robustness. A graphical user interface (GUI)-based deep learning model designed specifically for cattle LSD detection was created by Naikar et al. The model's user-friendly interface allows veterinarians and farmers to easily upload images for analysis, facilitating practical applicability in veterinary settings.

By providing a dataset of images of lumpy skin, Kumar and Shastri assisted in the training and evaluation of deep learning models. This dataset serves as a valuable resource for researchers developing automated systems for LSD detection.

Jain et al. introduced an explainable machine learning model for LSD occurrence detection, emphasizing the importance of interpretability in automated systems. The model's transparency allows users to understand the reasoning behind predictions, enhancing trust in the system.

Girma et al. classified LSD using Convolutional Neural Networks (CNN) and Support Vector Machine (SVM) models, achieving a 96.5% accuracy. Combining CNNs and SVMs for accurate cattle skin disease classification is demonstrated in their study. Using a dataset of lumpy skin diseases, Evgin et al. used an Artificial Neural Network (ANN) model to achieve a 94.6% F1 score and a prediction accuracy of 98.6%. Their research highlights the potential of ANN models in accurately predicting LSD in cattle.

Yazdi et al. used MobileNet to predict skin diseases with an accuracy of 86.57% and a precision of 93.34%. The use of lightweight deep learning models in the effective detection of cattle skin diseases is the subject of their investigation. Seven different skin diseases, including LSD, were classified by Jessica et al. using MobileNet and CNN models. Their research demonstrates the versatility of deep learning models in classifying multiple skin diseases in cattle.

Afshari Safavi assessed machine learning techniques in forecasting LSD occurrence based on meteorological and geospatial features. Their study emphasizes the importance of environmental factors in predicting LSD outbreaks.

A dataset of images of lumpy skin was provided by Kumar et al. to aid in the training and evaluation of deep learning models. This dataset serves as a valuable resource for researchers developing automated systems for LSD detection.

3. METHODOLOGY

The proposed system takes an input RGB facial image along with a target age label to generate a photorealistic age-transformed version of the same person. The model follows an encoder-decoder architecture with residual blocks and skip connections to ensure both age-specific transformation and identity preservation.

1. Dataset Preparation

- Dataset structured in three folders: train, val, and test
- Two classes: 'healthy' and 'lumpy_skin'
- Images sourced from Kaggle/public datasets
- Labels automatically detected from folder names

2. Data Preprocessing

- Rescale image pixel values using 1./255
- Apply real-time data augmentation:
- Rotation (20°), width/height shift (0.2)
- Zoom (0.2), horizontal flip

- Target sizes:
 - 224×224 for most models
 - 299×299 for InceptionV3, Xception
3. Model Architecture (Transfer Learning)
 - Pretrained models used:
 - DenseNet121, InceptionV3, MobileNetV2, ResNet50
 - Base model layers frozen to retain learned features
 - Custom layers added:
 - Global Average Pooling → Dropout → Dense (sigmoid)
 4. Model Training
 - Optimizer: Adam (lr=0.001)
 - Loss Function: Binary Crossentropy
 - Metrics: Accuracy
 - Training run for 50 epochs
 - Used flow_from_directory for efficient data loading.
 5. Evaluation & Visualization
 - Evaluated on separate test set
 - Plotted training vs validation accuracy
 - Printed final test accuracy for each model
 - Models saved for future inference: .h5 format
 6. Model Saving & Deployment
 - Model files saved with names like:
 - MobileNetV2_lumpy_skin.h5
 - ResNet50_lumpy_skin.h5
 - Ready for deployment in web diagnostic systems
 7. Web Application Prediction
 - Select Algorithm
 - Input Image and get Prediction

4. CONCLUSION

Deep learning has been shown in multiple recent studies to be a strong tool for detecting Lumpy Skin Disease in cattle from images. Models like MobileNetV2, Xception, DenseNet121 and others reach high accuracy under controlled datasets. However, for these systems to be truly effective in practical, real world settings, improvement is needed in dataset variability, field testing, computational efficiency, and model explainability. The path forward includes creating richer datasets, ensuring fairness and robustness, and developing models suitable for deployment in rural and resource constrained environments.

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