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CNN-Based Classification for Lumpy Skin Disease Detection (Bovine-HealthGuard)

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Abstract- Lumpy Skin Disease (LSD) is a disease that affects cattle all over the world, characterized by distinctive skin nodules caused by the nettling virus. This disease poses significant financial challenges due to its negative effects on milk production, skin quality, and overall cattle health, Although LSD originated in sub-Saharan Africa, recent outbreaks in Europe and the Middle East. The disease continues to have an incredible ability to spread across cattle worldwide. In order to prevent animal disease outbreaks, technological solutions are urgently required, as the present conventional methods for LSD detection are time-consuming and require skilled experts. By examining into the epidemiology, patterns of transmission, and economic effects of LSD, this study seeks to improve on detection of lumpy skin disease. With the implementation of the trending technology - Deep Learning, (Convolutional Neural Networks (CNNs)) on lumpy skin disease image datasets for detection. Image preprocessing were utilized and resized to 640x640 pixels on YOLOv5 model and 200x200 pixels on Xception and ResNet models. Regions of interest were identified as an adaptive thresholding segmentation, while noise was reduced and image intensity was balanced using Gaussian filtering and histogram equalization. Experimental results demonstrated that YOLOv5 outperformed the two other models with 82.89% of accuracy compared to ResNet and Xception. The study shows that the importance of web integration to enable the detection of widespread lumpy skin diseases in a real time application.

Indexed Terms- Lumpy Skin, Convolutional Neural Network, Image Processing, Bovine-Health guard, Disease Detection.

I. INTRODUCTION

Lumpy Skin Disease (LSD) is a significant viral disease affecting cattle, characterized by distinct skin nodules caused by the Nettling virus, it is significant contributor to of financial losses in the livestock business of some countries. Lumpy Skin Disease (LSD) is a terrible viral disease that mostly affects cattle and is identified by prominent skin nodules brought on by the Nettling virus. Lumpy skin disease affects cow populations worldwide, particularly in Nigeria, and presents significant economic hurdles in addition to health issues. LSD outbreaks might have a catastrophic impact on local economies and food security in Northern Nigeria, where raising cattle is a major source of income. At first, Lumpy Skin Disease was mistaken for poisoning or bug bite sensitivity [1]. The possibility of additional regional extension, which might involve Nigeria's neighbors and possibly the whole West African region, is made clear by recent LSD breakouts in a number of locations [2]. Concerns over the disease's potential effects on cattle populations in Nigeria's north, where livestock husbandry is common, are raised by its appearance in new areas. Blood-feeding insects, especially mosquitoes and stable flies, which are prevalent in Nigeria's grasslands and savannas, are the main cause of LSD transmission. Significant economic ramifications result from the disease, which eventually affects the lives of cattle producers in Northern Nigeria by causing permanent damage to hides, impaired producing milk, loss of weight, sterility in bulls, and premature delivery in pregnant cows [3]. Additionally, LSD interferes with the trade in cattle and their products, which hurts the economics of areas where epidemics occur. Developing successful control and preventive initiatives in Nigeria requires an understanding of the epidemiology and mechanisms of LSD transmission. The disease's unique clinical symptoms require laboratory confirmation using diagnostic techniques like polymerase chain reaction

(PCR) and serological testing. Researchers from all around the world are examining the possibilities of deep learning, a subset of artificial intelligence, in the medical industry due to its rapid development and strong interest in applying it to medical imaging issues [4]. Deep learning techniques, including Convolutional Neural Networks (CNNs), have shown remarkable success in image classification tasks [5]. These methods can greatly increase the accuracy of image-based classification as they have great potential to improve the early detection of medical conditions. Conventional detection methods usually depend on clinical symptoms, and Lumpy Skin Disease shares clinical similarities with other cattle diseases, making it difficult to distinguish based only on noticeable symptoms [6]. The proposed diagnostic approach for Cattle's Lumpy Skin Disease (CLSD) leverages deep learning algorithms, including a 10-layer Convolutional Neural Network and color histogram-based segmentation, coupled with an Extreme Learning Machine classifier, achieving a high accuracy of 90.12% [7]. This AI-based system offers a time-efficient and scalable solution, contributing to early disease detection and presenting a competitive edge compared to traditional diagnostic methods. Through extensive study, this study aims to build upon the work cited in [2] and further demonstrate the complexities of Lumpy Skin Disease by providing a valuable insights that could guide focused on control measures. This study covers the developments in disease awareness, detection techniques, integration of technology, and the broader application of artificial intelligence in veterinary healthcare. The aim of this research is to add to the existing understanding on Lumpy Skin Disease with a focus on its incidence, transmission patterns, and economic implications. With user-friendly web tool for the early diagnosis of Lumpy Skin Disease in cattle, this study additionally seeks to empower farmers by reducing the financial effect, facilitating prompt interventions, and improving livestock health monitoring in general. Furthermore, this will benefit cow numbers around the world and the farming communities that depend on them.

II. LITERATURE REVIEW

To gain a deeper understanding and insight into the most successful technique for this research, a thorough examination of pertinent literature was conducted. A thorough analysis of earlier research was necessary for this. The following literature review highlights important findings and contributions from previous studies:

Abunadi *et al.* in [8] developed deep learning and machine learning techniques for diagnosing skin diseases early using dermoscopy images. using ANN, FFNN and convolutional neural networks (ResNet-50, AlexNet). Pre-processing techniques were employed to enhance datasets, remove noise, and eliminate hair. Experimental results showed the effectiveness of the systems, with the ANN algorithm achieving 95.3% and 97% accuracy on ISIC 2018 and PH2 datasets, respectively, outperforming FFNN in the former but not the latter. ResNet-50 and AlexNet CNN models exhibited superior performance, with ResNet-50 achieving accuracies of 90% and 95.8% on the ISIC 2018 and PH2 datasets, respectively. However, the study encountered limitations related to significant feature similarity among some skin diseases, potentially causing confusion for classification algorithms during diagnosis.

Another author in [9] adapted Google's EfficientNet-b4 as the CNN backbone, pre-trained on ImageNet, and added seven auxiliary classifiers to intermediate layer groups. Retraining the modified model using PyTorch, the framework achieved an overall accuracy of 0.948, sensitivity of 0.934, and specificity of 0.950. Comparative analyses with existing CNN models demonstrated superior performance, with the highest area under curve (AUC) of 0.985. However, the study potentially reduced accuracy on unseen data, real-world diagnostic considerations beyond images, limited disease range in the dataset, and a lack of exploration into web integration for broader clinical applications.

Muhaba *et al.* in [10] developed an automatic skin disease diagnosis system using deep learning from clinical images and patient information, where clinical images were captured using various smartphone cameras and patient data were collected during registration. The study achieved a multiclass classification accuracy of 97.5%, sensitivity of 97.7%, and precision of 97.7% for five common skin diseases, demonstrating excellent diagnostic performance. Further validation in real-world clinical settings is necessary to evaluate the robustness and reliability of the proposed smartphone application. Another in [12] proposed a brain tumor detection system based on deep learning approaches and magnetic resonance imaging (MRI), utilizing an optimized YOLOv7 architecture with advanced features like SPPF+, BiFPN, Decoupled Head, and Attention Mechanism. The model was fine-tuned and trained on an MRI dataset with transfer learning from the COCO dataset, achieving enhanced feature extraction and localization. The result demonstrated superior performance in detecting of pituitary, meningioma, and glioma tumors with a prediction accuracy of 99.5%. However, further validation on larger and more diverse datasets are required so as to ensure robust generalization on models' performance. Krishan *et al.* [12] proposed an ensemble model on liver cancer detection and classification with CT images. The study datasets were sourced from hospitals and ethical clearance from radiologists which included normal and abnormal liver images, with features extracted from manually selected regions of interest called (ROIs) and implemented on Adaptive Boosting, Random Forest, Support Vector Machine, Generalized Linear Model, and Neural Network and an ensemble of these classifiers achieved higher accuracy of 98.39. However, user friendly application was not implemented in this study. Hussain *et al.* [13] experimented a Computer Vision Approach for Liver Tumor Classification Using CT Dataset, proposing a Multi-Class Liver Tumor Identification (MLTI) framework for early-stage liver tumor detection. The methodology involved dataset preprocessing, multi-feature extraction (histogram, texture, binary, RST), feature optimization using correlation-based feature selection, and classification using machine learning algorithms (J48, RF, RT, LMT). The dataset consisted of liver tumor CT images with four classes (hemangioma, cyst, hepatocellular carcinoma, and metastasis). The MLTI framework demonstrated promising results in liver tumor classification, achieving 97.48% accuracy using optimized feature sets obtained through correlation-based feature selection and 10-fold cross-validation. ML classifiers - (J48, LMT, RF, and RT) were employed on regions of interest (ROIs) in liver CT images, with RF achieving 97.48% of accuracy on 17x17 ROIs. However, the study gave further research on implementing the datasets on other ML classifiers for model generalization. Suparyati *et al.* [14] proposed different sampling and oversampling with SMOTE, to predict Lumpy Skin Disease (LSD) using a Random Forest algorithm. The study addressed class imbalance in the LSD dataset and standard metrics - precision, recall, F1-Score, and ROC AUC was evaluated. The under sampling achieved balanced class distribution but encountered challenges with closely mixed data. More so, oversampling with SMOTE significantly improved model performance, achieving high recall, precision, and F1-score while reducing the false-negative rate. The study effectively demonstrated the utility of data balancing techniques for LSD prediction with SMOTE showing superior performance. Bousabarah *et al.* in [15] proposed an automated detection and delineation system for hepatocellular carcinoma (HCC) on multiphasic contrast-enhanced MRI using a deep convolutional neural network (DCNN) with a U-Net architecture. The study, a retrospective single-center analysis, implemented on a dataset from 2010 to 2018, the datasets was partition to training, the U-Net on 70% and validating and testing were implemented on the remaining 30% of datasets. With a dice similarity coefficient (DSC) requirement of larger than 0.2 between individual lesions and their segmentations, the DCNN obtained detection rates of 73% on validation sets and 70% on testing sets, respectively. The average false positive rate (AFPR) was enhanced by post-processing using a random forest (RF) classifier and thresholding (TR). However, because the study depended on particular MRI sequences, validation on larger and more varied datasets is necessary to assess the model's generalizability. Bassel *et al.*in [16] developed an automatic skin cancer classification system using a hybrid deep learning approach, leveraging a dataset from the ISIC archive with 70% for training and 30% for testing, comprising 1800 benign and 1497 malignant skin cancer images. The pre-trained models such: ResNet50, VGG16, and Xception were used for feature extraction, and a stacked CV model that combined SVM, KNN, random forest, decision tree, and regression was used for classification. Performance measures - accuracy, sensitivity, F1 score, and AUC score were evaluated. The result shows that Xception outperformed other models with 90.9% of accuracy. However, this model relied on a single dataset and was not implemented on user-friendly application.

The review addresses numerous strategies applied in skin disease identification via image processing and machine learning techniques. Several researchers have built systems leveraging multiple methodologies, including deep learning, CNN architectures, and machine learning algorithms to detect and categorize skin disorders. While many studies demonstrate promising results, several common limitations emerge, such as reliance on specific datasets, limited exploration of computational constraints, potential dataset dependencies, and the need for further validation in real-world deployment scenarios. Additionally, the studies often lack comprehensive benchmarking against state-of-the-art methods and may not fully address issues related to model generalization and scalability. Overcoming these limitations is crucial to ensuring the effectiveness and reliability of skin disease identification systems in clinical practice.

III. MATERIALS AND METHODS

This session provided the system structured to delineate the architecture, methodologies, and algorithms adopted in accordance with the proposed research framework. Initially, the study outline the proposed system architecture in Fig. 1, subsequent sections delve into the explanation of methodologies and algorithms utilized for executing and evaluating various stages of the process, including image preprocessing, image segmentation, feature extraction, and classification. The primary objective of this study is to develop and deploy a sophisticated classification system for the detection of Lumpy Skin Disease in animals, employing deep learning algorithms for enhanced accuracy and efficiency.

A. Dataset Preparation

The Data set consists of a total of 300 lumpy skin and 700 normal Cow images from Kaggle and through Google search. These images were captured using a digital mobile camera under specific conditions and this undergo several processes as discussed below:

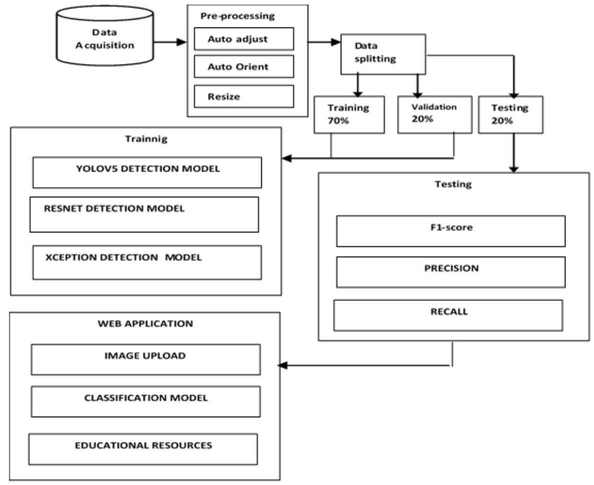

Fig. 1: Block Diagram for the Proposed System

Image acquisition

This study procured the datasets from Kaggle, leveraging internet connectivity to access and download the dataset in the PNG (Portable Network Graphics) file format. To augment the dataset and enrich the study's analysis, the data was expanded by acquiring additional datasets from publicly available sources using the Google search engine. Subsequently, the collected image data from both Kaggle and supplementary sources, focused on extracting relevant information related to Lumpy Skin Disease. The review addresses numerous strategies applied in skin disease identification via image processing and machine learning techniques. Several researchers have built systems leveraging multiple methodologies, including deep learning, CNN architectures, and machine learning algorithms to detect and categorize skin disorders.

Image Pre-Processing

The sourced image datasets goes through image preprocessing, this is a crucial stage that improves the original image dataset's quality by eliminating unnecessary elements like background noise. The following image dataset preprocessing were carried out in this study:

Resizing the image

Each image were first downsized to a standard of 640 by 640 pixel size so as to maintain consistency throughout the dataset, this scaling made compatibility and reliable feature extraction possible. There reasons for this resizing are: first, it made the image more compatible so that they could be easily incorporated into the analysis process. Secondly, the amount of characteristics retrieved from each image was unified by standardizing the image size, which made the next processing stages easier for this study.

.Auto-adjusting contrast

Machine learning models are dynamically modify the different input data while training are known as auto-adjusting the difference training models. Through this technique, an image's appearance can be changed without affecting its content by adjusting the intensity distribution of its pixel values. By altering the contrast, the models were able to identify objects in a variety of lighting scenarios, backdrops, and other environmental aspects, such as generalization and increased model robustness.

Auto orient

For consistent processing of images taken from various positions, automatic orientation is a feature that was added to the image datasets so that it automatically aligns images to a desired alignment. Orientation correction, text recognition, image annotation and processing pipelines, algorithmic approaches, and integration with image processing libraries are some of the aspects that fall under this category.

B. Data Splitting

In order to ensure the reliability and consistency of the convolutional neural network (CNN) models for the detection of lumpy skin disease classification, a data splitting approach was used. Three subsets of the dataset were created - 70% of the data was used for training, 20% was used for validation, and the remaining 10% was used for testing.

C. Training and Testing Phase

In the training phase, three different CNN models were employed: YOLOv5, Inception, and ResNet. Each of these models implemented on the training data subset to learn the underlying patterns and features associated with lumpy skin disease lesions. After the training, the performance of the trained models was evaluated using the testing subset. The evaluation metrics employed includes the Accuracy, F1-Score, Precision, and Recall.

D. Model redeployment

i. ResNet Model

The ResNet model was implemented on the image datasets through a convolutional layer which contains 64 filters, kernel size of 7x7, and stride 2, the batch normalization and ReLU were also carried out. The output was then down sampled using max pooling with a kernel size of 3x3 and stride 2. The output which then passed through a series of residual blocks, that consist of two convolutional layers, batch normalization, and ReLU, on the other hand, the residual connection add up the input together with the output. By this, the model to learn residual functions that ease the training process and then improved the performance of the model. The output passes through a final convolutional layer with a kernel size of 1x1 and a softmax activation function for classification. Resent is calculated as the following Eqs. 1 to 7.

The Input image is given as Eq. 1 while output *Y* of a convolutional layer is given as Eq. 2.

$$\boldsymbol{X \epsilon R^{H\times W\times C}} \quad (1)$$

$$\boldsymbol{Y_{i,j,k}} = \sum_{m=0}^{F-1} \sum_{n=0}^{F-1} \sum_{c=0}^{c-1} \boldsymbol{W_{m.n.c,k}} \quad (2)$$

Where:

$\boldsymbol{F}$ is the filter size (7), $\boldsymbol{S}$ is the stride (2), $\boldsymbol{W}$ are the weights of the filters, $\boldsymbol{C}$ is the number of input channels,

$\boldsymbol{K}$ indexes the output filters (64) ans $\boldsymbol{H}$ is Height of the input.

The Batch normalization normalizes the activations of the previous layer for independent mini-batch. Given an activation $\boldsymbol{x}$ over a mini-batch $\mathbf{B} = \{\boldsymbol{x1...m}\}$: in Eq. 3 to 7.

$$\mu\boldsymbol{\beta} = \frac{1}{m}\sum_{i=0}^{m} x_i \quad (3)$$

$$\sigma^2 = \frac{1}{m}\sum_{i=0}^{m} (x_i - \mu\boldsymbol{\beta})^2 \quad (4)$$

$$\frac{\hat{a}^2 = x_i - \mu\beta}{\sqrt{\sigma_\beta^2 + \epsilon}} \quad (5)$$

$$y_i = \gamma \hat{a}_2 - \boldsymbol{\beta} \quad (6)$$

Where $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ are learned parameters, and $\boldsymbol{\epsilon}$ is a small constant for numerical stability.

$$f(x) = \mathbf{max}(\mathbf{0}, x) \quad (7)$$

In case the dimensions of $\boldsymbol{F(x)}$ = and $\boldsymbol{x}$ do not match, a linear projection $\boldsymbol{W_x}$ can replace this and this is given as Eq. 8:

$$\boldsymbol{y = F(x) + Ws^x{}_x} \quad (8)$$

The softmax function is used for classification and is given b Eq. 9

$$\boldsymbol{\sigma(Z)_i = \frac{e^2 j}{\sum_{k=0}^{k} e^2 k}} \quad (9)$$

Where $\boldsymbol{z}$ is the input to the softmax is function, and $\boldsymbol{k}$ is the number of classes.

ii. YOLOv5 Model

In this study the YOLOv5 model were implemented on the input image datasets by passing the input image through a series of convolutional and CSP blocks to extract the features contained. The output then passes through a prediction layer which predicts the bounding box coordinates, confidence score, and class probabilities. The predicted bounding boxes are then filtered using non-maximum suppression to remove redundant boxes. The model uses a loss function that combines these bounding box loss, confidence loss, and classification loss in order to optimize the model's performance which allowed the model to detect the objects in real-time with high accuracy. ResNet model is a deep neural network that uses residual connections to reduce complexity during the training process as this given by Eq. 10:

$$F(x) = W_2 * \text{ReLU}(\text{BN}(W_1 * x + b_1)) + b_2 \quad (10)$$

Where:

x represents the input feature map, W_1 and W_2 are the weights of the filters, $\boldsymbol{b}$ represents the biases, **ReLU** represents the Rectified Linear Unit activation function, BN represents Batch normalization function, b_1 and b_2 are biases for the two convolutional layers.

iii. Xception Model

The Xception model was implemented by passing the input image through a series of convolutional and max pooling layers so as to extract the features contained. The output derived from this was passes through a series of depthwise separable convolutional layers, that consist of a depthwise convolution with the pointwise convolution. This method made the model more efficient by ensuring that it could extract features with less data. Furthermore, a softmax activation function was applied to the output in order to classify it accurately. The model's architecture is designed to be efficient and scalable, making it suitable for a wide range of image classification tasks. The Xception model uses depthwise and Pointwise convolutions which is given as Eq. 11 and 12:

$$ydw = W_{dw} * x \quad (11)$$

$$ypw = W_{pw} * ydw \quad (12)$$

Where:

ydw *and* ypw are the output feature maps of the depthwise and pointwise convolutions, respectively.

W_{dw} iand W_{pw} represent the weights (filters) for depthwise and pointwise convolutions, respectively.

x represent input feature map

$*$ represent the Convolution operation

D. Model Evaluation

The model's performance was assessed using accuracy and loss metrics during both training and testing phases. Confusion matrices were employed to examine individual class predictions. Furthermore, distinct comparisons were made between the Xception and ResNet models regarding their accuracy during training and testing. To assess the performance of the stated models in the study, employed several evaluation metrics were employed including, Accuracy, Precision, Recall, and F-score indicated in Eqs. 13 to 16.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (13)$$

$$Precision = \frac{TP}{TP+FP} \quad (14)$$

$$Recall = \frac{TP}{TP+FN} \quad (15)$$

$$F1 - score = \frac{2*Precision*Recall}{Precision+Recall} \quad (16)$$

Where:

TP means True Positive, TN means True Negative, FP means False Positive and FN means False Negative. The result of standard metrics evaluations for the three deep leaning learning models employed in this study are depicted in Table I.

E. Web Application

In addition to the development of convolutional neural network (CNN) models for lumpy skin disease classification, this study encompasses the integration of these models into a user-friendly web application. The web integration serves as a practical platform for users to upload images, obtain real-time classification results for lumpy skin disease lesions, and access educational resources related to lumpy skin disease.

F. Educational Resources

In addition to facilitating image classification, the web application serves as a valuable educational resource hub for lumpy skin disease. Users can access a curated collection of educational materials, including articles, videos, and interactive tutorials, aimed at increasing awareness, understanding, and management of lumpy skin disease.

IV. RESULT AND DISCUSSION

The implementation of this study was carried out within a Python environment (version 3.8), utilizing Keras with TensorFlow backend to develop and train a CNN model. Additionally, image augmentation and model building were facilitated using the Roboflow platform, and PyTorch was employed for computational tasks. The model performance analysis in graph stated in Table I.

TABLE I. PERFORMANE ANALYSIS OF THHE THREE MODELS EMPLOYED

Model	Precision	Recall	F1 Score
ResNet	0.643	0.703	0.671
Xception	0.705	0.758	0.731
YOLOv5	0.829	0.950	0.885

The ResNet model achieved a precision of 0.643, recall of 0.703, and F1 score of 0.671, while the Xception model demonstrated precision of 0.705, recall of 0.758, and F1 score of 0.731. The YOLOv5 model outperformed the performance metrics with a precision of 0.829, recall of 0.950, and F1 score of 0.885. More so, all models performed excellently, the YOLOv5 model performance better compared to ResNet and Xception in terms of precision, recall, and overall F1 score and validation accuracy.

G. System Deployment

The study was implemented using Visual Studio Code (VS Code), an Integrated Development Environment (IDE) that is suitable for deep learning tasks in this study. The web application was built on the Django framework, so as to provide a robust features for efficient web development and deployment of deep learning models. Additionally, a database solution such as Dynamo DB was incorporated into the system architecture to store images post-classification, ensuring data persistence and accessibility. This comprehensive integration of technologies facilitated the seamless deployment of the deep learning model within a web environment, enhancing its usability and accessibility for end-users as shown in Fig. 2 to 4.

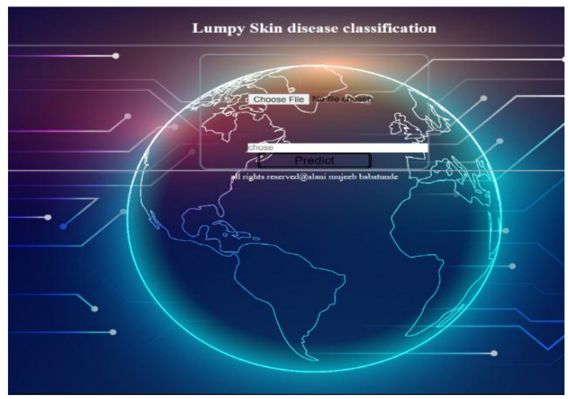

Figure 2: Home page

Fig. 2 depicts a user-friendly interface that allows users to upload images for classification

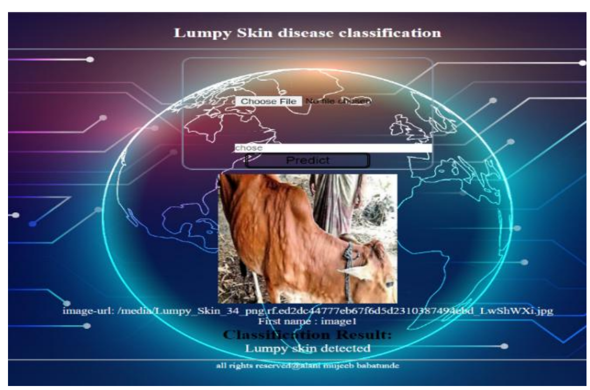

Figure 3: Lumpy skin classification to yes

Fig.3 is the lumpy Skin Classification that accurately classifies the images as either "Yes", that is, lumpy skin is detected.

Figure 4: Lumpy Skin classification to No

Fig. 4. Is the Lumpy Skin Classification that accurately classifies the images into category of "No" which means lumpy skin is detected.

CONCLUSION

This study successfully achieved its primary aim of developing an advanced Lumpy Skin Disease detection and classification system. By leveraging cutting-edge technologies such as TensorFlow, Django, and Python, we designed a highly effective and efficient system that integrates a comprehensive image dataset and a robust image classification model. The YOLOv5 model demonstrated superior performance with an accuracy reflected in its precision of 0.829, recall of 0.950, and F1 score of 0.885, showcasing its potential to enhance lumpy skin disease diagnosis. The web-based platform ensures user-friendly accessibility, making it a valuable tool for practical applications. Moreover, this study contributes significantly to the field of lumpy skin disease detection, paving way for further research works.

RECOMMENDATION AND FUTURE WORK

To further improve the performance and reliability of the lumpy skin disease detection model, this study suggests expanding the dataset size to include a more comprehensive representation of diverse cases, thereby enhancing accuracy and robustness. Furthermore, diversifying data sources beyond a single origin would improve the model's generalizability and performance across various populations and environments, ultimately leading to a more effective disease detection system.

AUTHOR'S CONTRIBUTIONS

The author conceived and designed the study, developed the deep learning approach using Convolutional Neural Networks (CNNs), conducted the experiments, analyzed the results, wrote the manuscript and approved the final submission.

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