Deep Learning-Based Cattle Disease Detection: A CNN Approach for Identifying Lumpy Skin Disease and Foot-and-Mouth Disease

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***Abstract*— Increasing prevalence of cow diseases such as Lumpy Skin Disease and Foot-and-Mouth Disease presents a significant challenge to livestock health and agricultural economies. traditional diagnostic Techniques are frequently costly, time-consuming, and prone to human error., necessitating the development of automated solutions. Deep learning, specifically Convolutional Neural Networks , for classifying cow health conditions into three categories: healthy, LSD, and FMD. The methodology involves dataset collection, preprocessing, model training, evaluation, and performance visualization. A diverse dataset of cow images was collected and divided into training and testing sets. Preprocessing operations involved resizing, normalization, and data augmentation for increasing model robustness. Multiple CNN architectures, such as DenseNet121, ResNet50V2, InceptionV3, VGG16, VGG19, and Xception, were tested with pre-trained ImageNet weights for transfer learning. Max Pooling, dense layers with ReLU activation, dropout layers for regularization, and a SoftMax output layer for classification were appended as part of fine-tuning. Adam optimiser, and cross-entropy loss, as well as early stopping, were employed for model training to prevent overfitting. Accuracy, precision, recall, F1-score, and confusion matrices were employed to compare the performance. It was noticed that CNN-based models classify cow diseases effectively, especially with transfer learning and data augmentation. The proposed system can be utilized by farmers and veterinarians to diagnose diseases early and lower costs as well as better manage livestock health. This work improves automated cattle health monitoring using an efficient and scalable approach to disease classification of cattle.**

Keywords — Convolutional Neural Networks (CNNs), DenseNet121, Image Processing, InceptionV3, ResNet50V2, VGG16, VGG19.

I. INTRODUCTION

Computer-aided disease diagnosis of livestock via deep learning approaches has gained significant interest on the grounds of its capability to enhance the accuracy and speed of diagnosis of the health status of animals, especially cattle. Accurate and timely diagnosis of diseases is vital in controlling the spread of infections, protecting livestock health, and maintaining agricultural production. Among the different animal diseases, LSD and FMD are of utmost concern to the cattle industry. These extremely contagious diseases have the potential to result in huge economic losses, highlighting the need for early diagnosis and treatment. Traditional disease detection techniques are usually based on time-consuming manual checks and tend to be inaccurate, particularly in large-scale farms[1]. As opposed to this, deep learning-based methods offer a promising direction for automated, effective, and accurate disease identification by analyzing cattle images to ascertain their health state. Use of deep learning models, i.e., CNN, for classifying bovine images into three specific classes: healthy cattle, cattle suffering from lumpy skin disease, and foot-and-mouth disease-affected cattle[3]. By utilizing advanced CNN structures like DenseNet121, ResNet50V2, InceptionV3, VGG16, VGG19, and Xception, tap into power of deep learning to recognize patterns also exist in cattle images indicative of these maladies. CNNs are proven to be incredibly effective in tasks concerning picture classification, their capacity to pick up hierarchical characteristics reconstructions from raw picture data. The resistance of CNNs to subtle visual pattern changes makes them an excellent candidate for use in veterinary diagnosis, where fine nuances of animal form may indicate disease presence[4].

One of the most important data preparation processes is image preprocessing. Preprocessing is required to make the data compatible with the input of the neural

network. Preprocessing regime involves image resizing to a fixed resolution of 128x128 pixels and pixel value normalization between 0 and 1. In order to make the neural networks able to optimise data, the above normalisation is an important processing efficiency and speeding up the convergence in the training process[6][7].

Appropriate model architecture selection is crucial to the success of image classification operations using deep learning. This paper examines some of the leading CNN architectures, chosen for their specific strengths. A case in point is the DenseNet121, which is famous for its efficient feature propagation and ability to facilitate increased gradient flow, features very beneficial for medical image classification. This model incorporates dense connections among layers such that every layer receives data from all the layers that come before it, and this promotes feature reuse as well as the ability of the network to learn more intricate patterns. Other models such as InceptionV3, VGG16, VGG19, and Xception are part of this study with each having some benefits in the field of computational efficiency and performance. InceptionV3 is unique since it can handle multi-scale features through multiple convolutional filters simultaneously. VGG16 and VGG19, however, possess more linear models that are quite popular due to their depth and picture categorisation effectiveness. Xception, founded on depthwise separable convolutions, has been proven to outperform most picture categorisation tasks. Following the selection of a model and selection of an appropriate model architecture, training of the model from pre-processed data follows. The model learns during this step to recognize features of a class. The learning process is tracked by a validation set to prevent overfitting and an unseen picture test set is used to determine the generalisation ability of the model. [9].

Model is tested after training on set of metrics like F1-score, accuracy, precision, and recall. For disease detection, these metrics provide an overall sense of how well the model can distinguish between cow images. The results of the evaluation are used to further refine the model and increase performance. Visualization methods, like confusion matrices and class activation maps, are used to identify the regions of the image most indicative of the disease being present and to describe how the model is making its predictions.

II. RELATED WORK

Gerben Hofstra et al. [1] developed an automated system for monitoring and detecting livestock diseases using facial feature scoring. Their study focused on Foot-and-Mouth Disease (FMD) in cows, analyzing facial expressions to identify signs of infection. The system used image-based analysis and machine learning to track disease progression. Their results demonstrated the potential of facial feature monitoring for early disease detection. This approach offers a non-invasive, automated method for livestock health surveillance.

Shogo Higaki et al. [2] developed a computer vision-based system for objective dairy cow mobility analysis. They used a key point detection technique on top-view 2D videos to assess locomotion and detect lameness. Their method provided automated mobility scoring, reducing subjectivity in traditional assessments. The study demonstrated high accuracy in detecting movement abnormalities. This approach improves early lameness detection, enhancing dairy cow welfare and farm productivity.

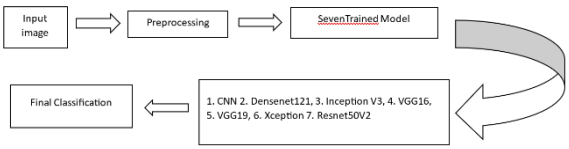
Finnian Logan et al.[3] evaluated the sensitivity and specificity of mobility scoring for detecting foot lesions in pasture-based Irish dairy cows. They compared mobility scores with actual hoof health assessments to determine accuracy. The study found that while mobility scoring is useful, it has limitations in detecting mild lesions. Sensitivity was lower for early-stage foot issues, highlighting the need for complementary diagnostic methods. Their findings emphasize improving mobility scoring for better hoof health management.

Saisai Wu et al. [4] proposed a multi-scale key point detection and motion feature extraction method for dairy cows using the ResNet101-ASPP network. Their model accurately identified key anatomical points and analyzed movement patterns to assess cow health. The approach improved motion feature extraction, aiding in early detection of mobility issues. The study demonstrated high precision in tracking cow posture and movement. Their findings support the use of deep learning for automated livestock monitoring.

Existing research primarily focuses on IoT-based monitoring and general disease detection but lacks clear classification results. While some studies use machine learning, they do not fully define disease classification performance. This study aims to

develop a deep learning model for accurately classifying external cattle diseases. By utilizing advanced architectures, it enhances precision and reliability in disease detection. The proposed method addresses gaps in prior research, improving automated cattle health diagnosis.

III. BLOCK DIAGRAM



The diagram illustrates an image classification deep learning system, from image acquisition to final classification. It converts raw visual data into meaningful classifications by employing a number of pre-trained architectures for accuracy and resilience.

The procedure starts with an input image, which is preprocessed prior to integration into a neural network. Preprocessing facilitates deep learning model compatibility and increases training stability and accuracy. Preprocessing entails resizing (reshaping image sizes), normalization (pixel value scaling), and data augmentation (variation introduction to increase the dataset).

Seven pre-trained CNNs—Densenet121, Inception V3, VGG16, VGG19, Xception, and ResNet50V2—each process the images. Each plays a distinct role: Densenet121 promotes information flow, Inception V3 extracts multi-scale features, VGG models extract deep features, Xception enhances efficiency, and ResNet50V2 tackles vanishing gradients.

All predictions of these models are ensemble through majority voting, weighted voting, bagging, and boosting to enhance accuracy. All the following domains utilize this workflow: object recognition, image retrieval, medical imaging, and autonomous vehicles.

Ensemble methods improve performance by limiting overfitting and offsetting model biases. Hardware accelerators such as GPUs and TPUs, and software optimizations such as model quantization and pruning, accelerate and make better use of computing resources for real-time usage.

IV. METHODOLOGY

1) Convolutional Neural Network (CNN)

Cow disease classification with CNNs entailed data gathering, preprocessing, model designing, training, evaluation, and visualizing the result. Precise machine learning model to classify cows into three classes: healthy, lumpy skin disease, and foot-and-mouth disease. Images were collected from diverse sources, labeled into the three classes, and manually sorted into training as well as test datasets. Training set consisted of varied images for enhanced learning, and test set evaluated the generalization of the model. Separate datasets were important in performance assessment on unseen data and overfitting prevention.

Input Layer:

$$X \in \mathbb{R}^{128\times128\times3}$$

Where X is the input image of height 128, width 128, and 3 colour channels (RGB).

Preprocessing was a critical component of the methodology, facilitating effective data management and model tuning. Normalization was conducted using TensorFlow's ImageDataGenerator, rescaling pixel intensities to an interval [0,1] to improve convergence of neural networks. Rotation, zooming, shifting, shear transformation, and horizontal flipping are examples of data augmentation techniques, were applied to training set to improve generalization. The test set was rescaled without augmentation to preserve its integrity for evaluation.

Convolutional Layer 1:

$$H_1 = ReLU(W1 * X + b_1)$$

Where:

- W_1 and b_1 are the weights and biases of the first convolutional layer.
- $*$ represents convolution operation.
- H_1 is the output feature map after applying 32 filters of size 3×3.

The CNN model, built with TensorFlow's Keras API, used a Sequential structure with three convolutional layers (32, 64, and 128 filters) and max-pooling layers (2×2) for feature extraction and dimensionality reduction. Flattened feature maps were passed through a dense layer (128 neurons, ReLU activation), with 50% dropout to prevent overfitting. A final softmax layer classified images into healthy,

lumpy skin disease, and FMD, ensuring efficient image classification.

Max Pooling Layer 1:

$$P_1 = MaxPool(H_1, pool\_size = 2)$$

Where:

- p_1 = reduces the spatial dimensions of H_1 by a factor of 2.

Adam optimiser was used to construct the model, which was then trained across 20 epochs using categorical cross-entropy loss. Accuracy was monitored to ensure convergence and detect overfitting. Evaluation involved computing test accuracy, a confusion matrix, also a classification report with precision, recall, and F1-score. Predictions on random images validated model's ability to classify unseen data. Confusion matrix helped identify misclassifications, confirming high accuracy across all classes. Sample images with predicted labels provided a visual assessment of classification effectiveness. The study highlights CNNs' potential in veterinary diagnostics and AI-driven livestock health management.

Convolutional Layer 2:
$H_{2=}ReLU(W_2 * P_1 + b_2$

2) DenseNet121

The DenseNet121-based cow disease classification follows a structured methodology, including data preparation, preprocessing, model development, training, evaluation, and visualization. Images are categorized into three classes also split into training along with testing sets. Data augmentation using Tensor Flow's Image Data Generator improves generalization and prevents over fitting. Augmentation techniques include rotation, zooming, shifting, shear transformations, and flipping. Pixel values are normalized to [0,1] for stable and efficient training. The test set is only rescaled to maintain evaluation integrity. This ensures a robust and unbiased model capable of generalizing to new data.

Input Layer

The input to the model is a batch of images with dimensions (B,H,W,C)(B, H, W, C)(B,H,W,C), where:

- B is the batch size,
- H and W are height and width (128 × 128 in your case),
- C is the number of color channels (3 for RGB).

$$X_{input} \in \mathbb{R}^{B\times 128\times 128\times 3}$$

DenseNet121 Backbone

$$Y_1 = \mathcal{F}_1([X_0, X_1, \dots\dots, X_{1-1}])$$

Where:

- F_1 is composite function of Batch Normalization , ReLU activation, and convolution.
- $[X_{0,}X_{1,\dots\dots,}X_{1-1}]$ indicates that feature maps from earlier levels have been concatenated.

Trained model is evaluated on test dataset to assess its generalization ability. Test accuracy confirms its effectiveness in classifying cow diseases. A confusion matrix visualizes true vs. predicted labels, helping identify misclassifications. Precision, recall, and F1-scores are provided for every class in the classification report. These measurements draw attention to both the model's advantages and shortcomings.

Global Average Pooling (GAP)

$$X_{GAP} = \frac{1}{H \times W}\sum_{h=1}^{H}\sum_{w=1}^{W} X_{dense}[h, w, c]$$

Where:

- H and W are the spatial dimensions of the last feature map,
- c is the channel index.

Custom Layers

1. A dense layer with ReLU activation:

$$X_{dense} = ReLU(W_1.X_{GAP+}b_1)$$

2. A dropout layer to prevent overfitting:

$$X_{dropout} = Dropout(X_{dense})$$

3. An output dense layer with softmax activation for classification

$$\hat{y} = Softmax(W_2.X_{dropout+}b_2)$$

3) ResNet50V2

This research formulates, trains, and tests a deep learning model based on ResNet50V2 to classify cow images for the detection of lumpy skin disease and FMD. The dataset, separated into training as well as test sets, is three classes with healthy cows, cows with lumpy skin, and cows with FMD. Images are kept in individual directories and are loaded through the use of Keras' flow_from_directory function, which loads the labels automatically. Preprocessing is done by resizing images and normalization of pixel intensity to [0,1] for uniform input format. Shearing, shifting, zooming, and rotating are data augmentations that add diversity to the dataset to avoid overfitting. These augments enable generalization of the model and boost classification accuracy. The approach secures strong learning of features suitable for real-life disease detection on cattle.

Feature Extraction with ResNet50V2:

$$F_{ResNet50V2}(x) = f^{(50}\big(f^{(49)}(\dots.f^{(1)}(x)\dots)\big)$$

Where $f^{i}\ is\ the\ i-th$ layer of the ResNet50V2 architecture, including convolution, ReLU activations, and residual connections.

ResNet50V2 is selected for cow disease classification because of its residual deep structure, which avoids the vanishing gradient problem. Transfer learning is employed by loading a pre-trained ResNet50V2 model with ImageNet weights, enabling effective feature extraction. The convolutional layers of the base model are frozen, and global average pooling, a thick ReLU layer, dropout (0.5), along with softmax output layer for three-class classification are some of the special layers that are added. For multi-class classification, model is constructed with Adam optimiser and categorical cross-entropy loss.

Global Average Pooling:

$$z = \frac{1}{H.W}\sum_{h=1}^{H}\sum_{w=1}^{W} F_{ResNet50V2}(x)h,w,c$$

where c stands for the number of channels and H and W for the height and breadth of the feature map.

Fully Connected Layers:

1. First dense layer:

$$h_1 = ReLU(W_1 z + b_1)$$

2. Dropout layer (regularization):

$$h_1^{dropout} = Dropout(h_{1,} rate = 0.5)$$

3. Output layer (SoftMax activation):

$$\hat{y}\imath = \frac{e^{W_2} h_1 dropout + b_2}{\sum_{j=1}^{C} W2_{h_1} dropout + b_2}$$

Where C is the number of classes (3 in your case: healthy, lumpy skin, FMD), and $\hat{y}\imath$ represents the predicted probability for class i.

4) InceptionV3

This project applies deep learning to classify cow images into three categories: healthy, LSD, and FMD using InceptionV3. The dataset is organized into directories, with images resized to 128x128 pixels and normalized to a [0,1] range for consistency. Image Data Generator handles real-time augmentation, applying transformations like rotations, zooms, and shifts to enhance generalization. The test dataset is only normalized to ensure unbiased model evaluation. This approach helps the model learn distinctive features while avoiding over fitting, improving classification accuracy.

Input

The input to the InceptionV3 model is a 3D tensor,$X \in \mathbb{R}^{H\times W\times C,}$ Where,

- H: Height of the image (e.g., 299 pixels).
- W: Width of the image (e.g., 299 pixels).
- C: Number of channels (e.g., RGB with 3 channels).

Inception Modules:

$$Y_{Inception} = Concat([Y_{1x1,} Y_{3x3,} Y_{5x5,} Y_{pool}])$$

Where:

- $Y_{1x1} Y_{3x3} Y_{5x5}$: Outputs from convolution operations with respective filter sizes.
- $Y_{pool:Output\ from\ pooling.}$

Model's evaluation metric is accuracy, and it is built using adam optimiser along with categorisation of many classes using categorical cross-entropy loss. It

uses validation data to track generalisation and identify overfitting during its 20 epochs of training with a batch size of 32. After training, the model is saved for future inference on new images.

Auxiliary Classifiers (Optional)

$$Z_{aux} = Softmax(W_{aux.}F_{aux+}b_{aux})$$

Where:

- $F_{aux:\ Flattened\ intermediate\ feature\ map.}$
- $W_{aux:\ Weights\ for\ auxiliary\ classification.}$
- $b_{aux:}$ Bias term.

Output Layer:

$$\hat{y} = Softmax(W_{out.}Z + b_{out})$$

Where:

- $\hat{y}$: Predicted probabilities for each class.
- $W_{out:}Weights\ of\ the\ output\ layer.$
- $b_{out:\ Bias\ term.}$

5) VGG16

The VGG16 model is utilized to classify cow images as healthy, LSD, and FMD. The dataset is organized into test and teaching groups, with images saved in labeled directories and preprocessed for model compatibility. Images are resized to 128x128 pixels, normalized to the [0,1] range, and augmented with operations such as rotations and zooms to improve generalization. The test set is only rescaled to ensure precise performance measurement on original images.

Convolutional Layers:

$$Output_{i,j} = \sum_{m,n} Input_{i+mj+n} \cdot Filter_{m,n} + Bias$$

Where:

- $Output_{i,j}$ is the output at position (I,j)(I,j)(I,j) of the feature map,
- $input_{i+m,j+n}$ is the value of the input image or feature map at position (i+m,j+n).
- $Filter_{m,n}$ is filter applied to the image,
- Bias is the bias term added after the convolution operation.

Activation Function (ReLU):

$$ReLU(x)=max(0,x)$$

Adam optimiser and categorical cross-entropy loss are used to construct the VGG16 model, which is subsequently 20 epochs of training with a 32-person batch size. Validation is performed using the test set to monitor performance and prevent overfitting. Following training, the model's accuracy is assessed and stored for further use.

Pooling Layers:

$$\text{Pool Output}=\max(Input_{i,j})$$

Model's performance is assessed using a confusion matrix, classification report, as well as visual demonstrations. Heatmap and key metrics like precision and recall provide insights into classification accuracy.

Fully Connected Layers:
Output=Activation(W·Input+b)

Where:

- W is the weight matrix,
- b is the bias vector,
- Activation is the activation function (e.g., ReLU or SoftMax for classification)

6) VGG19

The methodology trains a VGG19-based CNN to classify cow images into three categories: healthy, lumpy skin, and FMD. The dataset is collected, preprocessed with augmentation techniques for training set, and normalized for efficient model learning. Transfer learning is applied by loading VGG19 with pre-trained ImageNet weights, then incorporating unique categorisation layers. The model is built with the Adam optimiser and categorical cross-entropy loss to get the highest multi-class classification performance possible.

Convolutional Layers (Conv)

$$FeatureMap_{i,j} = \quad \sum_k (Input)_{i,j,k\times} Filter_k \times b_k$$

where:

- $FeatureMap_{i.j}is\ the\ output\ of\ the\ convolution\ at$

$$spatial\ position\ (i,j),$$

- $Input_{i,j,k}\ is\ the\ value\ of\ the\ input\ image\ at$

$position\ (i,j)\ for\ the\ k-th\ channel,$

- $Filter_k$ is the filter applied to the image (a learned parameter),
- b_k is the bias term for the filter k.

Max Pooling Layer:

$$Pooling\ Output_{i,j} = max(FeatureMap[i,j])$$

Fully Connected (Dense) Layers:

$$\text{Output}= \sigma(\sum_i(W_i \times Input_i)+b_i)$$

where:

- $W_i\ are\ the\ weights\ of\ the\ dense\ layer,$
- $Input_i$ is the input from the previous layer,
- $b_i\ is\ the\ bias\ term,$
- σ is an activation function (ReLU for intermediate layers, softmax for the output layer in your case).

7) Xception

The Xception-based deep learning model classifies cow health conditions into healthy, lumpy skin, and FMD categories. The methodology includes data preparation, model design, training, evaluation, and deployment. Transfer learning, data augmentation, as well as preprocessing ensure robustness and generalization. Images are organized into directories, split into training along with testing sets, also preprocessed using TensorFlow's ImageDataGenerator. Augmentation techniques enhance training data, while testing images are only rescaled for performance evaluation.

ReLU Activation:

$$F(x)= \max(0,x)$$

Xception model is chosen for its efficiency in image classification, leveraging depthwise separable convolutions to reduce parameters while maintaining accuracy. Pre-trained on ImageNet, it utilizes transfer learning to enhance feature recognition for cow disease classification. Custom layers include GlobalAveragePooling2D, ReLU-activated dense layer with a dropout layer to avoid overfitting. Final SoftMax layer outputs probabilities for three classes: healthy, lumpy skin, and FMD.

Global Average Pooling:

$$y_c = \frac{1}{H\times W}\sum_{h=1}^{H}\sum_{w=1}^{W}X(h,w,c)$$

Fully Connected Layers:

$$y = \dot{Software}(W_X+\text{b})$$

where Wis the weight matrix, b is the bias vector, also SoftMax computes the class probabilities.

Model.evaluate() computes test loss and accuracy to evaluate generalisation when trained model is tested on unseen test data. Classification report offers precision, recall, and F1-score for more in-depth analysis, while a confusion matrix is created and shown using a heatmap to examine classification mistakes. To further validate performance, random test images are displayed alongside predicted labels and confidence scores, helping identify misclassifications. The model can also be reloaded for inference on new images, ensuring practical usability in diagnosing cow diseases.

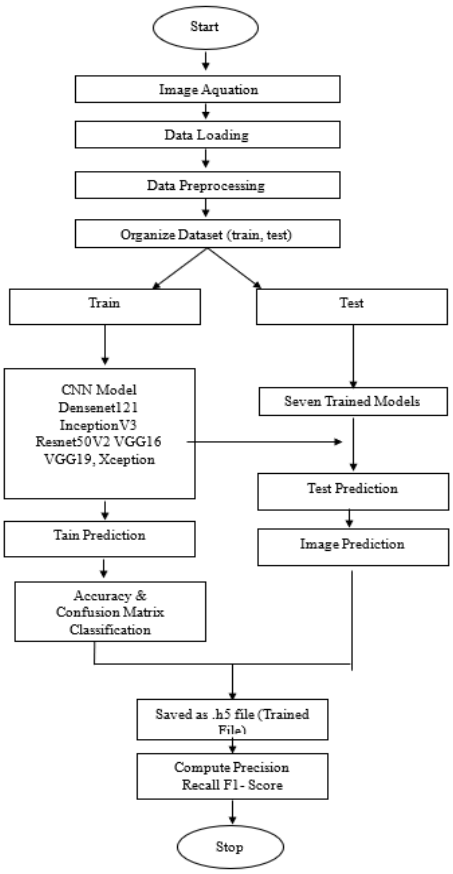
Depth wise Separable Convolutions

$$X \in \mathbb{R}^{H\times W\times C}$$

V. MODEL ARCHITECTURE

CNN is a deep learning model that can recognise hierarchical patterns in picture data, making it possible to perform tasks like detection and classification. The layers that make up its architecture include convolutional, pooling, flattening, and fully linked layers. Fully connected layers classify these features, pooling layers reduce computational cost, and convolutional layers gather low-level to high-level information. ResNet50V2, InceptionV3, VGG16, VGG19, and Xception are a few sophisticated architectures which employ techniques like depthwise separable convolutions, multi-scale feature extraction, and residual learning to improve CNN performance.

ResNet50V2 makes use of residual connections to improve gradient flow, whereas InceptionV3 is effective employing multi-scale feature extraction. VGG16 and VGG19 employ effective simple small filters with increasingly deeper feature extraction. Xception replaces regular convolutions with depthwise separable convolutions, reducing computational cost while maintaining feature richness. These architectures even improve CNN capabilities, making them highly efficient for complex image classification problems.



VI. DIFFERENT TYPES OF CLASSIFICATION RESULTS

The performance of seven CNN models—DENSENET121, ResNet50V2, InceptionV3, Xception, CNN, Vgg16, and Vgg19—was compared based on accuracy, F1 score, recall, and precision. DENSENET121 obtained the maximum accuracy (92.31%) and F1 score (0.96), followed by ResNet50V2 (94.55% accuracy, 0.97 F1 score). InceptionV3 and Xception were of mid-level performance with a roughly 92-93% accuracy, while DENSENET121 obtained 92.31% accuracy and 0.96 F1 score. Vgg16 and Vgg19 scored lower at 90.91% and 88.11% accuracy, with F1 scores of 0.95 and 0.91, respectively. All models had perfect recall (1.00), but precision was different, with CNN and ResNet50V2 recording the highest (0.96 and 0.94). The results demonstrate the efficiency of deep CNN architectures for cow disease detection, with potential for improvement in precision and interpretability

Table 1. Analysis of Comparative Table

Model Name	Accuracy	F1 Score	Recall	Precision
DENSENET121	92.31%	0.96	1.00	0.92
CNN	96.55%	0.98	1.00	0.96
RestNet50V2	94.85%	0.97	1.00	0.94
InceptionV3	92.66%	0.97	1.00	0.94
Vgg16	90.91%	0.95	1.00	0.90
Vgg19	88.11%	0.91	0.99	0.85
Xception	93.01%	0.96	1.00	0.92

VII. CONCLUSION

The growing incidence of cow diseases like LSD and FMD underscores demand for sophisticated detection techniques. Conventional methods, including manual examination and laboratory analysis, are often costly, time-consuming, and prone to human mistake. A good alternative is offered by deep learning, particularly CNN, which automate the highly accurate diagnosis of diseases. This research investigates CNN-based disease classification of cows with a view to creating a good model that can classify healthy cows, cows infected with LSD, and cows infected with FMD. The process entails the collection of datasets, preprocessing, and selection of the model in order to guarantee strong disease classification. Images were classified into three categories and resized, normalized, and augmented in order to improve generalization. Several deep learning architectures, such as DenseNet121, ResNet50V2, InceptionV3, VGG16, VGG19, and Xception, were contemplated, with the aid of transfer learning to enhance performance. Custom layers, dropout, and softmax activation refined predictions, while training optimization techniques like Adam optimizer and early stopping prevented overfitting.

Metrics for evaluation, such as confusion matrix, F1-score, recall, accuracy, and precision, confirmed model's ability to differentiate between various cow health situations. Results demonstrated that CNNs, supported by transfer learning and data augmentation, are highly effective in automating livestock disease detection.

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