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Lumpy Skin Disease Detection

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Abstract: The Lumpy Skin Disease is one of the major factors. Lumpy Skin Disease is known as a major risk to cattle production and substantial impacts on livelihoods and food security especially for our country. Currently, detection of Lumpy Skin Disease in our country is assessed manually. However manual evaluation takes significant amount of time and requires trained professional and experienced person. Therefore, technology is needed to prevent animal disease epidemics. Automated detection of Animal Lumpy Skin Disease has advantages over the manual technique. Detection of Lumpy Skin Disease in Cows is developed in literature. But Animal Lumpy skin disease has different classification based on its severity. There is a need to further identify the different stages of Lumpy skin disease to know to what extent the animal is affected by lumpy skin disease.

Keywords: Lumpy Skin Disease (LSD), Machine Learning (ML), Prediction, Feature Selection, Datasets, Algorithms Evaluation Metrics, Support Vector Machines (SVM), Random Forests, Neural Networks, Accuracy Improvement, Clinical Practice, Patient Outcomes, Healthcare Management, Early Identification.

I. INTRODUCTION

Lumpy skin disease (LSD) is a highly contagious viral infection that affects cattle, causing significant economic losses in the livestock industry worldwide. The disease is characterized by the development of nodular lesions on the skin, leading to reduced milk production, weight loss, and decreased fertility. Early detection and management of LSD are crucial to prevent its spread and minimize its impact on cattle populations. In recent years, advancements in machine learning algorithms have shown promise in accurately identifying and diagnosing lumpy skin disease, offering a potential solution to improve disease surveillance and control. Machine learning techniques, particularly those based on computer vision and image processing, have emerged as valuable tools for automating the detection of LSD lesions in cattle. These algorithms can analyze digital images of cattle skin and identify characteristic features associated with the disease, such as the size, shape, and texture of the nodules. By training machine learning models on large datasets of labelled images, researchers can develop robust algorithms capable of distinguishing between healthy and diseased cattle with high accuracy.

One approach to lumpy skin detection involves the use of convolutional neural networks (CNNs), a type of deep learning algorithm specifically designed for image analysis tasks. CNNs can automatically learn hierarchical representations of image features, enabling them to effectively identify complex patterns associated with LSD lesions. By feeding CNNs with annotated images of cattle skin, the model can learn to recognize the distinctive visual characteristics of lumpy skin disease, allowing for accurate and efficient detection.

Another promising machine learning technique for lumpy skin detection is the use of support vector machines (SVMs) and other supervised learning algorithms. SVMs excel at binary classification tasks by finding the optimal hyperplane that separates data points belonging to different classes. By extracting relevant features from images of cattle skin, such as colour histograms or texture descriptors, SVMs can learn to classify regions of interest as either healthy or affected by lumpy skin disease. Through iterative training and refinement, SVM-based models can achieve high levels of sensitivity and specificity in detecting LSD lesions.

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II. OBJECTIVE

The objectives of this project encompass several key aims. Firstly, the focus is on constructing a comprehensive dataset that encompasses various states of normal skin, enabling effective classification. Secondly, the goal is to develop robust classification algorithms capable of accurately discerning between different states of normal skin, thus aiding in medical diagnosis and treatment planning. Additionally, the project aims to design and implement a customized Convolutional Neural Network (CNN) model tailored specifically for detecting lumpy skin, leveraging the dataset constructed earlier. Finally, an integral objective involves devising strategies to prevent normal skin from potential infections, thereby ensuring the overall health and well-being of individuals. By addressing these objectives, the project endeavors to contribute to advancements in dermatological diagnosis and healthcare practices, ultimately benefiting patient outcomes and quality of life.

III. PROBLEM STATEMENT

The problem at hand is to develop an accurate and efficient deep-learning based system for the detection of Lumpy Skin Disease Using Image Processing technique and Machine Learning Algorithms. In this study, Lumpy skin disease detection model is constructed using Convolutional Neural Network (CNN) for feature extraction and SVM for classification. Developing algorithms that can accurately distinguish between benign and malignant cells is a challenging task.

IV. LITERATURE REVIEW

The researchers collected data on the prevalence of various skin diseases through clinical examinations of animals visiting the veterinary clinic. Additionally, they analyzed potential risk factors associated with the occurrence of these diseases, such as management practices, environmental factors, and animal demographics. By examining the prevalence and risk factors of skin diseases in ruminants, the study aimed to provide valuable insights for veterinarians, livestock owners, and policymakers in Ethiopia. [1],

In this study, the researchers employed deep learning, a subset of artificial intelligence, to analyze images of cow skin lesions and identify those indicative of LSD. Deep learning algorithms, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in image recognition tasks. The researchers trained their CNN model on a dataset containing images of cow skin lesions, both with and without LSD, to enable the model to learn distinguishing features of the disease. [2].

The paper begins by providing an overview of CNN architecture, highlighting its key components such as convolutional layers, pooling layers, and fully connected layers. CNNs are designed to automatically learn hierarchical features from raw input images, making them well-suited for image classification tasks. The authors delve into the intricacies of how CNNs process and extract features from images through convolutional operations and non-linear activations. Furthermore, the paper discusses various CNN architectures that have been proposed in the literature, including LeNet, AlexNet, VGGNet, GoogLeNet, and ResNet. [3].

Furthermore, the review covers the clinical manifestations of LSD in affected cattle. Characterized by the formation of firm nodules or lumps on the skin, LSD can cause significant discomfort and pain to affected animals. The authors discuss the various clinical signs and symptoms of LSD, including fever, nasal discharge, reduced milk production, and lameness. Additionally, they explore the potential complications associated with LSD, such as secondary bacterial infections and reproductive losses, which can exacerbate the economic impact of the disease on livestock farmers. [4].

V. METHODOLOGY

In this section, the methodology of the proposed system for detection of Lumpy Skin Disease is described. Methodology is the specific procedures or techniques used to identify, select, process, and analyze information about a topic. In research, the methodology specifies the step-by step procedure followed and methods used for solving the problem and achieve its objective.

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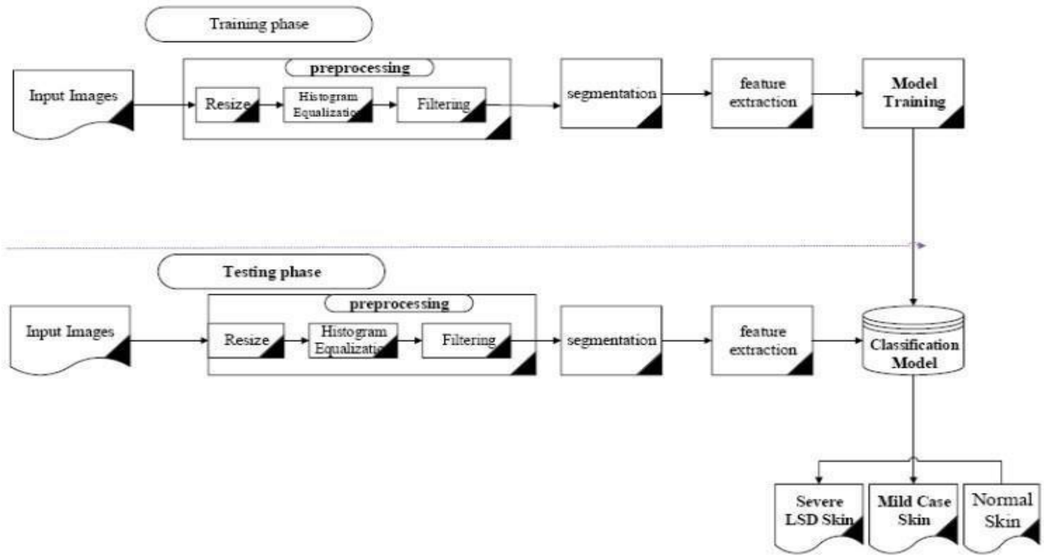

Fig 1 Methodology

a) System Architecture

The system architecture for detecting and managing lumpy skin disease involves a multi-faceted approach that integrates various components to achieve effective diagnosis, treatment, and prevention. At its core, the architecture comprises several interconnected modules, including data acquisition, preprocessing, feature extraction, classification, and preventive measures. The process begins with the acquisition of skin images or data samples, which are then preprocessed to enhance quality and remove noise. Feature extraction techniques are subsequently applied to capture relevant characteristics from the preprocessed data, facilitating the identification of lumpy skin disease indicators. These features are then fed into a classification model, such as a Convolutional Neural Network (CNN), which is trained to distinguish between normal and lumpy skin states.

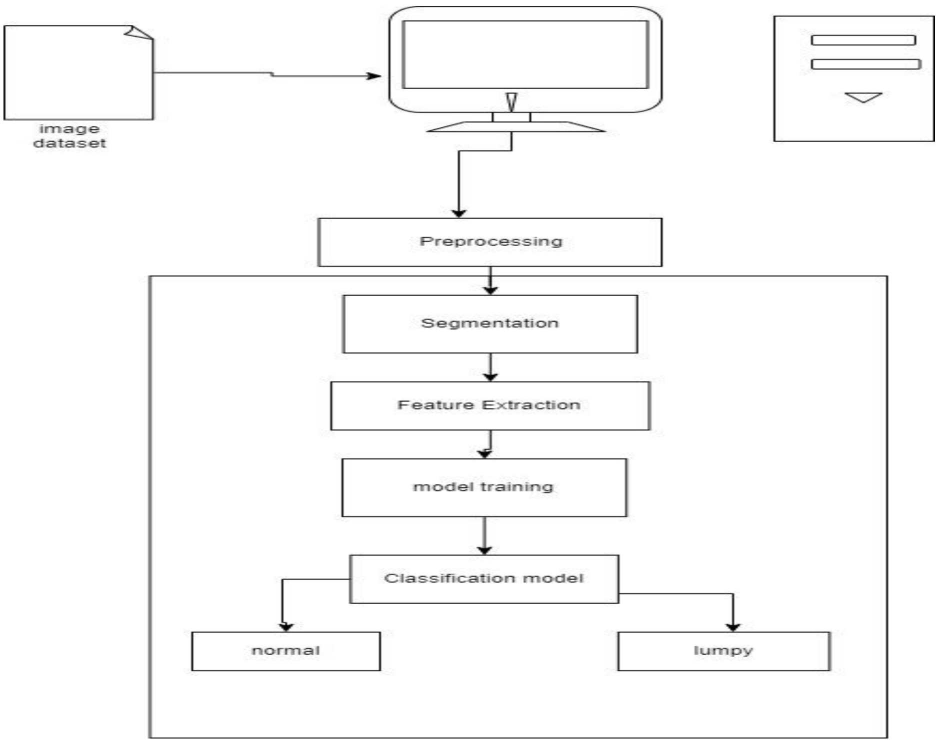

Fig 2. System Architecture

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VI. RESULT

In this study, the experiment has been performed on different CNN models namely DenseNet,. A total of Two hundred sixty six RGB images of cattle's skin from the skin dataset is divided into two classes namely normal skin and lumpy skin where each class contains a number of images. The whole dataset is further split into training and testing datasets that contains one hundred and one hundred images respectively.

```
Epoch 1/10
21/21 [==============================] - 187s 8s/step - loss: 0.8193 - accuracy: 0.6333 - val_loss: 0.5861 - val_accuracy: 0.6402
Epoch 2/10
21/21 [==============================] - 156s 8s/step - loss: 0.5179 - accuracy: 0.7561 - val_loss: 0.4202 - val_accuracy: 0.7927
Epoch 3/10
21/21 [==============================] - 147s 7s/step - loss: 0.4595 - accuracy: 0.7939 - val_loss: 0.3709 - val_accuracy: 0.8415
Epoch 4/10
21/21 [==============================] - 151s 7s/step - loss: 0.4074 - accuracy: 0.8197 - val_loss: 0.3164 - val_accuracy: 0.8780
Epoch 5/10
21/21 [==============================] - 150s 7s/step - loss: 0.3245 - accuracy: 0.8667 - val_loss: 0.3517 - val_accuracy: 0.8293
Epoch 6/10
21/21 [==============================] - 161s 8s/step - loss: 0.2874 - accuracy: 0.8848 - val_loss: 0.3023 - val_accuracy: 0.8476
Epoch 7/10
21/21 [==============================] - 133s 6s/step - loss: 0.3379 - accuracy: 0.8530 - val_loss: 0.2901 - val_accuracy: 0.8780
Epoch 8/10
21/21 [==============================] - 148s 7s/step - loss: 0.2928 - accuracy: 0.8833 - val_loss: 0.4673 - val_accuracy: 0.8049
Epoch 9/10
21/21 [==============================] - 148s 7s/step - loss: 0.3189 - accuracy: 0.8697 - val_loss: 0.2984 - val_accuracy: 0.8841
Epoch 10/10
21/21 [==============================] - 168s 8s/step - loss: 0.2736 - accuracy: 0.8985 - val_loss: 0.2718 - val_accuracy: 0.8659
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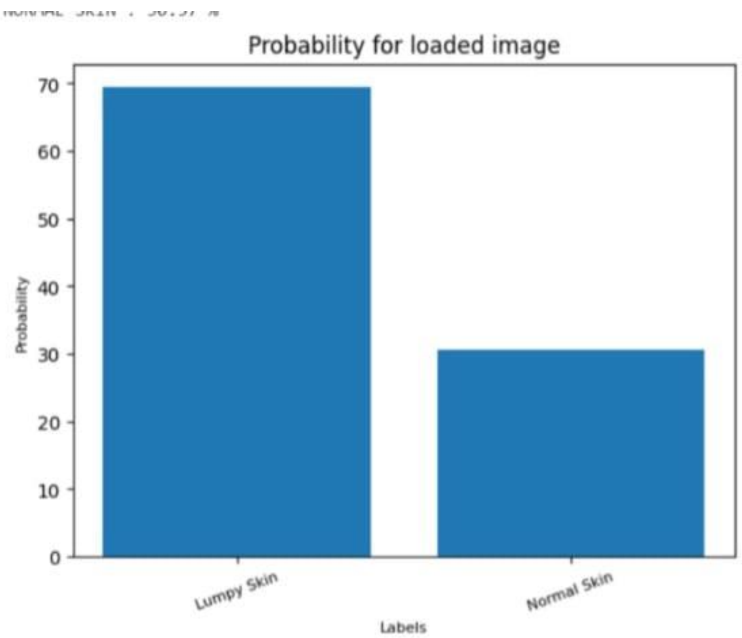
Fig. 3 Accuracy of the model



VII. CONCLUSION

In conclusion, the detection of lumpy disease presents significant challenges due to its complex nature and the variability of symptoms across affected livestock. However, advancements in technology, particularly in the fields of machine learning and image processing, have shown promising results in automating the detection process. By leveraging these tools, researchers and veterinarians can achieve faster and more accurate identification of lumpy disease cases, enabling timely intervention and management strategies to prevent its spread and minimize economic losses. Looking to the future, further research is warranted to enhance the robustness and scalability of lumpy disease detection systems. This could involve refining algorithms to handle variations in imaging conditions and disease manifestations, as well as integrating data from multiple sources such as clinical history and genetic information to improve diagnostic accuracy. Additionally, efforts should be made to develop user-friendly tools that can be readily adopted by veterinarians and farmers in the field.

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