An Ensemble Deep Learning Approach to Detect Common Chicken Diseases from Fecal Matter Images

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Abstract

Disease detection from chicken fecal matter images can be a significant step towards automation in the poultry industry. Poultry diseases pose substantial threats to global food security and economic stability. Traditional diagnostic methods are often time-consuming and require specialized skills. In Bangladesh, the poultry sector plays a vital role in fulfilling protein requirements yet faces challenges due to prevalent diseases such as salmonellosis, Newcastle disease, and coccidiosis. Recent advancements in deep learning offer promising alternatives for rapid and non-invasive disease detection. This paper investigates the efficacy of various deep-learning architectures for classifying poultry health based on fecal image analysis. Five prominent models were evaluated: EfficientNetB7, VGG19, MobileNetV3, Vision Transformer, and Swin Transformer, utilizing a publicly available poultry disease dataset from Kaggle. The results demonstrate that EfficientNetB7 achieved 95%, MobileNetV3 91%, VGG19 96%, Swin Transformer 99%, and Vision Transformer 99% accuracy, respectively. The aim is to contribute to the development of a reliable and efficient deep learning-based system for early detection of poultry diseases using fecal samples. Notably, we combined all the models and performed ensemble learning majority voting, achieving a remarkable accuracy of **99.25%**. This study underscores the potential of advanced technologies in enhancing disease surveillance and control, offering promising prospects for sustainable and safe poultry farming practices.

CCS Concepts

• **Computing methodologies → Computer vision**.

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CNN, Deep Learning, EfficientNetB7, Ensemble Learning, Image Processing, MobileNetV3, Swin Transformer, VGG19, Vision Transformer.

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1 INTRODUCTION

Poultry diseases in particular are potent threats to human food security and economic welfare [1]. Thus it is very important that disease control and prevention starts at the earliest stages [2]. Conventional Poultry disease diagnostic approach presupposes identification through physical examination, laboratory examination or necropsy, which are commonly slow, costly and technical procedures.

Bangladeshi poultry sector satisfies nearly 36% of the nation's protein needs and there are about 80000 poultry farms in the country [3]. This industry has great implication on the economy and also on food availability. A new poll featured a range of ailments that are common in poultry and showed that among them salmonellosis (15.41%), NCD (13.33%), as well as coccidiosis (7.53%) [4].

New development in deep learning provide a viable solution for effective, fast, and non-invasive diagnosis of poultry diseases [5]. Studying fecal samples is useful for birds health assessment, and employing deep learning based on images of the samples can have a breakthrough potential [6], [7], [8].

The presented work has made several important research contributions to detect poultry diseases using deep learning algorithm. First of all, we introduced an ensemble deep learning model, which takes the result from five widely used models (EfficientNetB7, VGG19, MobileNetV3, Vision Transformer, Swin Transformer) and obtained the accuracy rate up to 99.25%. Secondly, the comparative analysis of these models shows how they can be applied to a dataset from Kaggle, which is public to derive certain knowledge. Third, one can observe a problem of insufficient data and an imbalanced class distribution which outlines the use of data augmentation to improve the stability of the models. Finally, disease detection has been rapid and non-invasive. Therefore it can be used to support sustainable and safe poultry farming practices.

The rest of this paper is organized in the following manner. Section 2 gives literature review on the research carried out in this area of study. Section 3 presents the methods used in this study which consist of deep learning models selected, the dataset used among others. Section 4 shows findings from the experiments that were conducted. Last, Section 5 contains the conclusion of the paper and briefly describes further possible research.

2 RELATED WORK

Disease is a threat in the field of chicken farming, it poses a threat to the stability of food security around the world as well as the source of livelihood for the farmers involved. Each break out leads to substantial losses financially, which amplifies concerns over food scarcity an issue that the COVID-19 pandemic has make even worse [15], [16]. In an attempt to come up with new strategies of diagnosing diseases at an early stage in poultry, the researchers have shifted gear to utilizing sophisticated artificial intelligence known as deep learning in light of the growing need in efficient disease control.

On the same note, Hossain et al. [2] developed a smart poultry system app that could diagnose diseases with high levels of precision using ensemble learning. Four of these pre-trained models were incorporated into their proposed system coupled with Random Forest in an ensemble learning strategy. Their level of success was an incredible 99.99%. This holds a glimmer of hope to poultry farmers who are most often confronted with diseases.

Degu et al. [9] designed a smartphone application which improved the detection and differentiation of poultry diseases from poop images proficiently. By using the YOLO-V3 for region of interest (ROI) segmentation and ResNet50 for classification, they claim that their system reveals the disease quickly and accurately and is useful for both poultry farmers and veterinarians.

Suthagar et al. [10] also contributed to the study on the early identification and differentiation in poultry diseases. He used machine learning(ML) and artificial intelligence(AI). The dataset of the work they are using for training is 6812 images of chicken disease types that include healthy chicken, Coccidiosis, Salmonella, and Newcastle classes. CNNs were used by them, they adopted DenseNet, Inception, and MobileNet as the routes of pre-trained models. Based on the results, DenseNet achieved the best result with a 97% accuracy.

In their studies, Chen et al. [11] proposed an advanced ResNeXt50 version of ResNe-Xt503A model utilizing deep learning for the identification of chicken manure disease in the broiler breeding sector. They adopted a mixed attention mechanism in order to improve perception and learning. From a Kaggle data set with four classes, including cocci, newcastle disease, salmonellosis and healthy chickens, the researchers obtained an excellent accuracy of 97.4% on the test data set. Their model has higher performance compared to classical models such as ViT, Vgg19, RegNetY 400MF and the original ResNeXt50 with better disease identification in steering meat quality and productivity.

The final innovative study proposed by Yogi et al. [12] is associated with the development of a CNN-based system to support early identification of poultry diseases using fecal images, which is rather important for maintaining the poultry production and reducing losses. Using deep learning and transfer learning with EfficientNetB7 their model has achieved an impressive accuracy of 97.07% for detecting diseases in poultry such as Salmonella, Coccidiosis, Newcastle and other healthy conditions. This approach underscores the possibility of scientific progress in improving disease detection and elimination.

In this particular research, Cinar et al.[13] recommended the use of Playces365-GoogLeNet for the identification of poultry diseases and a very high accuracy of 98.91% was attained. On the other hand, Akbudak et al.[14] used different models like Xception, VGG16, MobileNetV2 and ResNet50. Opting for MobileNetV2 due to its accuracy and suitability for mobile devices, both research teams employed their models to detect three diseases. They are coccidiosis, new castle disease (NCD), salmilonellosis and being able to differentiate the healthy chickens.

3 METHODOLOGY

The objective is to identify diseases in chickens from image analysis of their feces. The model will help to understand if the chicken is minimal if healthy and otherwise, discover the disease.

3.1 Experimental Design

The detailed stream of the experimental design, illustrated in Fig 1, starts with the appropriate preprocessing of the dataset, using state-of-art data augmentation techniques and mentation strategies that led to increased diversity representation and improved effectiveness quality. Fig 2 shows the complete data set and is followed by That is, the data is divided into separate groups by different characteristics.

The dataset used in the study is split equally into 80% data for training and the remaining for testing, to provide the basis for an effective evaluation of the obtained settings ensuring, at the same time, the sufficient comparison of model generalization. For model training, three CNN-based architectures: VGG19, ViT and Swin, efficientNet and MobileNetV3 are also employed. Transformer, two transformer-based models at the cutting edge of im- age classification research. Weights of the models are initialized without re- relaying on pretraining from other datasets to enhance time which is taken to converge and enhance performance. After the assessment of testing By evaluation, the testing is meant to involves assessment of the testing recommend and support the testing practice. set, ensemble learning strategies including the majority voting are used to refine predictions and for making the results more accurate. This leads to sound experimental measurements within a well suited experimental paradigm for treating the challenges of image classification with accuracy and efficiency.

3.2 Dataset

The study followed a selection process, and after due consideration, the following: regard, a dataset from kaggle poultry diseases detection [17] was chosen.

Table 1: Comparative summary of different approaches to poultry disease recognition across various studies

References	Contribution	Limitation	Algorithm	Accuracy
Hossain et al.[2]	Smart poultry system app with exceptional accuracy using ensemble learning	Overlooks practical implementation challenges like cost and continuous updates	Ensemble learning with Random Forest	99.99%
Degu et al.[9]	Developed a smartphone-based system for classification of poultry diseases from fecal images	Does not address real world challenges like lighting conditions	YOLO-V3 for ROI segmentation, ResNet50 for classification	87.48% and 98.7%
Suthagar et al.[10]	Early detection and classification of poultry diseases using CNNs	Small dataset size and lack of exploration of varying environmental conditions	DenseNet, Inception, MobileNet	97%, 92% and 94%
Chen et al.[11]	Improved ResNeXt50 model for disease recognition in broiler breeding	Model performance and generalizability not assessed across diverse conditions	ResNeXt50-3A with mixed attention mechanism	97.4%
Yogi et al.[12]	CNN-based system for early detection of poultry diseases using EfficientNetB7	Need for larger datasets and real time implementation challenges	EfficientNetB7	97.07%
Cinar et al.[13]	Playces365-GoogLeNet for poultry disease detection	Reliance on a specific dataset limits generalizability	GoogLeNet	98.91%
Akbudak et al.[14]	Utilized multiple models including MobileNetV2 for detecting diseases	Need for large annotated datasets and integration with real time monitoring systems	Xception, VGG16, MobileNetV2, ResNet50	88%, 72%, 83% and 66%

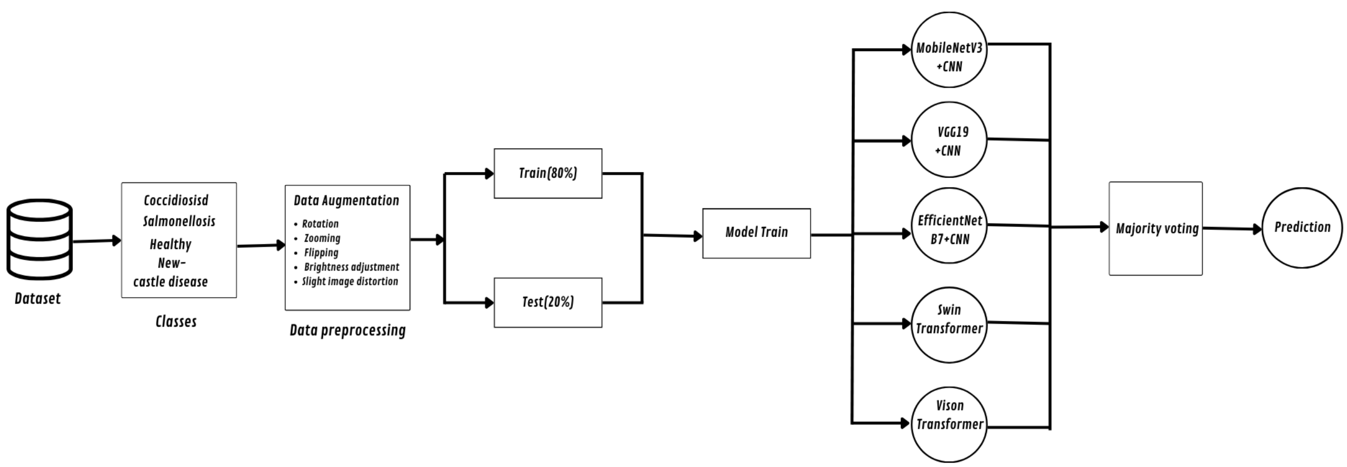

Figure 1: Experimental Design

Applying data augmentation to poultry disease detection dataset enlarged up to 7937 images, which are divided into four distinct classes: Healthy, Coccidiosis(Cocci), Salmonellosis(Salmo). and Newcastle disease (NCD), which are outlined in Fig. 2. The images are distributed across the classes as follows :

- Healthy: 2,057 images
- Cocci: 2,103 images
- Salmo: 2,276 images
- NCD: 1,501 images

The images in fig 3 serve as the basis for training and testing our models.

3.3 Dataset Preprocessing

The initial dataset obtained from Kaggle contained relatively few examples for the Non-Contagious Disease (NCD) class , which include Unfortunately, the similar classes contain only 376 images compared with the others. To rectify this a class imbalance issue and to make the model more resistant, we employed augmentation. These techniques comprised of rotation, zooming, flipping, brightness monitor, and slight displacement. distortion. To this extent, the prescriptive structure of the NCD class was expanded to incorporate 1501 images. It will put down that this augmentation process aided in resolving the issue of imbalance of classes. and strengthened the model further in order to test it under a wider variety of conditions. of images. Afterward, we divided the dataset into two parts: 80% as

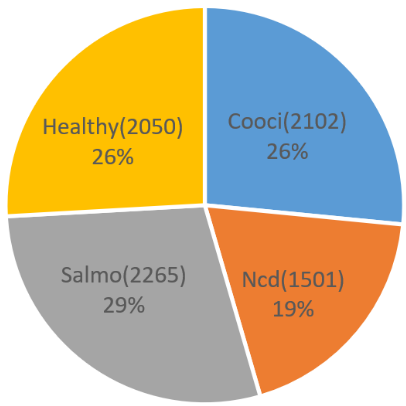

Figure 2: Chicken disease detection dataset

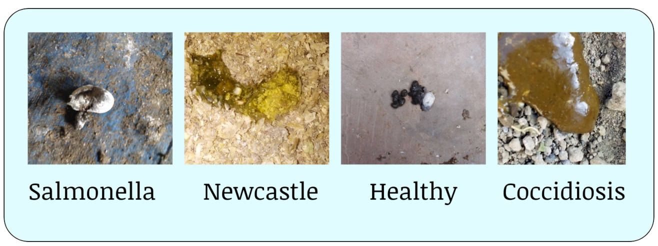

Figure 3: Four Fecal Classes of Chickens

a set apart for training the model and another 20% for as a testing set. This enabled the model to train on numerous examples at the same time but being evaluated on new ones.

3.4 Proposed Method

The proposed method entails pre-processing the data to enhance quality and choosing some of the pretrained model such as VisionTransformer, Swin-Transformer, VGG19, MobileNetV3, and EfficientNet-B7 are the selected base models used in the study. All these models are built on about 6350 images to identify the patterns and are assessed using 1,590 images. Following that, a majority voting It turns out that using ensemble approach is used, that is, all the predictions made by various models are summed up predict the class which was most frequently predicted for the given input. This The mentioned above process is illustrated in the Fig 4.

(1) **Data Preprocessing:** The dataset is preprocessed by applying several transformations, including resizing, zooming in, flipping, and other necessary steps to enhance its quality and usability.
(2) **Model Selection:** Several pre-trained models are utilized for the classification task. Including Transformer based models such as Vision Transformer (ViT) and Swin Transformer, along with Convolutional Neural Network (CNN) architectures like VGG19, MobileNetV3, and EfficientNet B7.

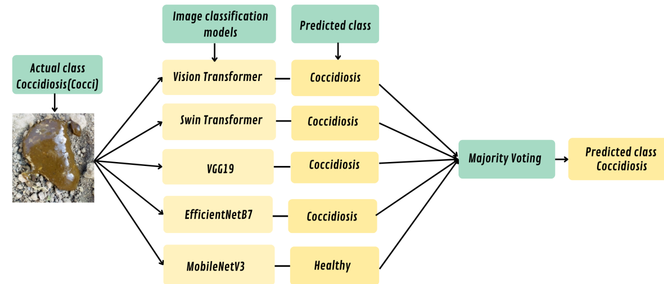

Figure 4: Structural design of the proposed chicken disease detection system

(3) **Training Process:** The selected models are trained using the training dataset to learn the underlying patterns and features within the data.
(4) **Evaluation:** The trained models are evaluated using the test dataset to assess their performance in terms of accuracy, precision, recall and F1 score. This evaluation provides insights into how well the models have learned from the training data and their ability to generalize to unseen data.
(5) **Majority Voting:** The final prediction is obtained by gathering predicted class labels from each individual model and employing a majority voting scheme. This approach selects the most frequently predicted class label as the final prediction, ensuring a robust classification outcome.

3.5 Model Architecture

Cutting-edge deep learning architectures, including Convolutional Neural Networks (CNNs) and transformer-based models, are integrated to diagnose diseases in chickens through fecal image analysis.

The Vision Transformer (ViT) for image classification includes two main parts: consisting of the ViT model and a classifier head. The patch size is 16 and used the number of iterations equal to 10 and the batch size was 128. The ViT model entails an embedding layer for transforming the input img- age patches, an encoder with self-attention [18] mechanisms and positional encoding are used. batch normalization, residual feedforward networks and layer normalization. The classifier head include linear layers, ReLU activation and dropout layers, which we produce ed as logits for classification.

Specifically, the Swin Transformer model adopted is the tiny patch version with the patch size of 4, which has been trained with 10 epochs at the batch size of 128. In the swin transformer architecture, input images are first split into patches [19], which can be followed by a convolutional embedding layer of (4, 4) kernel size and the layer normalization. At the center, the transformer layers SwinTransformerBlocks perform windowed self-attention, layer normalization, MLPs with the GELU activation function and DropPath regularizer. In patch merging, the feature map is downsampled and the channel dimension is increased with a layer normalization. A classification head, comprising linear layers ReLU activation and dropout delivers the logits for classification.

The model based on VGG19 that was pretrained from the dataset of ImageNet. Preprocessed input images are then resized to a square

Table 2: Performance Metrics of Various Models

Model	Classes	Precision	Recall	F1-score	Accuracy
VGG19	Ncd	0.98	0.93	0.95	0.96
	Salmo	0.96	0.94	0.95	0.96
	Healthy	0.92	0.98	0.95	0.96
	Cocci	0.99	0.98	0.98	0.96
MobileNetV3	Ncd	0.98	0.99	0.98	0.91
	Salmo	0.76	1.00	0.87	0.91
	Healthy	1.00	0.67	0.80	0.91
	Cocci	1.00	0.98	0.99	0.91
Swin Transformer	Ncd	1.00	1.00	1.00	0.99
	Salmo	0.97	0.99	0.98	0.99
	Healthy	0.99	0.97	0.98	0.99
	Cocci	1.00	1.00	1.00	0.99
Vision Transformer	Ncd	0.98	0.99	0.99	0.99
	Salmo	0.98	0.99	0.99	0.99
	Healthy	0.98	0.98	0.98	0.99
	Cocci	1.00	0.99	0.99	0.99
EfficientNet B7	Ncd	0.93	0.96	0.95	0.95
	Salmo	0.96	0.94	0.95	0.95
	Healthy	0.94	0.92	0.93	0.95
	Cocci	0.97	0.98	0.98	0.95

of 240240 pixels with normal 3 channel dimension. While maintaining the convolutional feature extraction function of VGG19, and the last three fully connected layer of convolutional layered pass through fine-tuning. preprocessing, which enables a certain measure of training for adaptation to the needs of the classification. To elaborate it the architecture includes a flattening layer to transform the output tensor, followed by dropout regularization (dropout rate: 0.3) to prevent overfitting. It was the densely connected layer but with ReLU activation function designed by 128 units to refine features and additional dropout regularization (dropout rate: 0.2). The last which forms the topmost layer is a compact that uses a Softmax activation function to give probability values of the different layers in the classification task.

EfficientNetB7 architecture is pre-trained on ImageNet, excluding the top classification layer. The model consists 4 different types of layer. Like firstly an additional layers including batch normalization [20], a dense layer with ReLU activation (256 units), a dropout layer (dropout rate: 0.2) and a final dense layer with softmax activation for classification. Training is facilitated using the Adamax optimizer (learning rate: 0.001) and categorical cross-entropy loss, with accuracy serving as the evaluation metric. The model parameters total 64,764,571, with 661,764 being trainable and 64,102,807 non-trainable, combining EfficientNetB7's feature extraction prowess with classification layers.

MobileNetV3 top classification layer is not included. Additional layers howard2019searching are added to the model to improve its classification. To normalize with the base model, a batch normalization layer is used. Next, a 256-unit dense layer with ReLU activation is added. The dropout regularization rate in the model was 0.45. This rate is used to mitigate overfitting. Class probabilities are then generated using a dense layer with softmax activation. The model was assembled using the Adamax optimizer where cross entropy loss was used and the learning rate was 0.001. A total of 3,247,236 parameters are displayed in the summary. 3,220,916 are trainable and 26,320 are not trainable from them.

These individual models include a range of architecture and each is learned separately. Each of them takes an input image and provides its own prediction on what class label the image belongs to. After that, majority voting strategy is imposed for compiling together these predictions, where out of all the given predictions the most common one is chosen as final result of input image. This approach takes advantage of the variety of prediction that the models in the ensemble give and incorporates the results into the construction of the ensemble model.

Table 3: Performance Metrics of Majority Voting

Classes	Precision	Recall	F1-score	Accuracy
Ncd	1.00	1.00	1.00	0.9925
Salmo	0.99	0.99	0.99	
Healthy	0.99	0.99	0.99	
Cocci	1.00	1.00	1.00	

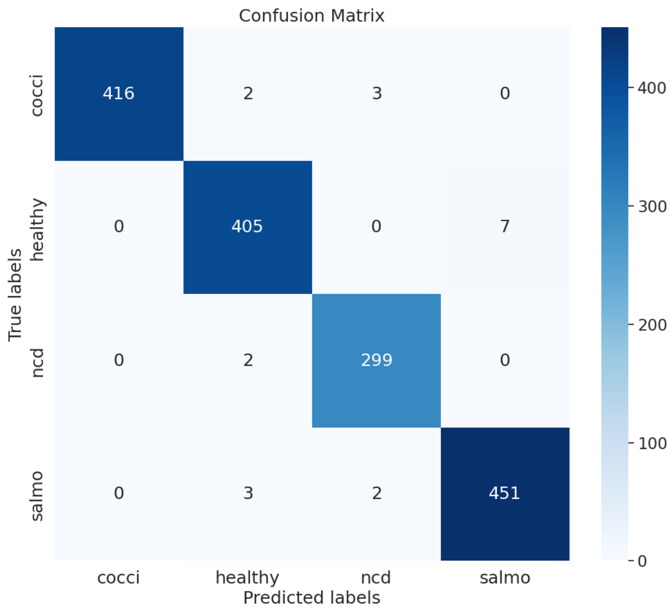

Figure 5: Confusion Matrix of Vision Transformer

The majority voting ensemble technique was chosen relative to other most used techniques concerning its simplicity, interpretability, form of robustness, and relatively low computational efficiency[21]. Majority voting can easily be implemented and explained hence easily understandable to the stakeholders in the poultry industry. It improves reliability by using the average of the multiple models which significantly reduces biases and errors from individual models. Experimental results showed that new knowledge consistently garnered better results and when all of the seven models were combined, a stunning accuracy of 99.25% was attained, higher than each of the models trained on its own. In this, it is also worth mentioning that majority voting is less complex computationally than another approach to ensemble learning, which makes it more prospective in terms of scalability.

3.6 Performance Analysis

The results based on the four chosen methods of assessment were the F1 score, the accuracy, the precision, and the recall of the models. These metrics were derived from the confusion matrix of each model in which True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) are used. From all the tested models VGG19, EfficientNet, MobileNet, Vision Transformer, Swin Transformer the latter one performed the best. In particular, the Swin Transformer produced the result 1.00 for recall, precision and F1 score for the classes NCD and cocci. For the classes salmo and healthy it achieved a recall, F1 score and precision which were between 0.97 and 0.99. Finally when using the majority vote after ensemble learning, the overall precision, recall, and F1 score for the salmo and healthy classes improved to 0.99 showing how ensemble learning improves the accuracy of the results.

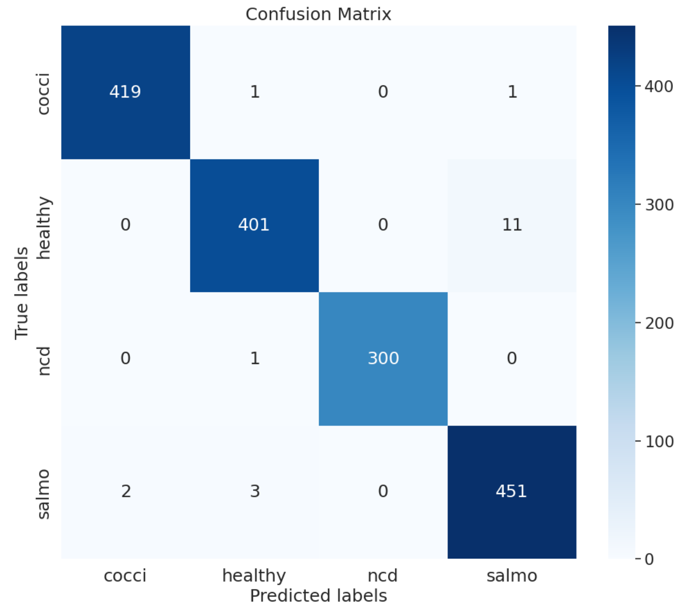

Figure 6: Confusion Matrix of Swin Transformer

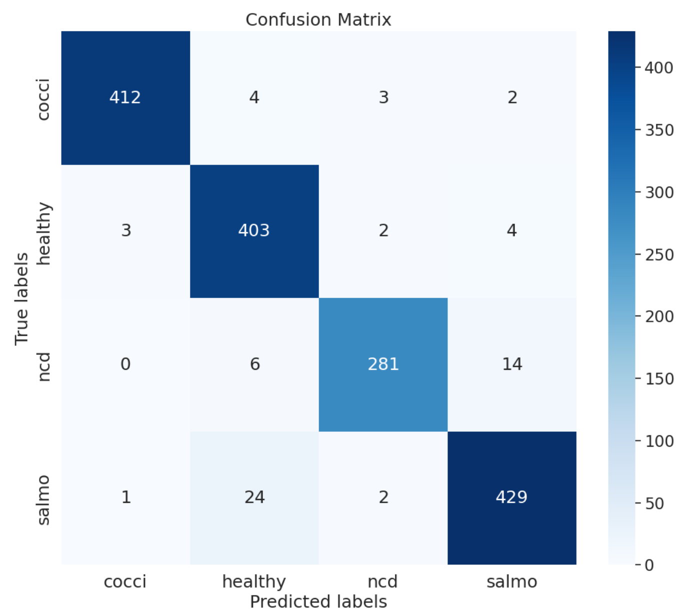

Figure 7: Confusion Matrix of VGG19

Table 2 presents the recall, accuracy, F1 score and precision of each individual model, while Table 3 showcases the corresponding metrics for the ensemble model.

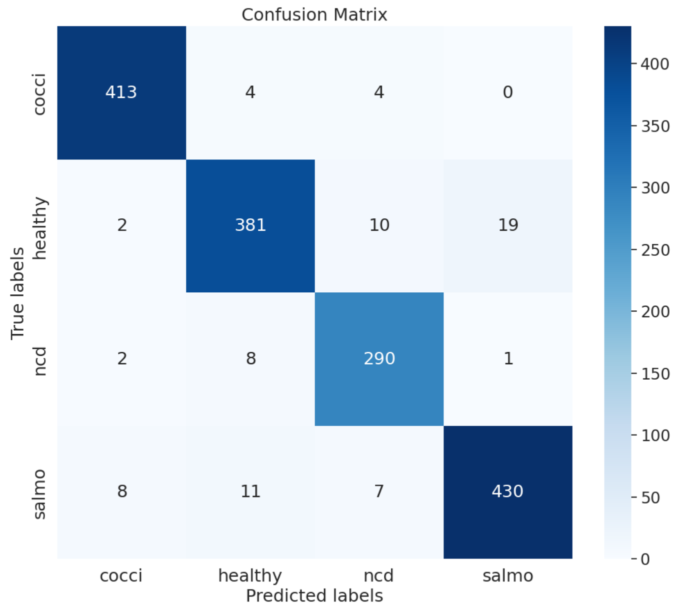

Figure 8: Confusion Matrix of EfficientNet B7

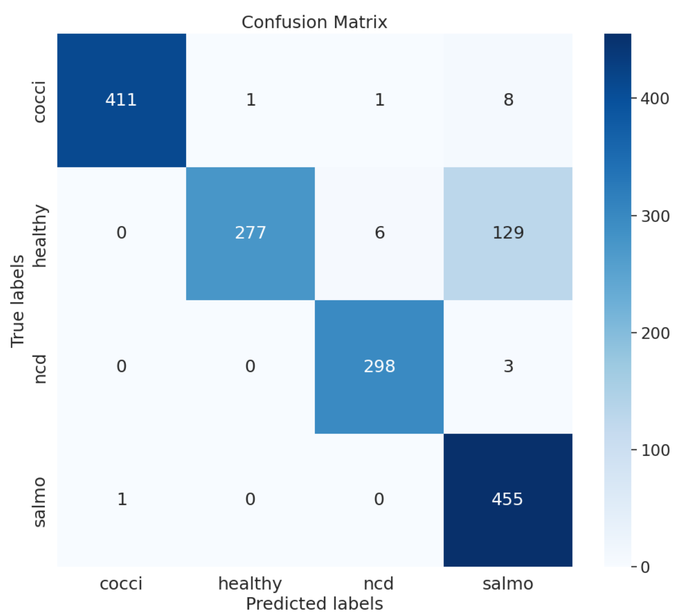

Figure 9: Confusion Matrix of MobileNetV3

4 RESULTS

In the Vision Transformer model, accuracy was boosted to 99%. Out of 1590 test images, 1571 had been correctly classified as seen in fig

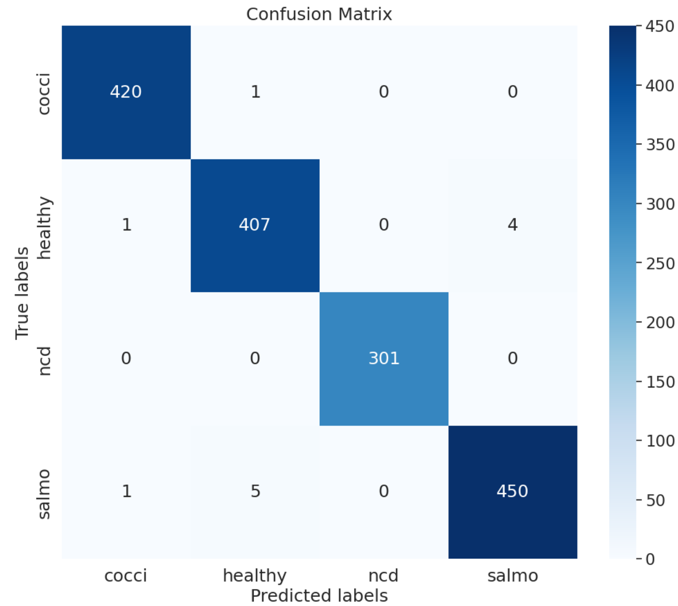

Figure 10: Confusion Matrix of Majority Voting

Figure 11: Successful Classification Results of Chicken Fecal Images.

(1). 8 healthy images were misclassified along with five cocci and samlo images.

The Swin Transformer model was also equally good, with an accuracy of 99%. However, it was slightly higher with misclassification where 11 healthy images and 5 salmo images were classified wrong according to the confusion matrix shown in fig 6.

While the transformer models outcompete, the VGG19 model is notably worse than the two architectures of transformers. It achieved 96% accuracy, the confusion matrix fig 7 indicate relatively high misclassification rate on various classes.

The efficiency obtained was low with the model yielding 95% efficiency in general but the confusion matrix indicates some errors that were committed. Confusion matrix of EfficientNet B7 is shown in the figure 8.

A marked degradation in performance is observed for the MobileNetV3 model, where the accuracy was 91%. The confusion matrix reveals some shortcomings. Particularly the misclassification of healthy class images,135 of the images can be seen in fig 9.

Table 4: Comparison of the Proposed Approach with Previous Works

References	Model	Dataset	Accuracy
[2]	Random Forest	Own dataset: 1200 images	99.99%
[9]	YOLO-V3, ResNet50	Zenodo: 8067 annotated images	87.48%, 98.7%
[10]	DenseNet, MobileNet, Inception	Tanzania (ODK): 6812 images	97%, 94%, 92%
[11]	ResNeXt50	Kaggle: 10202 images	97.4%
[12]	EfficientNetB7	Zenodo: 6812 images	97.07%
[13]	Playces365-GoogLeNet	Kaggle: 8067 images	98.91%
[14]	Xception, VGG16, MobileNetV2, ResNet50	6812 images	88%, 72%, 83%, 66%
Proposed Method	EfficientNetB7, MobileNetV3, Swin Transformer, VGG19, and ViT were utilized, with a majority voting mechanism	Kaggle: 7937 images	99.25%

Finally, to address this classification problem, majority voting by ensemble learning was used and generated excellent performance as shown in Fig 10. A total of 12 images were misclassified, the least in all the models while having an accuracy rate of 99.25%.

To assess the real life performance of the ensemble model, actual pictures of chicken fecal samples were incorporated to the experiment. The results were promising. In figure 11, a sample view of such images is provided to show how effectiveness of the classification done by our model is. This paper has demonstrated how the use of data augmentation was crucial in fixing the class imbalance to enhance model effectiveness. The findings indicate that augmentation brought not only better mitigation on all classes but also a better performance on the minor class "NCD." The following table 4 summaries the result of the proposed approach beside other works in the field of poultry disease detection.

5 CONCLUSION

In conclusion, the approaches to the ensemble learning have been used for the diseases prediction in chickens. Different CNN and Transformer models including VGG19, EfficientNetB7, MobileNetV3, Vision Transformer and Swin Transformer were used. It is a combination of multimodel experimental list. In this way, to make the decisions and predictions from these models were combined by the majority voting method. This approach shows how the use of multiple models for classification is useful for monitoring poultry health in complex classification scenarios.

Future work plans to extend dataset to other disease categories hence raising the chances of the model to detect more chicken diseases. Further, there will be development of mobile application to detect different chicken diseases.

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