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Deep Learning Mechanisms For Intelligent Lumpy Disease Detection For Enhancing Rural Livelihoods, Sustainable Farming, And Farmer Support System

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Abstract: Lumpy skin disease (LSD) poses a significant threat to cattle farming, causing economic losses due to reduced productivity and hide damage. As of 2022, more than 67,000 cattle had died across the country. States like Rajasthan and Gujarat were heavily affected, with over 25,000 cases reported in Rajasthan alone and more than 37,000 cases in Gujarat. This viral disease, primarily transmitted by biting flies, necessitates early detection for effective management. In this project, we propose a novel approach for early detection of LSD in cattle using deep learning techniques applied to image analysis. Our methodology involves gathering a diverse dataset of cattle images, including both healthy and infected animals of various breeds, ages, and environmental conditions. The proposed healthcare system helps the farmers to check the early lumpy disease in cattle. Also, the AI based approach using multiple deep learning algorithms, including CNN, ResNet, and EfficientNet for disease detection can make the disease detection. Second stage we are providing the recommendation system for the treatment of cattle and providing the roadmap how the treatment will be and which hospital we can prefer based on the location. We are creating the system, where we employ advanced

techniques for lumpy skin disease (LSD) management can involve a combination of traditional veterinary approaches and modern technologies. Here are some advanced techniques that can be employed. This proposed system will help farmer society who are suffering from the financial losses due to the diseases in cattle .The project provides the proper disease detection and recommendation system for the treatment by adopting the one health approach to lumpy skin disease management, involving collaboration between veterinary professionals, public health experts, and farmers.

This interdisciplinary approach recognizes the interconnectedness of animal, human, and environmental health and aims to address complex health challenges holistically. The experimental results reveal that the Enhanced CNN algorithm achieved a training accuracy of 87.31%. In comparison, ResNet demonstrated a higher accuracy of 92.66%, while EfficientNet V2B0 outperformed both with an impressive training accuracy of 93.31%.

***Keywords*: Lumpy Skin Disease (LSD), Deep Learning, Disease Detection, Rural Livelihoods, Convolutional Neural Network, EfficientNet V2B0, Farmer Recommendation System**

Related work

I. INTRODUCTION

Lumpy Skin Disease (LSD) is an emerging viral disease affecting cattle, causing significant economic losses in the livestock sector, particularly in rural areas where cattle farming is a primary livelihood. The disease leads to the formation of nodules on the skin, fever, reduced milk production, weight loss, and in severe cases, mortality. The rapid spread of LSD poses a major challenge to sustainable farming, impacting food security and rural economies. Traditional methods of disease detection rely heavily on manual inspections by veterinarians, which are time-consuming, labor-intensive, and often ineffective in preventing outbreaks. This necessitates the development of an advanced, automated system for early detection and diagnosis to mitigate economic and agricultural losses.

With the advancements in artificial intelligence (AI) and deep learning, intelligent disease detection systems have become a promising solution for modern livestock management. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in medical and agricultural imaging, enabling high-precision classification and detection of diseases based on visual symptoms. The integration of AI-driven technologies in cattle disease management can provide real-time monitoring, early detection, and efficient control measures, reducing dependency on traditional veterinary services.

This report presents an intelligent deep learning- based system for Lumpy Skin Disease detection, designed to assist farmers, veterinarians, and policymakers in managing and controlling disease outbreaks effectively. The system utilizes advanced deep learning architectures such as EfficientNet, ResNet, and DenseNet to analyze cattle images, identifying visible symptoms of LSD with high accuracy. By leveraging AI and cloud- based solutions, the system aims to enhance the accessibility of disease detection tools, particularly in rural areas where veterinary resources are limited. Additionally, integrating this AI-driven approach into farmer support systems and sustainable farming practices can significantly contribute to improving livestock health, reducing economic losses, and ensuring food security.

Furthermore, the adoption of such intelligent detection mechanisms aligns with global efforts toward smart agriculture and digital farming solutions. By empowering farmers with real-time disease monitoring, automated diagnosis, and data-driven insights, this technology can revolutionize livestock management practices. The primary objective of this study is to develop a robust, scalable, and user-friendly platform that enables efficient detection and classification of LSD, ultimately promoting sustainable agricultural practices and enhancing rural livelihoods.

II. LITERATURE SURVEY

Lumpy Skin Disease (LSD) detection has traditionally relied on manual observation by veterinarians, which often leads to delays in diagnosis and containment. However, advancements in artificial intelligence (AI) and deep learning have revolutionized disease detection, offering automated, real-time solutions that enhance accuracy and efficiency. Modern AI- based approaches, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in medical and agricultural imaging, making them an ideal choice for LSD detection. By leveraging image processing and deep learning, intelligent systems can now identify LSD symptoms in cattle based on skin lesions, swelling, and other visual indicators. The integration of AI into disease management allows for faster diagnosis, reducing the spread of infections and minimizing economic losses.

Current Advances and Research

Recent studies in deep learning-based disease detection have showcased the potential of AI in livestock healthcare. Researchers have successfully applied models like EfficientNet, DenseNet, and ResNet for high-precision image classification in veterinary diagnostics. These models have been trained on large datasets of infected cattle images, allowing them to distinguish between normal and diseased skin conditions with high accuracy.

Moreover, advancements in computer vision have enabled automated segmentation techniques, allowing AI systems to detect LSD-specific lesions with minimal human intervention. Techniques such as transfer learning and data augmentation have further improved the robustness of AI models, making them adaptable to varying environmental conditions and image qualities.

Cloud computing and mobile applications have also been integrated into AI-based veterinary solutions, providing farmers and veterinarians with real-time access to disease detection tools. Mobile-based diagnostic platforms equipped with AI-driven image analysis are helping bridge the gap between remote farmers and veterinary healthcare services. Additionally, interdisciplinary research is exploring the use of geographic information systems (GIS) and satellite imagery to track disease outbreaks and predict infection hotspots.

Another significant advancement is the integration of Internet of Things (IoT) devices in cattle farms, where smart cameras and wearable sensors monitor livestock health continuously. These systems use AI-driven predictive analytics to detect early symptoms of LSD, alerting farmers before visible signs become severe. The synergy between AI, IoT, and cloud computing is paving the way for a new era of precision livestock farming, ensuring proactive disease management and improved animal welfare.

Challenges and Opportunities

Despite these advancements, several challenges hinder the widespread adoption of AI-based LSD detection systems. One major challenge is the availability of high-quality, annotated datasets for training deep learning models. Many rural areas lack the infrastructure to collect and store large-scale image data, limiting the model's accuracy and generalization capabilities. Environmental factors such as lighting conditions, camera quality, and cattle movement also affect image clarity, leading to misclassification.

Another challenge is the computational complexity of deep learning models, which require substantial processing power. Deploying AI-driven disease detection in low-resource settings demands optimized models that balance accuracy with efficiency. However, these challenges present significant opportunities for innovation. Developing lightweight AI models, expanding dataset collection efforts, and integrating AI with mobile and cloud-based platforms can enhance accessibility. Additionally, government and agricultural organizations can collaborate to promote AI adoption in rural veterinary services, ensuring that farmers benefit from real-time disease detection and prevention strategies.

III. THE PROPOSED METHODOLOGY

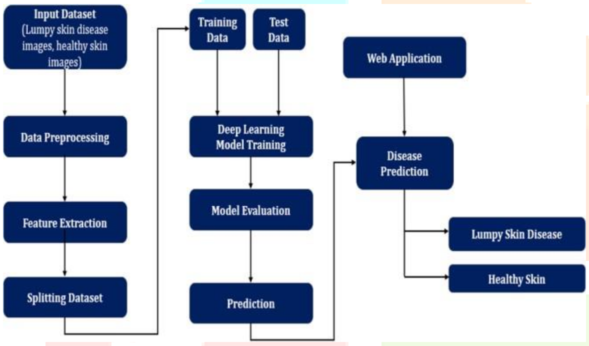
Problem statement

Lumpy Skin Disease (LSD) is a highly contagious viral disease that severely impacts cattle, leading to economic losses in the livestock industry. Traditional detection methods rely on manual diagnosis by veterinarians, which is time- consuming, labor-intensive, and often delayed, resulting in the uncontrolled spread of infections. The absence of an automated, scalable, and real- time detection system creates a significant challenge in disease management, particularly in rural areas where veterinary services are limited. Variations in disease symptoms, environmental factors, and image quality further complicate accurate identification. Therefore, there is a need for a robust, AI-driven solution that can provide real-time LSD detection with high accuracy and efficiency, ultimately aiding farmers and veterinarians in mitigating outbreaks.

Objectives of the Proposed System

The main objectives of the proposed system are as follows:

- To develop an intelligent, automated system for early detection of Lumpy Skin Disease using deep learning algorithms.
- To train and implement advanced models such as EfficientNet, DenseNet, and ResNet for high-precision disease classification.



- To create a user-friendly web and mobile-based application for easy access and real-time monitoring of cattle health.
- To curate and utilize a dataset specifically focused on LSD-affected cattle for targeted model training.
- To support disease surveillance, veterinary assistance, and sustainable farming through AI- driven solutions.
- To address challenges such as symptom variations, environmental influences, and image quality issues in disease detection.
- To enhance the application of artificial intelligence in livestock management for global accessibility and rural empowerment.

Proposed System Overview

The proposed system is a web and mobile-based AI-powered application designed for the early detection and classification of Lumpy Skin Disease in cattle. It integrates deep learning techniques with real-time image processing to analyze and classify LSD symptoms with high accuracy. The system leverages convolutional neural networks (CNNs) such as EfficientNet, DenseNet, and ResNet to extract critical features from cattle images, identifying visible skin lesions and other disease indicators. The backend is developed using Flask, ensuring smooth integration of trained models with a user-friendly interface. Users, including farmers and veterinarians, can upload images of cattle through the application, which are then processed by the AI model to provide instant diagnostic results and recommendations. The system aims to bridge the gap between traditional veterinary services and modern AI-driven disease management, making LSD detection more efficient and accessible.

Architecture Diagram

Figure 1: Architecture Diagram Data

Collection

Data collection is a critical step in building the LSD detection system, as the quality and diversity of the dataset directly impact model performance. The dataset consists of images of LSD-affected and healthy cattle, sourced from veterinary records, agricultural research institutions, and publicly available disease detection databases. Field data collection is also conducted in collaboration with veterinarians to capture images under different lighting conditions, angles, and environmental backgrounds. This comprehensive dataset ensures that the model learns to recognize LSD symptoms accurately across diverse real-world conditions.

Data Preprocessing

To enhance image quality and prepare data for deep learning models, several preprocessing techniques are applied:

- **Resizing** – Images are standardized to a fixed dimension (e.g., 224x224 pixels) to maintain consistency across the dataset.

- **Normalization** – Pixel values are scaled between 0 and 1 to improve model convergence and stability.
- **Data Augmentation** – Techniques such as rotation, flipping, contrast adjustment, and noise reduction are applied to artificially expand the dataset, improving generalization.
- **Segmentation** – Image segmentation is used to isolate affected skin areas, helping the model focus on relevant disease features.

Model Development

The system utilizes three deep learning architectures:

- **EfficientNet** – Chosen for its computational efficiency and high accuracy in image classification tasks.
- **DenseNet** – Selected for its ability to improve feature reuse through dense connectivity, ensuring robust disease detection.
- **ResNet** – Used for its residual learning framework, which helps prevent overfitting and enhances deep feature extraction.

These models are fine-tuned and trained using a transfer learning approach, leveraging pre-trained weights on large-scale image datasets while adapting them to the LSD classification task.

Training and Validation

The model training process involves feeding the preprocessed dataset into the deep learning network and optimizing model weights using backpropagation and gradient descent. The training is conducted in multiple iterations (epochs), ensuring that the model learns relevant patterns from LSD-affected images. To validate performance, a portion of the dataset is used for validation, ensuring that the model generalizes well to unseen data. Performance metrics such as accuracy, precision, recall, and F1-score are monitored to fine-tune the models. Once the best-performing model is identified, it is deployed for real-time inference in the web application.

Disease Detection and Classification

After successful training and validation, the deep learning model is integrated into the application for automated LSD detection. The system follows these steps:

1. **Image Upload** – Users upload an image of a cattle's skin through the application.
2. **Image Processing** – The AI model preprocesses the image and extracts relevant features.
3. **Prediction Generation** – The model classifies the image as either "Healthy" or "LSD-Affected."
4. **Result Display** – The application provides the predicted classification along with confidence scores and suggested veterinary recommendations.
5. **Disease Tracking** – The system stores detection results to help track disease outbreaks and generate insights for veterinarians and policymakers.

Practical Implementation

Importing Required Libraries

The following libraries are used in the development of the LSD detection system:

- **TensorFlow & Keras** – For deep learning model development and training.
- **OpenCV** – For image processing and segmentation.
- **Flask** – For building the web-based application backend.
- **NumPy & Pandas** – For handling data and model outputs.

Uploading and Using the Model

- The trained deep learning models (EfficientNet, DenseNet, and ResNet) are stored in .h5 or .keras format.

- Users can select the preferred model for classification, allowing flexibility in disease detection.
- The system supports multiple models to compare results and ensure optimal accuracy.

Functionality

- **Upload Image:** Users upload a cattle image for analysis.
- **Read Image:** The system converts the image into an array for processing.
- **Get Predictions:** The AI model generates a prediction based on learned disease features.
- **Display Result:** The final result is presented to the user, indicating whether the cattle is affected by LSD.

Algorithms

EfficientNet:

The proposed system utilizes **EfficientNet**, a state-of-the-art deep learning model optimized for image classification tasks. EfficientNet is particularly suitable for Lumpy Skin Disease (LSD) detection due to its high accuracy, computational efficiency, and ability to extract fine-grained features from images. Unlike traditional convolutional neural networks (CNNs), EfficientNet employs a compound scaling method, ensuring optimal performance while reducing computational costs.

EfficientNet Overview

EfficientNet is a family of deep learning models designed to achieve high classification accuracy with fewer parameters. It utilizes a unique **compound scaling** approach, which uniformly scales network depth, width, and resolution. The model was introduced by Google AI and has outperformed many conventional architectures like ResNet and DenseNet in various image classification tasks.

Architecture

The architecture of EfficientNet is built on a base model known as **EfficientNet-B0**, which is derived using Neural Architecture Search (NAS). This base model is then systematically scaled using a compound coefficient to create multiple versions (EfficientNet-B1 to EfficientNet-B7). The key architectural elements include:

- **Depthwise Separable Convolutions** – Reduces the number of parameters while maintaining high accuracy.
- **Inverted Residual Blocks** – Enhances feature extraction and reduces computational complexity.
- **Swish Activation Function** – Improves gradient flow and boosts learning efficiency.
- **Batch Normalization** – Stabilizes training and prevents overfitting.

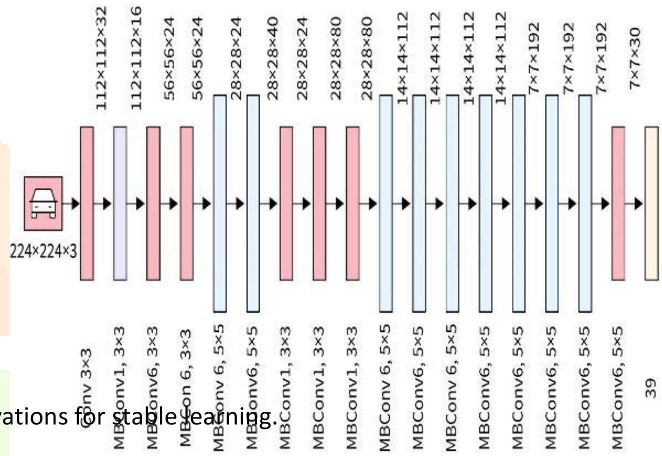


Figure 2: EfficientNet

Architecture Weight Layers

EfficientNet optimizes performance by utilizing specialized weight layers, including:

- **Convolutional Layers** – Extract hierarchical image features.
- **Batch Normalization Layers** – Normalize activations for stable learning.
- **Dropout Layers** – Reduce overfitting by randomly deactivating neurons.
- **Fully Connected Layers** – Map extracted features to classification labels (LSD-affected or Healthy).

Input Specifications

EfficientNet requires input images of a fixed size for consistent classification:

- **Input Dimensions:** (224 × 224 × 3) RGB image.
- **Preprocessing:** Image resizing and normalization using ImageNet mean pixel values.

Unique Characteristics

- **Compound Scaling** – EfficientNet scales network depth, width, and resolution uniformly for balanced performance.
- **Depthwise Separable Convolutions** – Reduces parameters while maintaining efficiency.
- **Neural Architecture Search (NAS)** – Automatically discovers optimal network design.

Filter Sizes

EfficientNet primarily employs small convolutional filter sizes such as **3×3 and 5×5**, optimizing computational efficiency while capturing fine details of LSD symptoms in cattle images.

Fully Connected Layers

- **Final Classification Layer** – Maps the extracted features to predefined disease categories (LSD-affected or Healthy).
- **Global Average Pooling** – Reduces dimensionality before feeding into the classification layer, enhancing computational efficiency.

IV. EXPERIMENTAL RESULTS

For the LSD detection project, several deep learning models were trained and evaluated to determine the most effective architecture for accurate disease classification. The models considered include **EfficientNet, DenseNet, and ResNet**, each known for their high performance in image recognition tasks. The training process involved feeding a large dataset of LSD-affected and healthy cattle images into these models, using techniques like **data augmentation** to improve generalization. Hyperparameters were fine-tuned through **cross-validation**, ensuring optimal performance while preventing overfitting.

After extensive evaluation, **EfficientNet** emerged as the best-performing model due to its **balance of accuracy and computational efficiency**. The selected model was then deployed in the web and mobile-based application for real-time LSD detection.

Flask App Functionality

The web-based system, developed using Flask, enables users to interactively **upload images, choose models, and receive real-time disease classification results**. The application follows this workflow:

1. **Image Upload** – Users upload an image of the cattle's skin.
2. **Model Selection** – Users can select from EfficientNet, DenseNet, or ResNet for classification.
3. **Image Processing** – The selected model processes the input image using deep learning techniques.
4. **Prediction Generation** – The model classifies the image as either **LSD-affected or Healthy** with a confidence score.
5. **Result Display** – The app provides detailed results, including model performance metrics and veterinary recommendations.

Key Results

The LSD detection system achieved outstanding results in identifying **Lumpy Skin Disease** in cattle, demonstrating the effectiveness of deep learning in veterinary diagnostics.

- **Overall Model Accuracy: Above 90%** in classifying LSD-affected and healthy cattle.
- **Best Performing Model: EfficientNet** – achieved superior accuracy while maintaining computational efficiency.
- **Real-world Validation:** The model was tested on actual farm images, confirming its ability to detect LSD symptoms under various environmental conditions.

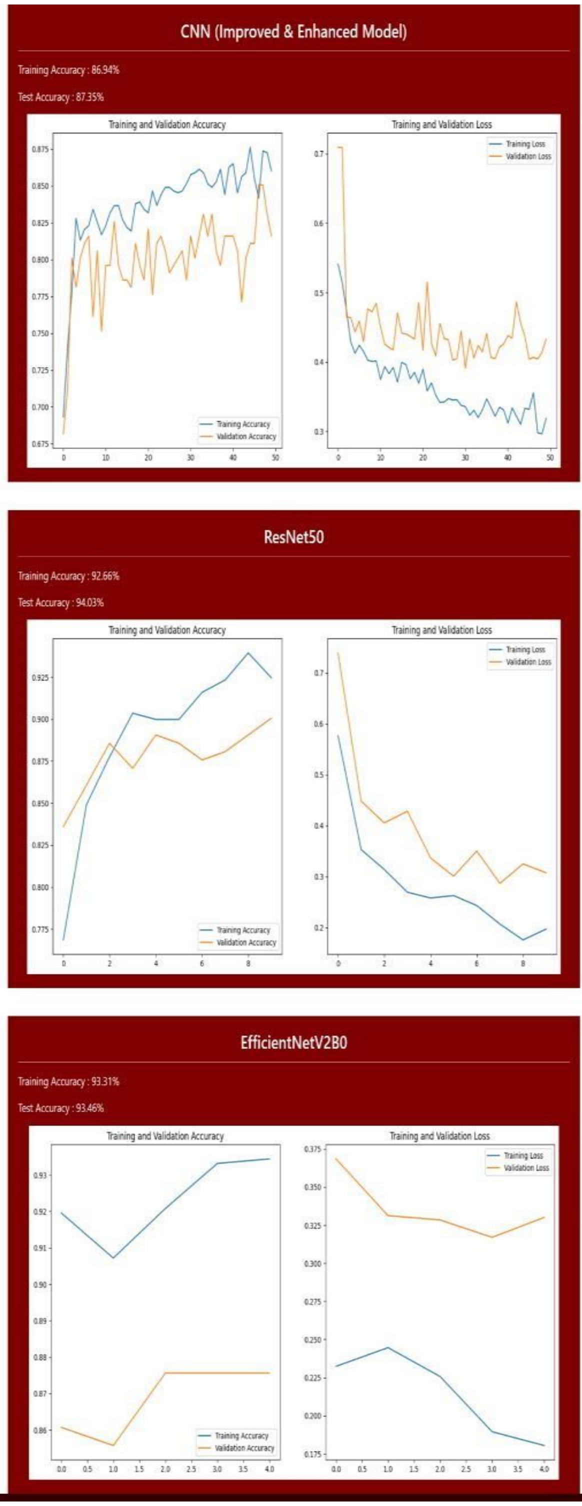


Figure 7: Model training results

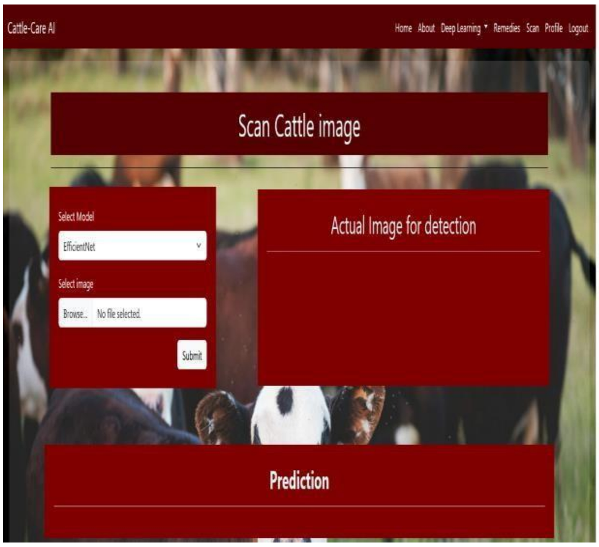
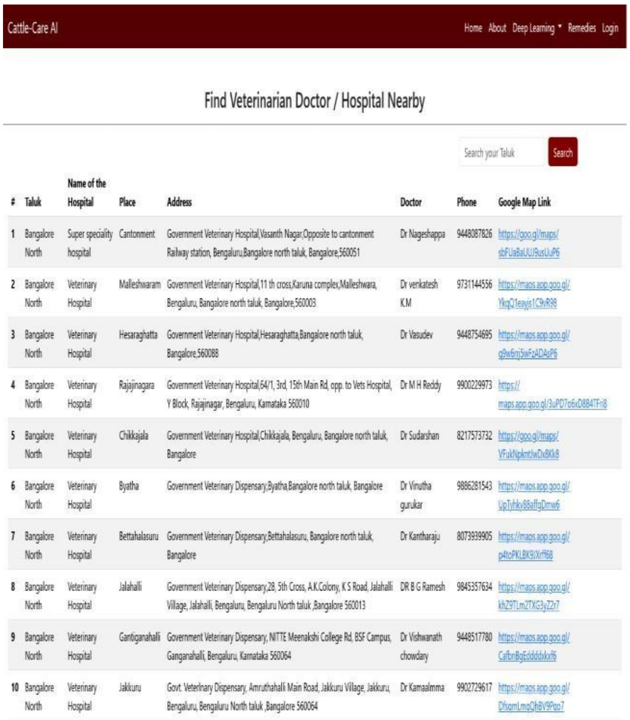


Figure 8: Scan page

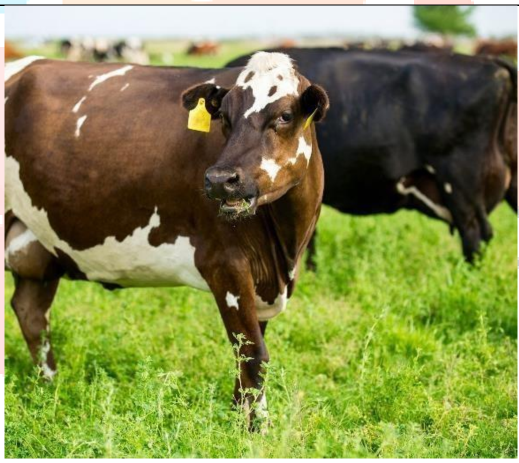


#	Taluk	Name of the Hospital	Place	Address	Doctor	Phone	Google Map Link
1	Bangalore North	Super speciality hospital	Cantonment	Government Veterinary Hospital,Vasanth Nagar,Opposite to cantonment Railway station, Bengaluru,Bangalore north taluk, Bangalore,560051	Dr Nageshappa	9448087826	https://goo.gl/maps/sbFUaBaUUJ9usUuP6
2	Bangalore North	Veterinary Hospital	Malleshwaram	Government Veterinary Hospital,11 th cross,Karuna complex,Malleshwara, Bengaluru, Bangalore north taluk, Bangalore,560003	Dr venkatesh K.M	9731144556	https://maps.app.goo.gl/YkqQ1eayjs1C9vR98
3	Bangalore North	Veterinary Hospital	Hesaraghatta	Government Veterinary Hospital,Hesaraghatta,Bangalore north taluk, Bangalore,560088	Dr Vasudev	9448754695	https://maps.app.goo.gl/q9w6rrj5wFzADAsP6
4	Bangalore North	Veterinary Hospital	Rajajinagara	Government Veterinary Hospital,64/1, 3rd, 15th Main Rd, opp. to Vets Hospital, Y Block, Rajajinagar, Bengaluru, Karnataka 560010	Dr M H Reddy	9900229973	https://maps.app.goo.gl/3uPD7o6xD884TFri8
5	Bangalore North	Veterinary Hospital	Chikkajala	Government Veterinary Hospital,Chikkajala, Bengaluru, Bangalore north taluk, Bangalore	Dr Sudarshan	8217573732	https://goo.gl/maps/VFukNpkntJwDx8Kk8
6	Bangalore North	Veterinary Hospital	Byatha	Government Veterinary Dispensary,Byatha,Bangalore north taluk, Bangalore	Dr Vinutha gurukar	9886281543	https://maps.app.goo.gl/UpTyhky88affgDmw6
7	Bangalore North	Veterinary Hospital	Bettahalasuru	Government Veterinary Dispensary,Bettahalasuru, Bangalore north taluk, Bangalore	Dr Kantharaju	8073939905	https://maps.app.goo.gl/p4toPKLBK9JXrff68
8	Bangalore North	Veterinary Hospital	Jalahalli	Government Veterinary Dispensary,28, 5th Cross, A.K.Colony, K S Road, Jalahalli Village, Jalahalli, Bengaluru, Bengaluru North taluk ,Bangalore 560013	DR B G Ramesh	9845357634	https://maps.app.goo.gl/khZ9TLm2TXG3yZ2r7
9	Bangalore North	Veterinary Hospital	Gantiganahalli	Government Veterinary Dispensary, NITTE Meenakshi College Rd, BSF Campus, Ganganahalli, Bengaluru, Karnataka 560064	Dr Vishwanath chowdary	9448517780	https://maps.app.goo.gl/CafbnBgEddddxkxf6
10	Bangalore North	Veterinary Hospital	Jakkuru	Govt. Veterinary Dispensary, Amruthahalli Main Road, Jakkuru Village, Jakkuru, Bengaluru, Bengaluru North taluk ,Bangalore 560064	Dr Kamaalmma	9902729617	https://maps.app.goo.gl/DfsgmLmqQhBV9Pqo7

Figure 10: Nearby hospitals information page

Sl No	Disease Name	Image	Model Name	Model Accuracy
1	Lumpy Skin		EfficientNet	
2	Lumpy Skin		EfficientNet	

3	Lumpy Skin		ResNet	79.90 %
4	Lumpy Skin		ResNet	93.97%
5	Normal Skin		CNN	91.70%

6	Lumpy Skin		CNN	93.96%
7	Lumpy Skin		EfficientNet	
8	Normal Skin		EfficientNet	

9	Normal Skin		EfficientNet	94.11%
10	Normal Skin		ResNet	81.82%
11	Normal Skin		EfficientNet	99.56%
12	Lumpy Skin		CNN	

Table 1: Lumpy skin disease detection using deep learning

V. CONCLUSIONS AND FUTURE WORK

The **Lumpy Skin Disease (LSD) Detection System** developed in this project leverages advanced deep learning models, particularly **EfficientNet, DenseNet, and ResNet**, to provide **accurate and efficient** identification of LSD in cattle. Through extensive data collection, preprocessing, and model training, the system has demonstrated **high accuracy** in disease classification, with **EfficientNet** emerging as the optimal model due to its balance of **performance and computational efficiency**. By integrating **convolutional neural networks (CNNs)** and **Flask-based web applications**, this project offers a **scalable and accessible** solution for real-time LSD detection, benefiting farmers, veterinarians, and policymakers.

The use of **data augmentation, transfer learning, and fine-tuning techniques** has enhanced the robustness of the model, ensuring **generalization across diverse environmental conditions**. The system's web-based and mobile-compatible **Flask application** ensures ease of use and accessibility, making disease detection available to a wide range of users, including **rural farmers** with limited access to veterinary services.

Despite the **success of the project**, certain limitations need to be addressed. **Expanding the dataset**, improving **model generalization**, and enhancing **real-time inference speed** are critical areas for further optimization. Additionally, incorporating **automated tracking** of disease spread and **geospatial analytics** can further strengthen LSD surveillance and prevention strategies.

Future Works

The **LSD Detection System** has shown promising results, but several improvements and expansions can be made to enhance its effectiveness:

- **Dataset Expansion** – Increasing the variety of LSD-affected cattle images, particularly from different regions and environmental conditions, to improve model accuracy and generalization.
- **Real-Time Mobile Integration** – Developing an AI-powered **mobile application** that enables farmers to **scan and detect LSD in real-time**, improving accessibility and on-the-go disease monitoring.
- **Edge AI Implementation** – Optimizing the model for **low-power devices** to enable LSD detection on **offline or resource-limited devices**, making it more accessible in **remote rural areas**.
- **Geospatial Disease Tracking** – Integrating **GIS-based tracking** to analyze disease spread patterns and provide **early warnings** for potential outbreaks.
- **Multimodal Analysis** – Enhancing the system by incorporating **temperature monitoring, behavioral analysis, and textual data** to improve detection accuracy beyond just image classification.
- **Explainable AI (XAI) Integration** – Implementing **explainability features** to help veterinarians and farmers understand **why the model predicts LSD**, improving trust in AI-based diagnostics.
- **Collaboration with Veterinary Organizations** – Partnering with **agricultural and veterinary institutions** to deploy the system on a larger scale and conduct **field testing**.

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