

# DETECTION OF LUMPY SKIN DISEASE IN CATTLE

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**Abstract:** Lumpy Skin Disease (LSD) is a very contagious viral disease in cattle that is of great concern to agricultural economies, particularly in nations such as India. This viral disease affecting cattle, characterized by fever, nodular skin lesions, and significant economic losses due to decreased productivity. Early and accurate detection of LSD is crucial for containment and treatment. In recent years (2021–present), advancements in the integration of machine intelligence, visual data processing, and earth observation technologies, and molecular diagnostics have transformed the detection landscape. The project includes a deep analysis approach using ConvNets model and RFID to address and solve the problem.

**Index Terms** - Lumpy Skin, LSD, Machine Learning, Deep Learning Analysis, Image Processing, Molecular Diagnostics, Disease Detection.

## I. INTRODUCTION

Lumpy skin disease, (LSD) was initially reported in cattle in Zambia in 1929, later on restricted to sub-Saharan Africa in the following decades. Nevertheless, LSDV kept growing in African nations in the last few years. LSDV outbreak outside the African continent was documented in Egypt in 1989. Since then, LSD outbreaks have been frequently observed in Middle Eastern nations and entered Europe in 2013. LSDV transmitted to east Asia for the first time, and was seen in China, India, and Bangladesh since 2019. Cattle and water buffalo (*Bubalis bubalis*) LSDV are transmitted mechanically by several blood-feeding arthropod vectors including mosquitoes (*Aedes aegypti*), ticks (*Amblyomma hebraeum* and *Rhipicephalus appendiculatus*), and stable flies (*Stomoxys calcitrans*). The morbidity rate ranges from 2 to 45% while the mortality rate is typically below 10 percent. Often, water buffalos are less affected and are quite resistant to the disease compared to cattle. Cattle under high production stress such as milking cows show clinical disease early. The idea proposed uses the image of the multiple images of the cattle and using CNN and deep analysis detects the disease. We use the RFID to identify and recognise the cattle affected.

## II. LITERATURE SURVEY

The study by Garima Rathore, S.K. Sharma, and Monika Joshi 2024, titled "Hyperspectral Imaging for Subclinical Detection of Lumpy Skin Disease," investigates the application of hyperspectral imaging (HSI) as a novel, non-invasive method for easier and earlier detection of the (LSD) in cattle. Lumpy skin disease, due to the causative poxvirus, is a highly contagious disease of cattle that results in huge economic loss due to reduced milk production, hide damage, and trade restriction. Its control demands early detection, particularly when it is in the subclinical phase with no observable signs. The study mainly concentrate on HSI to identify the signatures that are indicative of early skin inflammation, offering a considerable avenue for disease control improvement in veterinary medicine.[1]

The paper by Kumar & Sharma, 2024, in their research titled “**Reviewed image-based detection versus molecular diagnostics**” The paper compared studies of image-based (e.g., CNN, YOLO) and molecular (e.g., PCR, LAMP) LSD detection technologies in terms of accuracy, cost, and deployability. It incorporated meta-analyses of diagnostic performance and case studies in endemic areas. Molecular technologies (e.g., qPCR) provided the most accurate (>98%) but were laboratory-dependent. Image-based technologies had 85–93% accuracy and were more field-portable but less sensitive for subclinical cases. Hybrid strategies that integrated deep learning (for screening) with portable PCR (for confirmation) were suggested for best performance. Hybrid systems are in early stages and need to be confirmed. [2]

The Study titled “**YOLOv5-driven object detection model for LSD lesion detection**” by Anand et al., 2023. The YOLOv5 model, recognized for real-time object detection, was trained using annotated cattle images to detect and locate LSD lesions. The data set contained bounding box annotations of nodules, with preprocessing for scale and lighting variations. The model was tuned for speed and accuracy, evaluated on a validation set, and compared against other

versions of YOLO.YOLOv5 attained a detection accuracy of 93.2% with a processing rate of ~30 frames per second, which is appropriate for use on mobile phones. It performed well in detecting multiple lesions from a single image, even against cluttered backgrounds. [3]

The research conducted by Babiuk et al., 2022, titled **"ELISA-based serological test kit for field use"**. The research created an enzyme-linked immunosorbent assay (ELISA) for LSDV-specific antibodies in cattle serum. The test kit employed recombinant LSDV antigens to measure immune reactions after infection. The kit was field-tested in various farms, where the results were compared to virus neutralization tests. The ELISA kit by this study was used for diagnosing prior LSD infections (sensitivity ~90%) and tracking herd immunity following immunization. Nevertheless, it could not be used for early diagnosis since the antibody takes 2–3 weeks to appear after infection. The kit was also field-friendly in that it was portable and made minimal use of equipment. [4] The study titled **"Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy from Retinal Fundus Photographs"** by Arun Gulshan, Arunachalam, Subhashini, Kasumi Widner. The researchers developed a deep CNN trained on a large dataset of 128,175 retinal images. These images were graded by a panel of 54 U.S.-licensed ophthalmologists and ophthalmology residents. The algorithm was validated using two separate datasets: EyePACS-1 and Messidor-2. The research proved that a deep learning model was capable of identifying diabetic and diabetic retinopathy from retinal fundus images accurately. The high sensitivity and specificity indicate that such models would be useful to implement in clinics to help ophthalmologists diagnose these conditions, possibly leading to better and accurate patient outputs from earlier detection. [5]

The research by Rahman et al., 2023, in their study titled **"Developed a smartphone app using transfer learning (ResNet50, MobileNet) for LSD detection"** which transfers learning on pre-trained deep learning models (MobileNet, ResNet50) was employed in this study for classifying pictures of particular cattle as LSD-positive or negative. The models were fine-tuned using a dataset of images taken by farmers in Bangladesh and submitted for analysis, with ResNet50 attaining 92.5% accuracy. Users were able to upload images for real-time analysis, with results being verified by veterinarians. ResNet50 performed better than MobileNet (89% accuracy) because it had a deeper architecture, although MobileNet was quicker on low-end devices. The application was easy to use, boosting farmer participation in LSD reporting. [6]

The Patel et al., 2022, study entitled **"Introduced a convolutional neural network (CNN)-based model for LSD lesion classification"**. The research set out to create an automated system to identify LSD in cattle through computer vision. Towards this purpose, the authors designed a custom convolutional neural network (CNN) specifically to differentiate between healthy and LSD-infected cattle from images. The goal of the study was to implement an automatic Lumpy Skin Disease (LSD) detection system in cows using computer vision. For this, the authors built a customized convolutional neural network (CNN) specifically designed to differentiate between normal and LSD-affected cattle on the basis of images. [7]

The research by Singh et al., titled **"Used image processing algorithms to detect LSD lesions in digital cattle images."** The research utilized image processing methods, such as edge detection (e.g., Canny algorithm) and morphological processing (e.g., dilation, erosion), to examine high-resolution images of cattle. Features such as lesion size, texture (roughness), and color (grayishwhite nodules) were extracted and classified through a rule-based algorithm. The data contained images of infected and healthy cows under different illumination conditions. The approach was 85% accurate in detecting LSD lesions but was challenged by poor image quality (e.g., low resolution, shadows) and environmental changes (e.g., wet skin). [8]

The paper by Butarbush et al., 2021, in their research titled **"Field study in Jordan applying real-time PCR for LSDV detection in clinically suspected cases."** The research gathered samples (blood, skin nodules, saliva) from LSD-symptomatic cattle on several farms in Jordan. Real-time PCR was targeted towards the P32 gene, a conserved LSDV gene, with optimized primers and probes for high sensitivity. The test was conducted in a laboratory with controls to reduce cross-contamination. The P32-targeted PCR was nearly 100% sensitive and specific and was able to detect LSDV in early infection stages (5–7 days post-infection) before clinical signs of severe disease were evident. It surpassed symptom-based diagnosis, which frequently resulted in false positives because of cross-reactivity with diseases such as pseudo-lumpy skin disease or bovine herpesvirus infections. [9]

The Research entitled **"Discussed portable nucleic acid detection devices for rural areas."** by FAO/IAEA Collaborative Report, 2023. The study evaluated the implementation of portable PCR devices like GeneXpert in Africa and Asia's remote regions. The devices performed nucleic acid amplification and detection in one cartridge with minimal training. The research merged results with cloud-based analytics to monitor LSD outbreaks in real-time. GeneXpert

detected LSDV with >95% field sensitivity, with results delivered in ~1 hour. Analysis of data enabled geospatial mapping of the outbreaks for informing control measures. Which Allows rapid diagnosis in remote areas, reducing outbreak response delays. Enables real-time surveillance for transboundary disease control.[10]

The Study titled “**Early Detection of Lumpy Skin Disease in Cattle Using Deep Learning—A Comparative Analysis of Pretrained Models**” by authors Kumar et al. This research compared more than 10 pre-trained CNN models (e.g., VGG16, MobileNetV2, ResNet50, InceptionV3) for the identification of LSD. A collection of 1,200 images (400 healthy, 400 LSD, 400 other skin diseases) was augmented with rotation, scaling, and flipping. Models were fine-tuned by transfer learning, and performance was measured on accuracy, sensitivity, and specificity. MobileNetV2 had the best accuracy (97.87%). The research underlined the advantages of light models such as MobileNetV2 in environments with limited resources, e.g., smartphones used by farmers. Overfitting was avoided using data augmentation, and sensitivity (0.98) provided a robust detection of LSD cases. Future challenges were indicated in distinguishing LSD from other skin conditions (e.g., pseudo-LSD), prompting further research in multiclass classification.[11]

The study by Authors: Bhatti, M. H., Khan, M. J., Rasheed, A., & Ahmad, M. entitled “**Automated Detection of LSD in Cattle by using Deep Learning Techniques**”. A deep analysis framework based on EfficientNetB0 was proposed, using a data set of 1,000 images (500 healthy, 500 LSD-affected). The images were preprocessed through histogram equalization and normalized to 256x256 pixels. Adam optimizer and focal loss were used to train the system to handle class imbalance, achieving more accuracy of 96.2%. EfficientNetB0's lightweight architecture allowed for fast inference, suitable for mobile application. The model possessed high specificity (0.97), reducing false positives. Its drawbacks were lower image diversities (e.g., various light conditions). Cloud based deployment was suggested by the study for real-time LSD screening in rural areas. [12]

### **III. PROBLEM IDENTIFICATION**

- Traditional methods (visual inspection, lab tests) are slow & costly.
- Rural farmers lack access to veterinary facilities.
- Delayed diagnosis leads to rapid disease spread.
- Economic burden on the livestock industry.

### **IV. APPLICATIONS**

- Veterinary Field Diagnosis: Quick and accessible detection in rural or remote farms.
- Government Surveillance: Real-time outbreak tracking and epidemiological analysis.
- Farmer Empowerment: Smartphone tools for livestock health monitoring and reporting.
- Early warning system for infected cattle.
- Faster, more accurate diagnosis.
- Prevents milk contamination & loss.
- Disease surveillance & prevention programs.
- To minimize the risk of viral flue.

### **V. SUMMARY**

The identification and management of LSD or Neethling virus in cattle have come a long way with the application of artificial intelligence, specifically image-based deep analysis techniques such as CNNs. The models are capable of examining several images of cattle to correctly identify infection symptoms, including skin lesions. The system is further augmented by incorporating RFID technology, which enables each animal to be identified and traced uniquely. This blend facilitates the automated, high-volume monitoring and quick response, providing a scalable, effective, and proactive mechanism for LSD control in livestock.

### **VI. CONCLUSION AND FUTURE SCOPE**

The technique proposed consists of taking multiple pictures of each animal from varying viewpoints to gain holistic coverage of the skin surface. These photographs are input to a specially trained CNN model which built with the capacity for automatic feature extraction and learning essential visual cues predictive of the disease. Deep-level analysis by the model can correctly identify healthy as well as diseased cattle at high rates with minimal false positives and false negatives.

In order to guarantee that the health status of every animal is properly monitored over time, the project uses Radio Frequency Identification (RFID) technology. Every cow is implanted with an RFID chip with a unique identifier. Upon detection of a case of LSD through image analysis, the associated RFID information is utilized to record the case, determine the individual animal, and update veterinary records. This combination of biometric image recognition with RFID-based identification enables automated, mass-scale monitoring of cattle health across farms or geographies, enabling quick response, quarantine, and treatment procedures.

### **Future Scope**

- Developing multimodal systems combining thermal, hyperspectral, and RGB imaging.
- Expanding datasets for model generalization across regions and breeds.
- Create publicly available, labelled datasets for research and model training.
- Reducing the cost of diagnostics for broader accessibility.

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