A Novel Hybrid Deep Neural Network for Early Detection and Classification of Chicken Diseases

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***Abstract*—Detection and classification of chicken diseases has been a longstanding concern for farmers. Relying solely on expert opinions could be a costly option. Moreover, there are certain chicken diseases that spread quickly, and necessary procedures are immediately needed to carry on. On the other hand, the lack of research activity or low availability of data on this topic leads to many misunderstandings and challenges so as to correctly detect a certain type of chicken disease. The existing techniques show low accuracy on disease classification, which leads to a complex engineering problem and critical analysis is required for sustainable development. In this paper, we develop a novel hybrid deep neural network, namely ChickenNet21, which combines a Convolutional Neural Network (CNN) and a fine-tuned Visual Geometry Group (VGG) model to address this challenge. Using a large dataset of 6,812 farm-labeled fecal images, we assess the effectiveness of ChickenNet21 and it achieves 98.83% accuracy in identifying chicken diseases.**

***Keywords*— Chicken Disease, Classification, Deep Learning Model, Convolutional Neural Network.**

I. Introduction

Both in developed and emerging nations, the poultry industry helps to create jobs and economic prosperity. They promote rural development and poverty eradication by opening doors for farmers, processors, distributors, and retailers [1]. Compared to other livestock sectors, poultry farming is thought to be more environment friendly. It uses less land, water, feed, and has a lower carbon impact per unit of meat produced [2]. The majority of poultry species are raised for food, and chickens are the backbone of the poultry industry. High growth rates, effective feed conversion, and desired meat qualities have been achieved through selective breeding [3]. Delayed diagnosis and treatment of chicken diseases can encourage the transmission of infections across flocks and within them, endangering public health and biosecurity. Some bird diseases, like avian influenza, have the potential to spread to humans and pose a risk to their health [4].

Coccidiosis is a condition caused by Eimeria parasites. Eimeria tenella (E. tenella) stands out as one of the most harmful and pathogenic parasites, contributing significantly to poultry mortality rates. To diagnose coccidiosis, the standard procedure entails either quantifying the oocysts per gram (opg) in the feces or assessing the lesion scores through examination of the intestinal tract [5]. Salmonella, a genus of bacterial pathogens, poses a risk to both poultry and humans [6]. The detection and identification of different Salmonella strains are accomplished using the Polymerase Chain Reaction (PCR) technique [7]. Avian paramyxovirus serotype 1 (APMV-1) viruses are the causative agents of Newcastle disease, an acute viral infection affecting poultry & various bird species [8]. The diagnosis of Newcastle disease virus (NDV), specifically avian paramyxovirus serotype 1 (APMV-1), is typically achieved through serology, virus isolation tests, or the utilization of real-time reverse-transcription PCR procedures [9].

Chicken disease classification through images creates a primary challenge in the veterinary sector. It is complicated due to variations in symptoms, lighting conditions, and camera angles. Developing a reliable image classification model capable of accurately identifying different chicken diseases is vital for enhancing disease diagnosis and proactive treatment. This study's central aim is to create a hybrid architecture that merges CNN-based feature extraction with a fine-tuned pre-trained model that helps veterinarians to easily and accurately diagnose various chicken diseases, ultimately leading to improved poultry health management as a primary objective. This amalgamation empowers the automated identification of various chicken diseases using fecal sample images. By harnessing deep learning and transfer learning, this study advances automated disease detection in the poultry sector.

The paper introduces a novel hybrid deep neural network architecture wherein the strengths of both feature extraction techniques are leveraged, enhancing the model's ability to extract meaningful features from input images. The real-world large dataset of farm-labeled fecal images is used in the research. The performance of the proposed ChickenNet21 framework is evaluated on a large dataset, and it is indicated by the results that our framework is able to outperform previous studies found in the research.

II. Related Work

Wang et al. proposed an automated detection system for broiler digestive diseases utilizing a deep Convolutional Neural Network model, specifically the objective of the system was to categorize abnormal broiler droppings images into normal and abnormal classes using Faster R-CNN and YOLO-V3. Faster

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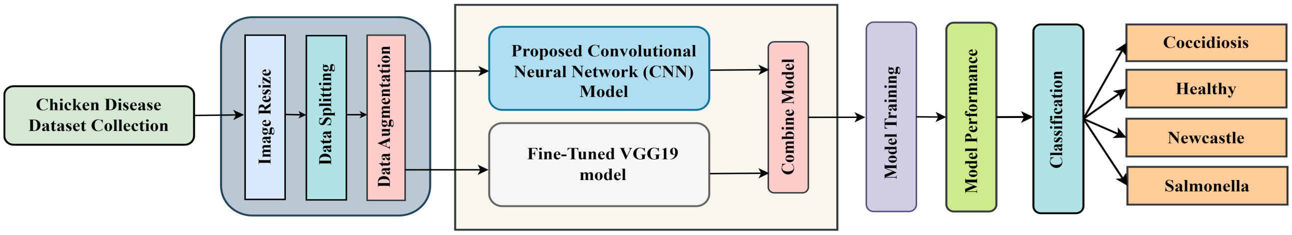

Fig. 1: System flow diagram of proposed research

R-CNN obtained an impressive recall rate of 99.1% and a mean average precision of 93.3%, while YOLO-V3 achieved a recall rate of 88.7% and a mean average precision of 84.3% on the testing dataset [10]. Okinda et al. introduced a machine vision-based monitoring system tailored for broiler chickens. The system employed 2D posture shape descriptors and mobility features to extract relevant feature variables. Subsequently, two sets of classifiers were constructed one utilizing solely the descriptors of posture shape, and the other incorporating all feature variables. Among the models tested, the Support Vector Machine (SVM) employing a kernel function based on the radial basis exhibited superior performance, achieving an accuracy of 97.5%. While the proposed system offers continuous and non-intrusive early detection and prediction of disease occurrences, it is crucial to validate its effectiveness across diverse chicken breeds and infection types [11]. In a separate study focusing on the detection of sick broilers, an early warning algorithm was proposed utilizing Support Vector Machine (SVM). The study involved extracting posture features from both healthy and sick chickens, establishing eigenvectors, and analyzing broiler postures using machine learning algorithms to predict the presence of disease. Accuracy rates of 84.2%, 60.5%, and 91.5% were achieved, with an impressive accuracy rate of 99.5% when utilizing all features [12]. Hemalatha et al. employed Support Vector Machine (SVM) for the diagnosis of avian pox in chickens. Images of chickens from the farm were collected and subsequently divided into training and test sets. By training the classifier on the available data, an impressive accuracy rate of 92.7% was achieved in accurately diagnosing avian pox [13].

Mbelwa et al. introduced a deep learning model utilizing convolutional neural networks (CNNs) and transfer learning to detect three prevalent chicken diseases. The study compared various architectures, namely VGG, Resnet, XceptionNet, and MobileNet, for transfer learning, along with a CNN architecture built from scratch. Experimental findings revealed that XceptionNet showcased better performance across all metrics evaluated. Notably, when utilizing pre-training, XceptionNet achieved a validation accuracy of 94%, outperforming the developed CNN, which attained a validation accuracy of 93.67% after undergoing full training on the same dataset [14]. Machuve Dina et al. conducted training on various deep convolutional neural network architectures, including a baseline CNN, VGG16, InceptionV3, MobileNetV2, and Xception. The training of models involved the use of labeled fecal images obtained from both farm and laboratory sources, followed by fine-tuning. Notably, freezing the batch normalization layer during fine-tuning contributed to improved model accuracy. The achieved accuracy were as follows: VGG16 - 95.01%, InceptionV3 - 95.45%, MobileNetV2 - 98.02%, and Xception - 98.24%. Furthermore, all classifiers demonstrated F1-scores above 75% across the four classes, indicating their robust performance [15].

III. Methodology

The proposed block diagram for detecting and classifying chicken diseases is visually depicted in fig. 1. In the initial step, the images are resized. To ensure unbiased evaluation, the data is split into separate training and test sets. Then followed by data augmentation techniques to enhance the dataset. Subsequently, the preprocessed datasets are inputted into the ChickenNet21 architecture, which merges a Convolutional Neural Network (CNN) with a Fine-tuned VGG19 model. Detailed explanations of each block and the design's architecture will be provided in the following sections.

A. Dataset Description

A publically accessible dataset available on Zenodo [16] acts as an important source of data for this research. The dataset was collected in Tanzania's Arusha and Kilimanjaro areas during September 2020 and February 2021 using the Open Data Kit (ODK) app on mobile devices. The dataset's sample, as shown in fig. 3. The 6,812 farm-labeled fecal images in this set are divided into 4 categories: Coccidiosis, Healthy, Newcastle, and Salmonella. The images in our dataset that have been utilized for our research are described in detail in table I.

TABLE I: Number of disease images of dataset

Diseases Class	Number of Disease Image
Coccidiosis	2,057
Healthy	2,276
Newcastle	2,103
Salmonella	376
Total	6,812

B. Data Preprocessing

Preprocessing and augmentation methods have been applied to improve the model's capability to generalize and decrease the potential risk of overfitting. The original image is resized to

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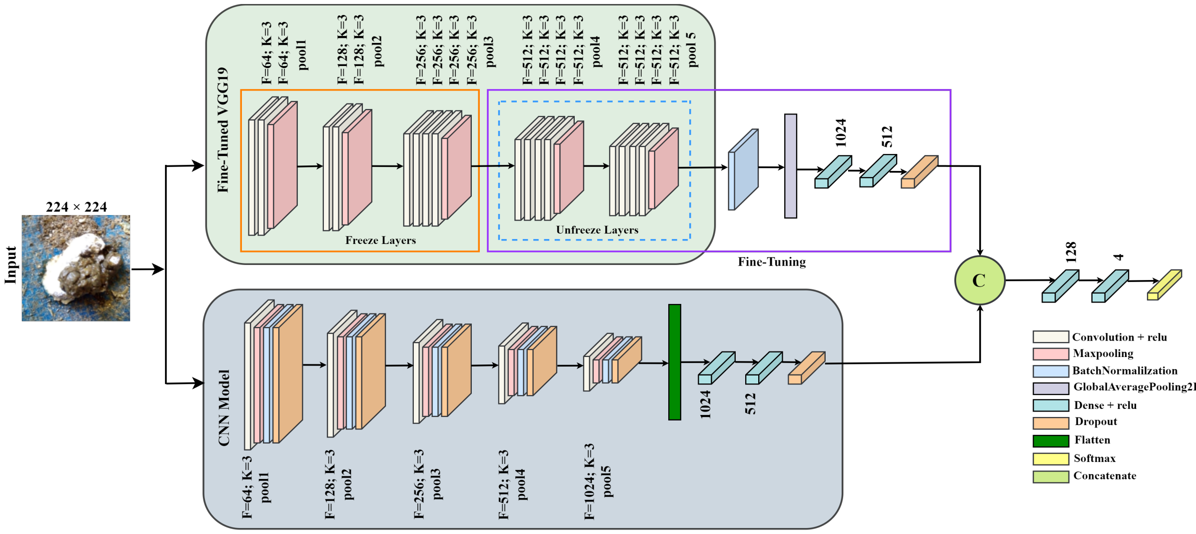

Fig. 2: Proposed architecture of ChickenNet21

dimensions of $224 \times 224 \times 3$ because VGG19, which the hybrid model is based on, requires this specific input shape for pre-trained weights. Several data augmentation techniques have been conducted to solve the overfitting issue and enhance the model's robustness. On the fly during the training process, the input images have undergone random rotation, random zoom, and random flips both horizontally and vertically. Preprocessing is done on the 4,768 Farm-Labeled fecal images to create the training set. To regulate the augmentation process, specific hyperparameters for each data augmentation technique have been defined. Table II shows the selected hyperparameters for the suggested model. A total of 4,768 images, or 70% of the dataset, were used for the training. As part of the validation procedure, the effectiveness of ChickenNet21 was tested using 2,044 images, which represent 30% of the dataset.

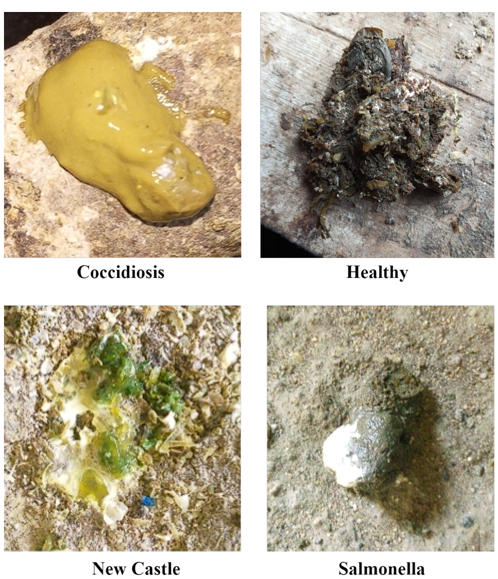

Fig. 3: Sample image of Chicken disease dataset

TABLE II: Hyper-parameter tuning for ChickenNet21

Augmentation Techniques	Hyper-Parameters
Random Zoom	0.2
Random Rotation	0.1
Random Horizontal flip	True
Random Vertical flip	True

C. *Proposed Methodology*

The proposed methodology, referred to as ChickenNet21 is shown in fig. 2, utilizes a hybrid architecture that combines the strengths of a Convolutional Neural Network (CNN) and a fine-tuned VGG19 model to extract meaningful features from input images. The overall architecture of ChickenNet21 can be described as follows:

1) Proposed CNN Architecture: The first component of ChickenNet21 is a CNN-based feature extractor. The input images undergo preprocessing and augmentation steps to enhance the training process. The preprocessed images are then passed through a series of convolutional layers. The first convolutional layer comprises 64 filters with a kernel size of 3, and it incorporates the Rectified Linear Unit (ReLU) activation function to introduce non-linearity. After that, Max Pooling is carried out using a pool size of 2 in an effort to condense the feature maps' spatial dimensions. To facilitate consistent and efficient training, Batch Normalization is utilized to normalize the activations. Additionally, Dropout Regularization with a rate of 0.3 is implemented to reduce the possibility of overfitting. Together, these methods help the model perform better and generalize more broadly during the training process.

The above procedure is repeated with increasing filter sizes of 128, 256, 512, and 1024 in the subsequent convolutional layers. Similarly, Max Pooling, Batch Normalization, and Dropout Regularization are used after each convolutional layer to improve the model's learning and generalization skills.

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Notably, L2 regularization is applied to the final two convolutional layers, namely the 512 and 1024 filter layers, with a coefficient of 0.01. Following the flattening phase in the architecture, two dense layers are included. The first dense layer comprises 1024 units, while the second dense layer consists of 512 units, with both layers utilizing the Rectified Linear Unit (ReLU) activation function to introduce nonlinearity and enhance the network's expressive power. Both dense layers are subjected to L2 regularization with a coefficient of 0.01 to avoid overfitting. Furthermore, dropout regularization with a rate of 0.2 is added following the second dense layer to improve generalization even further and reduce the chance of overfitting by randomly deactivating a subset of neurons during training.

2) Fine-tuned VGG19: In addition to the CNN features, the ChickenNet21 model incorporates a pre-trained VGG19 (considering result analysis of reference [17]) model to extract features. The same preprocessing and augmentation steps are applied to the input images to maintain consistency. The VGG19 model is initialized with pre-trained weights from the ImageNet dataset, excluding the top classification layers. By setting the majority of the VGG19 layers to be non-trainable, only the last few layers, specifically the last 10 layers, are fine-tuned. This allows the model to retain the learned representations from the pre-training while adapting to the specific classification task at hand. The feature maps obtained from the last convolutional layer of the VGG19 model are passed through batch normalization to normalize the activation. Next, a global average pooling operation is applied to obtain a fixed-length feature vector. This pooling operation aggregates the spatial information across the feature maps, resulting in a more compact representation while preserving the important features.

Following the global average pooling layer, two dense layers are added. The first dense layer consists of 1024 units with a Rectified Linear Unit (ReLU) activation function (equation 1) to introduce non-linearity. L2 regularization with a coefficient of 0.01 is applied to this dense layer to prevent overfitting. The second dense layer consists of 512 units with a ReLU activation function, and it also includes L2 regularization with a coefficient of 0.01. Dropout regularization with a rate of 0.2 is included after the second dense layer to further improve generalization by randomly dropping out a fraction of the activation.

$$\mathrm{ReLU} = \max(0, x) \tag{1}$$

3) Feature Concatenation: After extracting features from both the CNN-based model and the fine-tuned VGG19 model, the next step is to concatenate these features. The flattened feature vector from the CNN-based model and the fixed-length feature vector from the VGG19 model, both of length 512, are concatenated together. This concatenation operation combines the learned representations from both models, resulting in a unified feature representation that captures a comprehensive set of features from the input images.

4) Classification: To perform the classification task, a dense layer with 128 units is inserted after the feature concatenation phase. To provide nonlinearity to this layer, the Rectified Linear Unit (ReLU) activation function is used. To avoid overfitting and encourage improved generalization, this dense layer is also subjected to L2 regularization with a coefficient of 0.01.

The model's output layer consists of four units, representing the number of classes in the classification task. The softmax activation function (equation 2, where the function accepts a K-dimensional input vector z and returns a K-dimensional vector containing values within the range of 0 to 1 that sum up to 1) is used to calculate the class probabilities for each input image. The output is normalized using this function, which makes sure that all of the probabilities for each class add up to 1, essentially reflecting the chance that the input image belongs to each distinct class.

$$\sigma\left(\vec{z}\right)i = \frac{e^{zi}}{\sum_{j=1}^{K} e^{z_j}} \tag{2}$$

D. Hyperparameters

The hyperparameters used for the proposed hybrid combined model are summarized in table III. The model is trained using categorical cross-entropy (equation 3) as the loss function. The Adam optimizer was employed with a learning rate of 0.0001. The model was trained with a batch size of 64 and for a total of 60 epochs. These hyperparameters were determined based on experimentation and were found to yield the best performance after exploring different optimizer options for training the architecture.

$$\mathcal{L}(y, \hat{y}) = -\sum_{i} y_i \cdot \log(\hat{y}_i) \tag{3}$$

Here, the actual probability y_i of the i-th category is compared with the predicted probability $\hat{y}_i$, offering a measure of dissimilarity for each category's prediction.

TABLE III: Optimized hyper-parameters for ChickenNet21

Hyper-Parameters	Settings
Loss function	categorical-crossentropy
Optimizer function	adam
Metrics	accuracy
Epochs	60
Batch Size	64
Learning-rate	0.0001

IV. Result and Discussion

Our models were implemented in Python, harnessing the capabilities of TensorFlow and Keras to execute the proposed approach effectively. The experimentation was conducted on Google Colab, a cloud-based platform offering access to robust resources, including GPUs and TPUs, essential for building and training machine-learning models. Using a dataset with 6,812 images, we carried out our proposed ChickenNet21 model. After training for 60 epochs, a training loss value of

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approximately 0.0675 and a validation loss value of around 0.1080 were achieved, as depicted in fig. 5.The training and validation loss curve appears nearly identical due to the minimal difference between the training loss and validation loss and the lowest validation loss was attained at epoch 57.

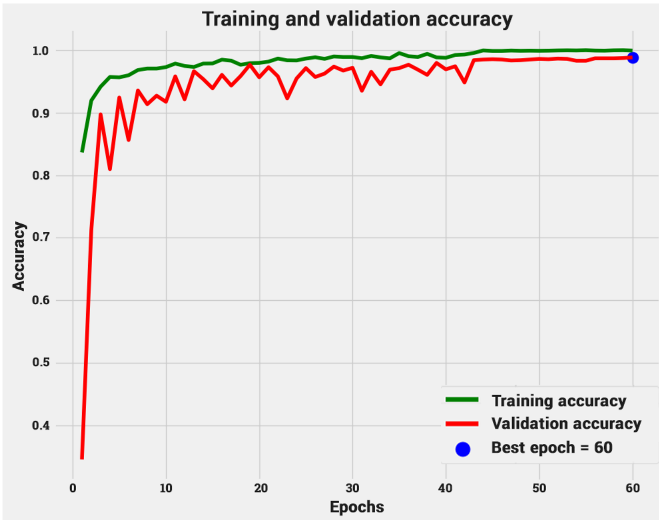

Fig. 4: Training and Validation acc. curve for ChickenNet21

TABLE IV: Classification report of ChickenNet21

Class	Precision	Recall	f1-Score
Coccidiosis	99.21%	99.84%	99.52%
Healthy	98.06%	98.54%	98.29%
Newcastle	99.04%	92.03%	95.40%
Salmonella	99.12%	99.26%	99.18%

Remarkably, our model has demonstrated an impressive validation accuracy of 98.83%, as illustrated in fig. 4. To confirm and reinforce the robustness of the proposed ChickenNet21 architecture, comparisons with the current models are made. The comparison table in table V shows how much better our proposed model performs compared to other models. The ROC Curve and confusion matrix of ChickenNet21 are presented in fig. 6 and fig. 7, respectively.

A variety of evaluation metrics, such as accuracy, precision, recall, and f1-score, are utilized to assess the effectiveness of the ChickenNet21 design and contrast our findings with those of previous studies. The calculated results are shown in table IV. Numerous performance measures, including accuracy, precision, recall, f1-score, and the confusion matrix, are used to evaluate the performance of our proposed approach. The following metrics are devised to evaluate performance:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

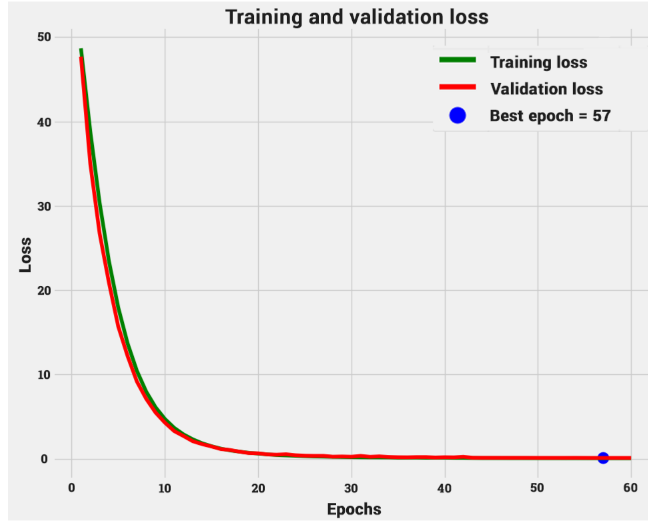

Fig. 5: Training and Validation loss curve for ChickenNet21

$$f1 - score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{7}$$

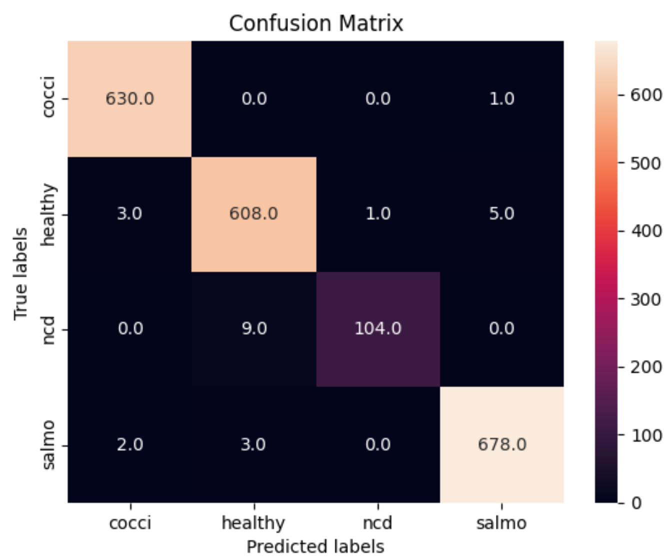

Fig. 6: Confusion Matrix for ChickenNet21

Two other research studies, [14] and [15], which also aimed at recognizing chicken disease using deep learning techniques, are compared with the results of our proposed ChickenNet21 model. Two models CNN and Xception were proposed by Mbelwa et al. [14] for the identification of chicken disease. The dataset they used for their research included 1,590 JPG images. CNN achieved 93.67% accuracy whereas Xception achieved a better result at 94% accuracy. On the other hand, Dina et al. [15] proposed four different types of Fine-tuning deep learning models and used a dataset of 6,812 farm-labeled fecal images. Their models VGG16 achieved 95.01% accuracy, Inceptionv3 95.45% accuracy, and MobileNetV2 98.02% accu-

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TABLE V: Comparison of the ChickenNet21 architecture with the other existing models

Methods	Classifier	Classification Type	Accuracy
Mbelwa et al. [14]	CNN XceptionNet	Multi class	93.67% 94%
Dina et al. [15]	CNN VGG16 InceptionV3 MobileNetV2 Xception	Multi class	83.06% 95.01% 95.45% 98.02% 98.24%
Proposed Method (ChickenNet21)	CNN+VGG19	Multi class	98.83%

racy whereas Xception obtained the better result from others at 98.24% accuracy. In this paper, ChickenNet21 was developed, a combination of CNN and Fine-Tuned VGG19 model, for the purpose of detecting and classifying chicken diseases based on farm-labeled fecal images. Through meticulous experimentation and optimization, our model achieved an impressive accuracy of 98.83%. When compared to the models presented by Mbelwa et al. [14] and Dina et al. [15], our ChickenNet21 model outperformed them in terms of accuracy, as illustrated in table V.

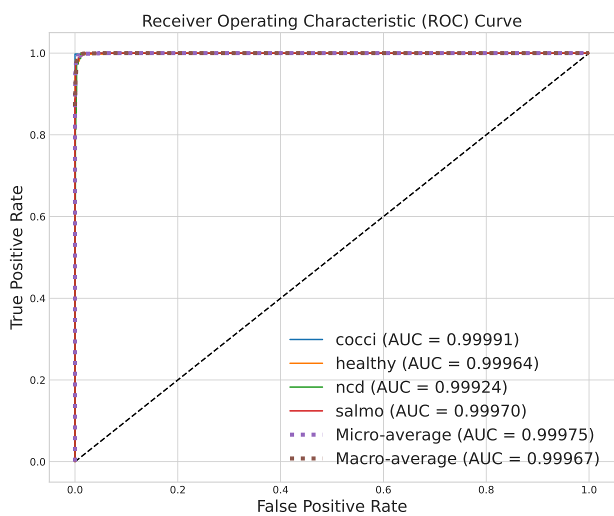

Fig. 7: ROC curve for ChickenNet21

V. Conclusion

In this paper, combining the powers of CNN and fine-tuned VGG19 model a deep hybrid neural network was designed and developed to enhance the accuracy of chicken disease identification and classification. The innovative image preprocessing and data augmentation methods enhanced the flexibility of the above model, helping to achieve a remarkable accuracy of 98.83%. The results of this study will significantly impact the automation of poultry farming, offering useful assistance in identifying healthy chickens from sick chickens and thereby, contributing to the sustainable development of poultry farms.

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