Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 31 No. 2s (2024)

Mathematical Formulation of Deep Learning Model for Poultry Disease Classification using EfficientNet- B3 CNN Model

Ajay G. Barsagade [1],*, Deepika Ajalkar [2] , Aniruddha S. Rumale [3]

[1]Scholar of PHD, Computer Science & Engineering, G.H. Raisoni University, Amravati

[2]HoD, CSE (Cyber Security & Data Science Department), GHRCEM, Pune associated with Raisoni University, Amravati, India

[3]Professor, Information Technology, Sandip Foundation's, Sandip Institute of Technology and Research Centre , Nashik, India

[1] ajaybarsagade32@gmail.com , [2] deepika.ajalkar@raisoni.net, [3] arumale@gmail.com

Article History:

Received: *24-03-2024*

Revised: *09-05-2024*

Accepted: *28-05-2024*

Abstract:

The agricultural industry, and particularly the poultry farming industry, is under pressure to increase output levels due to the growing human demand for animal products. There can be substantial economic losses and widespread chicken mortality as a consequence of an increase in infectious disease transmission caused by expanded poultry production. When compared to conventional ways for poultry disease identification, manual methods are time-consuming, labour-intensive, and error-prone. Also, experts' knowledge is usually necessary for making sense of the results. These restrictions raise the danger of the disease spreading across the flock and make it more difficult to diagnose diseases in a timely manner, both of which can have devastating effects. For a long time now, farmers have relied on specialists to identify and diagnose chicken illnesses. Consequently, many domesticated birds end up in the hands of farmers who suffer from either unreliable specialists or delayed diagnosis. The most prevalent chicken illnesses may be quickly recognised from pictures of chicken droppings using the techniques that are already accessible from artificial intelligence (AI) based on computer vision.

In this paper, a deep learning approach offered that uses a pre-trained Convolution Neural Networks (CNN) model to determine which of the three categories best describes chicken excrement and offer a method for identifying and categorising poultry illnesses. The EfficientNet-B3 model was utilised in the development of the system. Coccidiosis, Salmonella, New Castle Disease and Healthy were the four health problems that were classified using the segmented picture by the deep learning model. The models were trained using standard benchmark database images of excrement from chickens. The outcomes of experiment demonstrate that the proposed method for identifying and categorizing chicken illnesses may accurately identify three prevalent poultry diseases. Consequently, this approach has the potential to be an invaluable resource for farm veterinarians and poultry producers.

Keywords: Artificial Intelligence, Chicken Disease, Convolutional neural network, Deep learning, Fecal images, Image classification, Machine learning.

1. INTRODUCTION

India's agriculture sector includes a sizable portion of the poultry business. Chickens are not only one of the most popular animals kept by the general people, but they also provide an easily accessible supply of animal protein. Growing chickens is a simple business that can accommodate both small and big flocks, and it has huge potential for growth in Indonesia's poultry industry. In addition, developing nations' socioeconomic progress is greatly aided by poultry farming, since it supplies meat and eggs, which in turn guarantee nutrition and food security on a national, regional, and even home level. Beyond that, it boosts a country's GDP by over $100 million and gives people a steady stream of income [2, 3]. Due to the proliferation of infectious illnesses brought on by the rise of poultry farming, there may be significant financial losses and a high rate of mortality in the chicken sector [4]. But there are moments when everything goes swimmingly when you're raising hens. A sickness is one of several problems that poultry growers encounter. Many hens do not thrive, there is a lack of veterinary assistance on the farm, insufficient vaccine coverage, and inadequate poultry management can all contribute to the growth of chicken illnesses. On farms, chickens are most commonly infected with cholera, coccidiosis, new-castle, salmonella, and worm infestation disease.

It appears that many individuals are still involved in the process of keeping conventional poultry farms clean and well-kept. This issue prevents farmers from identifying the exact cause of chicken illnesses; they can only identify the first signs of illness. Diseases in chickens can spread rapidly due to a lack of understanding of their symptoms; this result in economic losses for farmers and the loss of chicken lives. Consequently, producers want a method of illness identification in hens that is more accurate and dependable.

Over the past few decades, there has been a significant advancement in the fields of computer vision (CV), image processing and pattern recognition. Researchers and enterprises are utilising deep learning (DL) to handle a variety of challenges, from simple item detection to complicated scene analysis, thanks to the availability of enormous amounts of data and sophisticated algorithms [16]. CV and DL have shown to be highly effective in the identification, classification, and location of diseases, particularly in healthcare applications. Computer vision technology has attracted interest from a variety of industries, particularly the medical sector, due to its potential to aid in illness diagnosis and the rapid advancements in AI for object detection. Among these technologies is the widely utilised Convolutional Neural Network (CNN), a technique in computer vision. To identify an item or picture in two dimensions, a multi-layer perceptron technique called a CNN was developed. CNN is able to detect patterns in vast volumes of data that are difficult for humans to notice. Additionally, by doing away with image feature extraction and manual segmentation, two of the numerous shortcomings of traditional methods, they are able to achieve these capabilities. Using CNN in this manner allows for the categorization of chicken illnesses. The suggested structure primarily offers the following benefits:

- Design an automated computer vision system that can analyse photos of chicken faces to identify and categorize illnesses in the poultry population.
- Employed pertained image classification algorithms using EfficientNet-B3 to classify prevalent poultry diseases.
- Used deep learning methodology to predict the four classes of chicken diseases, New Castle disease, salmonella, coccidiosis, and healthy.

- Created a model utilizing developed dataset of faecal pictures gathered from various poultry farms and inoculation locations for the early identification and categorization of illnesses in chickens.

Here is the outline of the paper. Section 2 delves into the relevant literature, data gathering, and neural network architecture, while Section 3 delves into the outcomes and findings of the experiments. Included in Section 4, after a conclusion and an appreciation, is the planned task. Section 5 includes a list of sources.

Here is the outline of the paper. Section 2 discusses the pertinent literature related to disease classification. In section 3, data collection, and neural network construction discussed. While Section 4 explores the experimental results and finally conclusions of the paper is presented at the end.

2. LITERATURE REVIEW

The computer vision technology overviews for poultry sector research summarizes the most recent developments in computer vision-based methods for monitoring the health of chickens, namely those based on deep learning (DL) and machine learning (ML) based systems [1]. This dataset, which comprises images of both healthy and unhealthy chicken feces captured by mobile cameras at certain farms in southwest Nigeria, may be used to train machine learning models to detect anomalies in poultry farms. [2]. Using the ResNet50 image classification model and the YOLO-V3 object detection method, a system for detecting and classifying poultry illnesses was reported [3]. A custom model developed using the YOLO v3 algorithm for the purpose of detecting poultry diseases in broilers [4]. An AI-based sensor detection approach is suggested in [5]. To aid in the early diagnosis of poultry illnesses, neural network (NN) models have been suggested for the purpose of classifying grill chickens as healthy or sick [6]. The four narrow-band filters used by the multi-spectral imaging system produce four spectrally separate pictures that are all shown on a single CCD focal-plane [7]. The chicken's demeanour and actions served as a gauge for its health [8]. A strategy of oversampling is used to make the sample data of the minority class as useful as that of the other majority classes. The fecal photos utilized to identify diseases in chickens using the Inception-V3 algorithm [9]. The use of a deep CNN model to automatically identify abnormalities in grill droppings and label them as normal or abnormal is suggested for use in an automated digestive illness detector [10]. A structure known as an attention encoder was proposed to improve the detection accuracy when characteristics were extracted from photos of chickens [11].

To identify hens of varying ages, one may use an object identification network that incorporates data from GAN-MAE (generative adversarial network-masked autoencoders) [12]. Diseases in birds detected using thermal-image processing and AI [13]. An all-inclusive approach that combines many models for classification and segmentation [14]. Although existing technologies are proving to be more effective than human inspection, early detection on farms has not made full use of clinical symptom-based monitoring systems [15]. A CNN-based framework has been proposed to classify chicken diseases by distinguishing between images of sick and healthy faces [16]. Using the chicken manure data set and the ResNeXt50 network model after implementing a mixed attention strategy [17]. The proportion of pictures correctly predicted based on the categorization of viral disorders experienced by hens using DL predicated on CNN [18]. Using a wildlife database, researchers have developed a programme that can accurately identify and categorise poultry illnesses in their early stages [19]. A deep CNN model was trained to identify diseases in chicken by differentiating between images of healthy and unhealthy feces [20]. CV model was created using the DL algorithm to monitor and manage bird diseases in order to increase the productivity and safety of the poultry business. [21]. Using a collection of pictures of chicken dung, researchers have developed an improved ResNet18-based model for illness image detection in chickens [22].

In order to segment the blood arteries in images of chicken embryos, a new approach was suggested that uses a matching filter in conjunction with the skeleton's curvature characteristic [23]. A novel CNN model named light-VGG11 was developed to automatically identify distress calls made by chickens from recordings made on a high-yield farm [24]. It was recommended to use a CNN-based deep learning method to categorize chicken feces into three groups [25]. Using a Kinect sensor, an automated CNN-based approach was demonstrated to identify chicken activity in a poultry farm [26]. For Taiwanese poultry farms, we developed and built a unique tiny removal method using a DL algorithm [27]. Using Generative Adversarial Networks (GAN) for the early identification of diseases in hens reared for poultry, a framework for predictive services that utilize the Internet of Things (IoT) is proposed [28]. The impact of new smart sensor technologies on chicken operations, the connection between big data analytics, sensors, and IoT, and how these advancements might increase chicken output are all explained. [29]. With the Faster R-CNN network as its foundation, we built a feeding behaviour detection network. This network is defined by the following: feature extraction through the Fusion of ResNet101 and Path Aggregation Network (PAN), and bounding box regression using the Intersection over Union (IoU) loss function [30]. Using EfficientNet with the convolutional block attention module (CBAM) [31] was the basis of a research. In order to localise the essential portions of insect pictures using Grad-CAM, a feature fusion network was suggested that would synthesise feature presentations in multiple backbone models utilising ResNet, Vision Transformer, and Swin Transformer [32]. A low-cost Internet of Things (IoT)-based system developed for monitoring environmental factors in a chicken farm in real time [36].

3. MATERIALS AND METHODS

An automated approach for detecting and classifying chicken diseases using deep learning approach is introduced. The proposed system uses images of the chicken droppings to detect the three most common infections in poultry: coccidiosis, salmonella, and new castle disease. The system development method includes the following steps: gathering and analysing image datasets; creating augmented photos; segmenting regions of interest; and train and test using a deep learning model for image classification. Figure 1 summarizes the methods used in the proposed model.

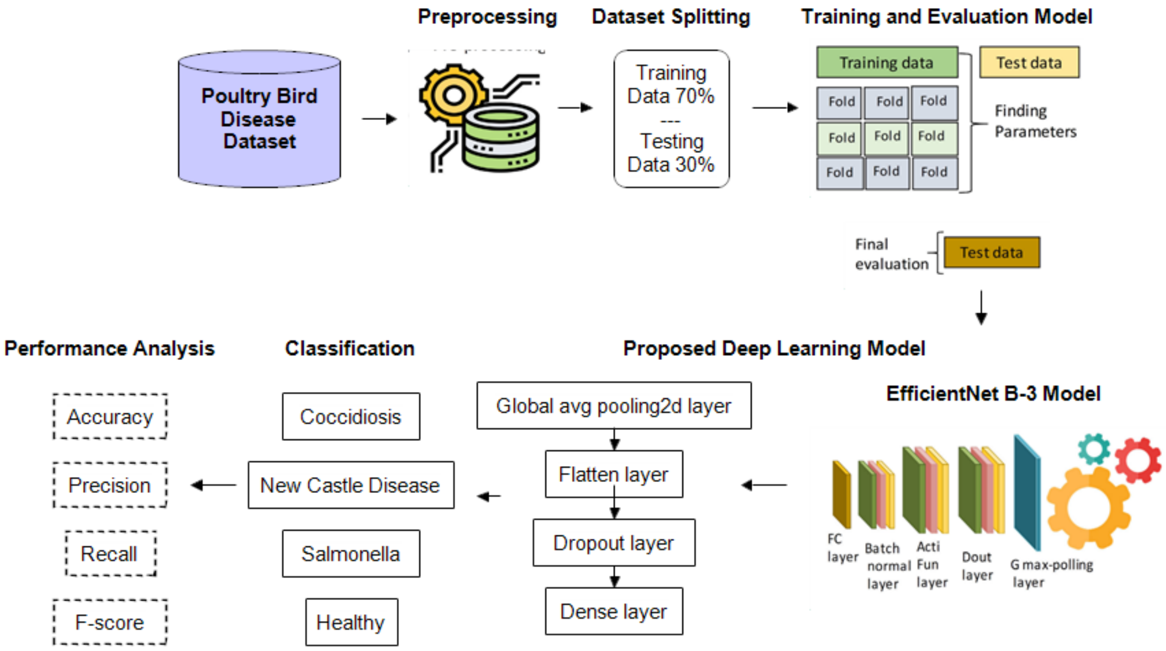

Figure 1: Proposed Framework for Classification of Chicken Fecal Images

Poultry Bird Disease Dataset

The poultry bird disease dataset [35] consists of poultry fecal images. Images of faeces taken by mobile devices running the Open Data Kit software were gathered from inoculation sites and small-scale farmers in the Kilimanjaro and Arusha areas between 2020 and 2021. The "Healthy" and "Coccidiosis" classes of faeces were collected from chicken farms, respectively, because of the prevalence of coccidiosis illness. After a week, the hens were inoculated with Salmonella, and pictures of their excrement were collected for the "Salmonella" class. Additionally, the hens were given a vaccine to protect them from Newcastle disease. For the "New Castle Disease" class, pictures are taken of their feces three days after the immunization. A total of 6812 photographs were gathered, of which 2103 were linked to the term "Coccidiosis," 2057 to the term "Healthy," 2276 to the term "Salmonella," and 376 to the term "New Castle Disease". Figure 2 displays a selection of photos from the dataset.

Figure 2: Sample photos from the dataset

Preprocessing

The collection includes four picture categories labelled "Coccidiosis", "Salmonella", "New Castle Disease" and "Healthy" each with a different size. In order to get the most out of the data used for classification, data preparation is performed to make it more accurate. In the case of data with an uneven class distribution, the effectiveness of conventional classifier learning methods might be drastically diminished, because they are predicated on the notions of a roughly equal distribution of classes and misclassification expenses. The architecture of the human brain served as inspiration for a class of ML algorithms. In order to learn from data, methods for deep learning employ multi-layered neural networks with progressively higher levels of abstraction achieved by non-linear data transformations. Because it learns from the picture attributes, DL shows great proficiency in solving picture categorization tasks. Feature mining and the classification component are the two mainstays of image classification algorithms. In order to reduce training time, the images in the dataset are tagged according to their respective classes, transformed to tensor records at two different sizes (512*512 and 224*224 pixels), and compressed. Scaling the images to a reasonable quality can help ensure that the data has a consistent input dimensionality, which CNN needs in order to train the best possible model.

Dataset Splitting

The number of tagged picture files is 9,600. The variety of images needed for disease categorization perfectly complements equal and annotated library. The dataset is divided into three parts in order to construct the CNN model. Of the total number of photographs, 80% are part of the train set, 10% are part of the validation set, and 10% are part of the test set.

Training and Evaluation Model

In order to train a deep learning model from scratch, you'll need a lot of photos and a powerful computer. To get over this problem, transfer learning methods enable you to retrain and change an existing model to fit a new use case. The feature extraction in this investigation was done using a pre-trained deep learning model. The central idea of the Deep CNN model EfficientNet-B3 is to skip layers via shortcut connections [15]. These components, referred to as "bottlenecks," are what make up this network: a layer with an identical number of filters will produce an equal number of feature maps, and a feature map that is smaller in size will produce twice as many filters. A two-stride convolutional layer is used to achieve down-sampling, which is subsequently followed by batch normalisation and finally the ReLU activation function [28].

Proposed Deep Learning Model

Using a compound coefficient, EfficientNet consistently scales all dimensions of breadth, depth, and resolution. It is a CNN design and scaling approach. Instead of arbitrarily scaling these elements, as is done in typical practice, the EfficientNet scaling approach uses a predetermined set of scaling coefficients to evenly scale the breadth, depth, and resolution of the network. For principled, consistent scaling of network breadth, depth, and resolution, EfficientNet employs a compound coefficient. The idea behind compound scaling is that a larger input picture necessitates more layers in the network to enhance the receptive field and more channels to pick up finer-grained patterns. Starting with MobileNetV2's inverted bottleneck residual blocks and adding squeeze-and-excitation blocks, the EfficientNet-B0 network builds upon itself. Four residual blocks, each with its own set of convolutional layers and residual connections, are subsequently applied to the combined feature maps. To prevent deep neural networks from experiencing the vanishing gradient issue, the model can use residual connections to bypass some layers while keeping the gradient flow intact. To get more nuanced and abstract features, each residual block processes the input feature maps through a succession of filters. The feature maps are averaged across the spatial dimensions by a global average pooling layer, and they are subsequently down sampled by a second max pooling layer. The outputs of these blocks are then transmitted through these layers. By maintaining a consistent ratio when scaling, the compound scaling approach achieves a balance between the width, depth, and resolution dimensions. The mathematical steps to do this are shown in the equations below:

$$f(T_{out}) = \sigma(W * T_{out} + b) \ldots (1)$$

Where, W is the weight matrix, b is the bias vector, and σ is the activation function, which is represented via equation 2,

$$\sigma(z) = \frac{1}{(1 + e^{-z})} \ldots (2)$$

The last step is to run the features through a series of fully linked layers. These layers will then utilise the features to guess the input image's class. Each convolutional layer employs the ReLU activation function to eradicate negative bias. When passed a negative value, the function returns zero; when passed a positive value, it returns the same value. Consequently, there is an abundance of production. The ReLU function is illustrated by the equation below. The suggested model's last layer employs a fully connected network to provide an output using the softmax function presented in equation 3.

$$c_{out} = SoftMax\left(\sum_{i=1}^{N_f} f_i * w_i + b_i\right) \ldots (3)$$

A neuron's output in a fully linked network is shown in the equation below.

$$onv_{out_{i,j}} = \sum_{a=-\frac{m}{2}}^{\frac{m}{2}} \sum_{b=-\frac{n}{2}}^{\frac{n}{2}} I(i-a, j-b) * LReLU\left(\frac{m}{2} + a, \frac{n}{2} + b\right) \ldots (4)$$

Where, m, n are the rows & columns of windows, a, b are rows & columns for strides. The Max Pooling layers evaluate a feature threshold via equation 5,

$$f_{th} = \frac{\left|\sum_{i=1}^{N_f} x_i - \sum_{j=1}^{N_f} \frac{x_j}{N_f}\right|}{N_f} \ldots (5)$$

Features with $f > f_{th}$ are passed for Depth Wise Convolutions (DWC), which are extracted via equation 6,

$$DWC(q, p) = \sum \log\big(F(p, q) * I(q, p)\big) \ldots (6)$$

The final classification was achieved by using a succession of Dropout and Dense layers following feature extraction. The classifier model used in this investigation is shown in its entire form in figure 3. Flatten lowers the feature extraction block's output to a one-dimensional array so that the fully connected layer may use it. To prevent overfitting, a dropout layer is used before the final classification layer. As a representation of the projected output, the last layer has four output units.

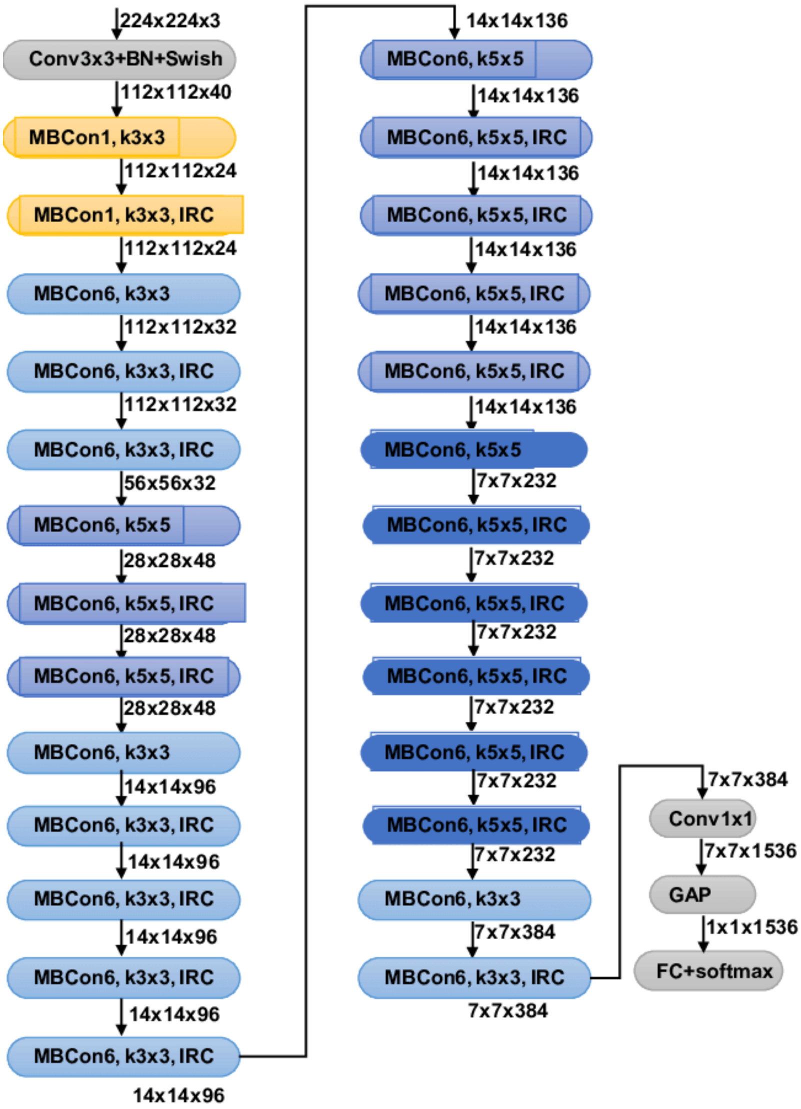

Figure 3: Model architecture of EfficientNet-B3

Training involves adjusting various hyperparameter values for the proposed CNN architecture and other state-of-the-art designs. The details of the employed hyper parameters are given in Table 1. The method is based on how the CNN model performs during training using a number of hyperparameter adjustments.

Table 1: Hyperparameters values set to train the model

Hyperparameters	**Values**
Loss Function	MSE
Optimizer	Adam
Batch Size	40
Epoch	40

Classification

The last layer consists of four output units that correspond to the following four chicken health conditions: Coccidiosis, Salmonella, New Castle Disease, and Healthy.

Performance Analysis

In the assessment phase, we check to see if the model is performing as expected and if the results of the calculations corroborate or contradict the experiment. Accuracy, Recall, Precision, and F1-Score will be obtained by calculating the algorithm model's performance level using a confusion matrix that is based on TP (True Positive) presented by t_p , FP (False Positive) presented by f_p , TN (True Negative) presented by t_n, and FN (False Negative) presented by f_n, used to derive the metrics from the model's confusion matrix by following equations. To see how effectively the model can differentiate across classes, an AUC-ROC plot was created.

$$Accuracy = \frac{1}{Ns}\sum_{i=1}^{Ns}\frac{t_{p_i}+t_{n_i}}{t_{p_i}+t_{n_i}+f_{p_i}+f_{n_i}} \dots (7)$$

$$Precision = \frac{1}{Ns}\sum_{i=1}^{Ns}\frac{t_{p_i}}{t_{p_i}+f_{p_i}} \dots (8)$$

$$Recall = \frac{1}{Ns}\sum_{i=1}^{Ns}\frac{t_{p_i}}{t_{p_i}+t_{n_i}+f_{p_i}+f_{n_i}} \dots (9)$$

$$F1\ Score = 2 \cdot \frac{Precision\ \cdot Recall}{Precision + Recall} \dots (10)$$

4. EXPERIMENTAL RESULTS AND DISCUSSION

Experimental Setup

The machine required for the development of the proposed framework contained 16 GB of RAM, an Intel Core i7 CPU Core from the 12th generation, and Windows 11 as the operating system for both design and training. A Python interface called PycharmIDE is used to set up all programmes on the training model. Libraries like as Tensorflow, Keras, and others are included into the setup. Yet, as said before, the photos need to be resized to 224 × 224 pixels.

Result Analysis

An image dataset consisting of 8067 chicken poop photos was used for the research. The dataset was organised into four classes: Coccidiosis 2476, Salmonella 2625, Newcastle disease 562 and Healthy 2404. Since the four classes make it evident that the data is unbalanced, the minority class oversample in order to bring it into line with the majority class. 10,500 data points total, 2,625 in each class are obtained via the data balancing process. The research approach divides the managed data into segments using the EfficientNet-B3 algorithm architecture. About 80% of the data is used for training, 10% is set aside for testing, and the remaining 10% is used for validation. The dataset was subjected to a classification test without prior balance in the first trial.

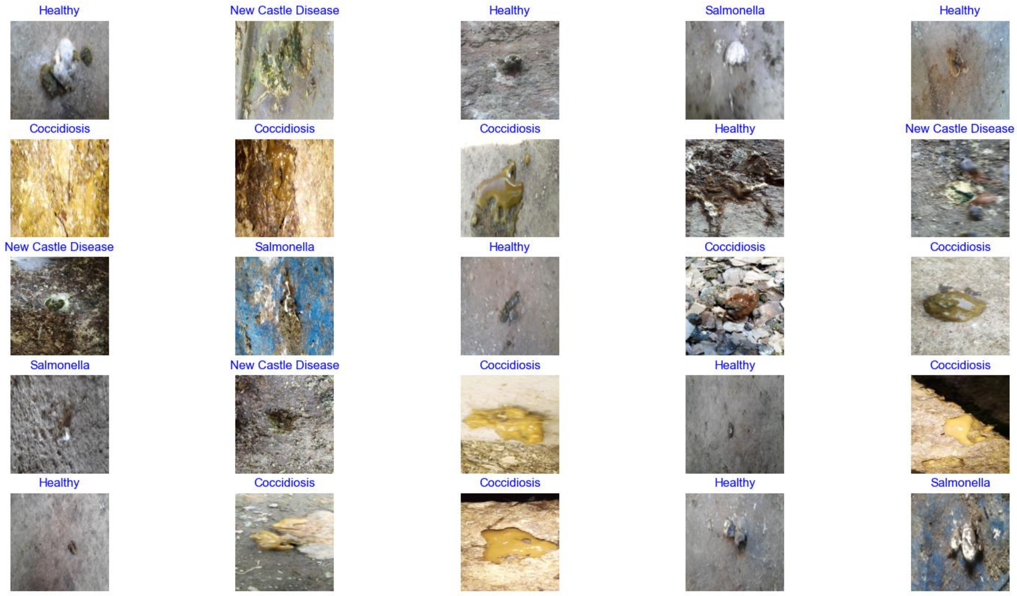

Figure 4: Sample test images

The random sample test images from standard benchmark dataset from four different classes [35] of is shown in figure 4. As per defined set of train, test and validate, model is trained and validated based on EfficientNet-B3 model. Figure 5 represents the model architecture used to build the model. Initially it consists of the layer of EfficientNet-B3, followed by dense and dropout layer with final output layer having four classes.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 efficientnetb3 (Functional)  (None, 1536)             10783535

 batch_normalization (BatchN  (None, 1536)             6144
 ormalization)

 dense (Dense)               (None, 256)               393472

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 4)                 1028

=================================================================
Total params: 11,184,179
Trainable params: 11,093,804
Non-trainable params: 90,375
_________________________________________________________________
```

Figure 5: Model architecture of EfficientNet-B3

The model is trained and validated over number of epochs. Figure 6 shows plot of the accuracy vs loss curve of training and validation. The training and validation loss achieved at best epoch of 10 and best values achieved for training and validation accuracy at best epoch value of 7. Finally, over several iteration, model trained accuracy achieved of 99.79% and validation accuracy of 96.65% with best test accuracy of 98.26%.

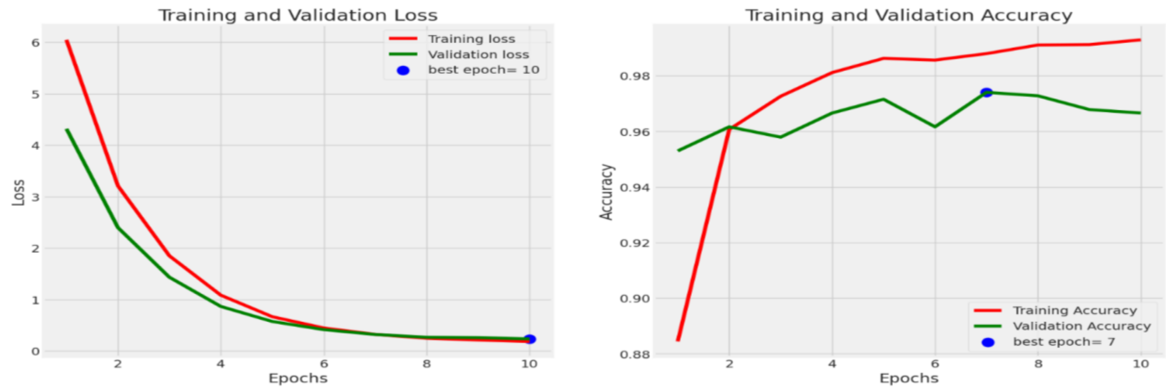

Figure 6: Accuracy vs Loss Curve of Training and Testing

Figure 7 depicts the test confusion matrix which represented the relationship between actual data verses for four predicted output data, Coccidiosis, Healthy, New Castle Disease, and Salmonella. It shows that Coccidiosis and Salmonella are the classes predict more correctly as compared to other classes.

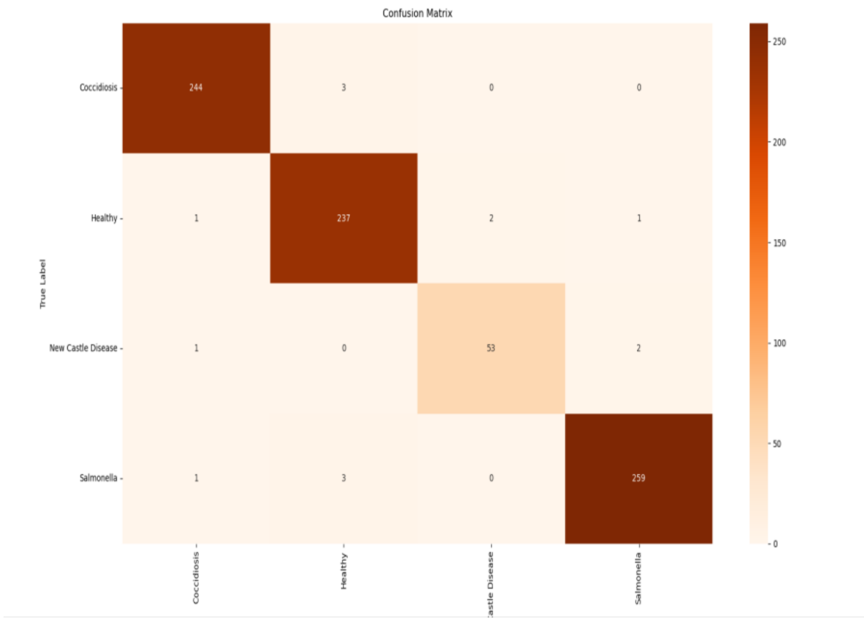

Figure 7: Predicted Confusion matrix

Table 2 shows the test classification performance in terms of precision, recall and f-score in four output classes, Coccidiosis, Healthy, New Castle Disease, and Salmonella. Coccidiosis and Salmonella output class achieved higher precision rate and f-score rate of 0.99, whereas Coccidiosis has higher recall rate of 0.99. In terms of overall performance, Coccidiosis output class perform much better among all classes as shown in figure 8.

Table 2: Classification Performance

Output Class	Precision	Recall	F-score
Coccidiosis	0.99	0.99	0.99
Healthy	0.98	0.98	0.98
New Castle Disease	0.96	0.95	0.95
Salmonella	0.99	0.98	0.99

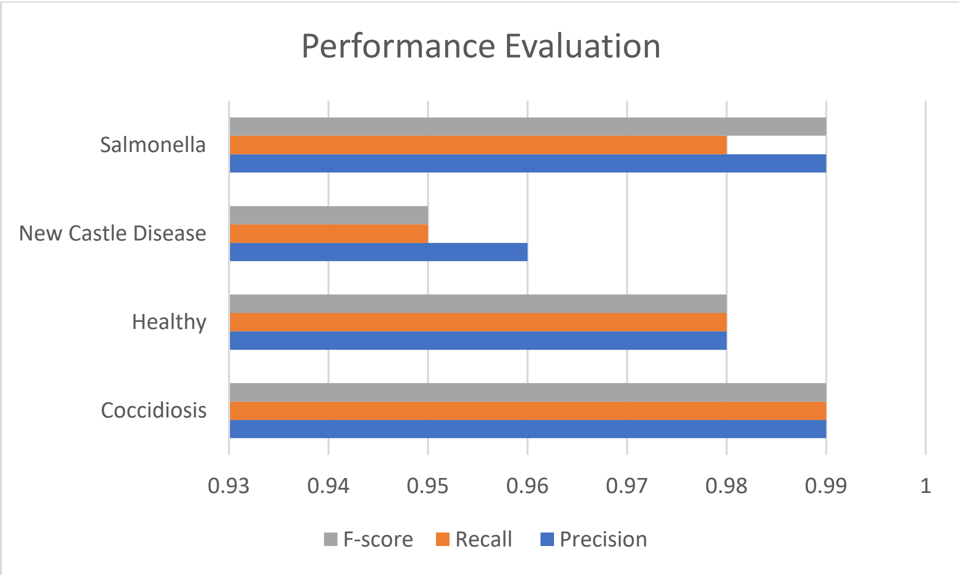

Figure 8: Performance Evaluation

Table 3 shows the comparative analysis performance for overall accuracy parameters. It depicts that the proposed deep learning model achieved 98.2% best accuracy rate as compared to other state of art models.

Table 3: Comparative Analysis

Ref Model	Accuracy (%)
[9]	94.05
[14]	94.52
[16]	93.23
[18]	95.28
Proposed Model	98.2

5. CONCLUSION

This paper presented a method for classifying and diagnosing illnesses in poultry using images of chicken faeces using deep learning approach. The system detects and classifies poultry illnesses using the EfficientNet-B3 pre-trained model, a deep learning model. The proposed deep learning model is implemented using several hyperparameter optimisation strategies; the top performing models were chosen and put into action. The best accuracy rate of 98.2% achieved while classification. The use of computer-aided tools and reliable data are two essential components to enhance the efficacy of field workers and poultry farmers in the early detection of illnesses in chickens. Enhancing image processing technologies to help farmers is urgently needed. It's evident that diseases may be detected before they kill hens, and these techniques have the ability to lower losses and boost productivity. In order to successfully treat poultry diseases, a lot of time, energy, and sophisticated computer resources are required. The proposed method for detecting and classifying chicken diseases can accurately identify three prevalent poultry diseases, according to our trial results. This means it may be utilised on farms to help veterinarians and poultry farmers.

Additional research may be conducted by experimenting with other structures, adding parameters, or employing different balancing approaches to improve accuracy. In the future, more faeces photographs can add to the collection so researchers may use the information to study other chicken diseases. Users will be able to easily engage with the designed model once it is delivered on mobile devices.

REFERENCES

[1] Supriyanto, Eko & Isnanto, R. & Purnomo, Sutrisno Hadi. (2023). Computer Vision in Chicken Monitoring System Using Machine Learning: A General Review. E3S Web of Conferences. 448. 10.1051/e3sconf/202344802014.

[2] Aworinde HO, Adebayo S, Akinwunmi AO, Alabi OM, Ayandiji A, Sakpere AB, Oyebamiji AK, Olaide O, Kizito E, Olawuyi AJ. Poultry fecal imagery dataset for health status prediction: A case of South-West Nigeria. Data Brief. 2023 Aug 23;50:109517. doi: 10.1016/j.dib.2023.109517. PMID: 37674505; PMCID: PMC10477973.

[3] Mizanu Zelalem Degu, Gizeaddis Lamesgin Simegn, Smartphone based detection and classification of poultry diseases from chicken fecal images using deep learning techniques, Smart Agricultural Technology, Volume 4, 2023, 100221, ISSN 2772-3755, https://doi.org/10.1016/j.atech.2023.100221.

[4] Kalaiselvi. T. C, Dinesh A, Arjun Karuppusamy, Bharath Sumathy, “Detection and Classification of Disease in Poultry farm”, (2023), Journal of Survey in Fisheries Sciences (SFS), Vol. 10 No. 2S (2023), https://doi.org/10.17762/sfs.v10i2S.320.

[5] Bao Y, Lu H, Zhao Q, Yang Z, Xu W. Detection system of dead and sick chickens in large scale farms based on artificial intelligence. Math Biosci Eng. 2021 Jul 13;18(5):6117-6135. doi: 10.3934/mbe.2021306. PMID: 34517526.

[6] Işık, Y., Kayabaşı, A. (2022). Automatic Classification of Healthy and Sick Broilers in Terms of Avian Influenza by Using Neural Networks. Mühendislik bilimleri ve araştırmaları dergisi (Online), 4(2), 212 - 226.

[7] Chao, Kevin, Y. R. Chen, William R. Hruschka and B. Park. “Chicken Heart Disease Characterization by Multi-spectral Imaging.” Applied Engineering in Agriculture 17 (2001): 99-106.

[8] Joo, Kevin & Duan, Shiyuan & Weimer, Shawna & Teli, Mohammad. (2022). Birds' Eye View: Measuring Behavior and Posture of Chickens as a Metric for Their Well-Being.

[9] Ahsan, Muhammad Salimy, Kusrini Kusrini and Dhani Ariatmanto. “Chicken Disease Classification Based on Inception V3 Algorithm for Data Imbalance.” SinkrOn (2023): n. pag.

[10] Jintao Wang, Mingxia Shen, Longshen Liu, Yi Xu, Cedric Okinda, "Recognition and Classification of Broiler Droppings Based on Deep Convolutional Neural Network", Journal of Sensors, vol. 2019, Article ID 3823515, 10 pages, 2019. https://doi.org/10.1155/2019/3823515

[11] Ren Y, Huang Y, Wang Y, Zhang S, Qu H, Ma J, Wang L, Li L. A High-Performance Day-Age Classification and Detection Model for Chick Based on Attention Encoder and Convolutional Neural Network. Animals. 2022; 12(18):2425. https://doi.org/10.3390/ani12182425

[12] Ma, Xiaoxiao, Xinai Lu, Yihong Huang, Xinyi Yang, Ziyin Xu, Guozhao Mo, Yufei Ren, and Lin Li. 2022. "An Advanced Chicken Face Detection Network Based on GAN and MAE" Animals 12, no. 21: 3055. https://doi.org/10.3390/ani12213055

[13] Sadeghi, Mohammad, Ahmad Banakar, Saeid Minaei, Mahdi Orooji, Abdolhamid Shoushtari, and Guoming Li. 2023. "Early Detection of Avian Diseases Based on Thermography and Artificial Intelligence" Animals 13, no. 14: 2348. https://doi.org/10.3390/ani13142348

[14] Nakrosis, Arnas, Agne Paulauskaite-Taraseviciene, Vidas Raudonis, Ignas Narusis, Valentas Gruzauskas, Romas Gruzauskas, and Ingrida Lagzdinyte-Budnike. 2023. "Towards Early Poultry Health Prediction through Non-Invasive and Computer Vision-Based Dropping Classification" Animals 13, no. 19: 3041. https://doi.org/10.3390/ani13193041

[15] He, Pengguang, Zhonghao Chen, Hongwei Yu, Khawar Hayat, Yefan He, Jinming Pan, and Hongjian Lin. 2022. "Research Progress in the Early Warning of Chicken Diseases by Monitoring Clinical Symptoms" Applied Sciences 12, no. 11: 5601. https://doi.org/10.3390/app12115601

[16] Srivastava, K., and Pandey, P. (2023) Deep Learning Based Classification of Poultry Disease. Int. j. autom. smart technol. https://doi.org/10.5875/ausmt.v13i1.2439

[17] Xiuzhe Chen and Xiaoxia Yang, “Chicken Manure Disease Recognition Model Based on Improved ResNeXt50”, 2023 J. Phys.: Conf. Ser. 2562 012009, DOI 10.1088/1742-6596/2562/1/012009

[18] M. Kholil, H. P. Waspada and R. Akhsani, "Classification of Infectious Diseases in Chickens Based on Feces Images Using Deep Learning," 2022 International Conference on Electrical and Information Technology (IEIT), Malang, Indonesia, 2022, pp. 362-365, doi: 10.1109/IEIT56384.2022.9967850.

[19] Suthagar, S., Mageshkumar, G., Ayyadurai, M., Snegha, C., Sureka, M., Velmurugan, S. (2023). Faecal Image-Based Chicken Disease Classification Using Deep Learning Techniques. In: Smys, S., Kamel, K.A., Palanisamy, R. (eds) Inventive Computation and Information Technologies. Lecture Notes in Networks and Systems, vol 563. Springer, Singapore. https://doi.org/10.1007/978-981-19-7402-1_64

[20] Machuve D, Nwankwo E, Mduma N, Mbelwa J. Poultry diseases diagnostics models using deep learning. Front Artif Intell. 2022 Aug 1;5:733345. doi: 10.3389/frai.2022.733345. Erratum in: Front Artif Intell. 2022 Sep 01;5:1016695. PMID: 35978651; PMCID: PMC9376463.

[21] Abuka Emmanuel Ifuchenwuwa, E.O. Osaghae, Frederick Duniya Basaky, “Deep Learning Implementation for Poultry Disease Detection and Control”, International Journal of Innovative Science and Research Technology, Volume 8, Issue 6, June 2023.

[22] Zhang, N., Ma, X., Huang, Y., Bai, J. (2023). Image Recognition of Chicken Diseases Based on Improved Residual Networks. In: Li, Y., Huang, Z., Sharma, M., Chen, L., Zhou, R. (eds) Health Information Science. HIS 2023. Lecture Notes in Computer Science, vol 14305. Springer, Singapore. https://doi.org/10.1007/978-981-99-7108-4_22

[23] Xue-Song Jin, Jing Li and Xin Du, “Image Classification of Chicken Embryo Based on Matched Filter and Skeleton Curvature Feature”, 2020 J. Phys.: Conf. Ser. 1651 012196.

[24] Mao A, Giraudet CSE, Liu K, De Almeida Nolasco I, Xie Z, Xie Z, Gao Y, Theobald J, Bhatta D, Stewart R, McElligott AG. Automated identification of chicken distress vocalizations using deep learning models. J R Soc Interface. 2022 Jun;19(191):20210921. doi: 10.1098/rsif.2021.0921. Epub 2022 Jun 29. PMID: 35765806; PMCID: PMC9240672.

[25] Hope Mbelwa, Jimmy Mbelwa and Dina Machuve, “Deep Convolutional Neural Network for Chicken Diseases Detection” International Journal of Advanced Computer Science and Applications(IJACSA), 12(2), 2021. http://dx.doi.org/10.14569/IJACSA.2021.0120295

[26] Pu, Haitao & Lian, Jian & Fan, Mingqu. (2017). Automatic Recognition of Flock Behavior of Chickens with Convolutional Neural Network and Kinect Sensor. International Journal of Pattern Recognition and Artificial Intelligence. 32. 10.1142/S0218001418500234.

[27] Liu, Hung-Wei, Chia-Hung Chen, Yao-Chuan Tsai, Kuang-Wen Hsieh, and Hao-Ting Lin. 2021. "Identifying Images of Dead Chickens with a Chicken Removal System Integrated with a Deep Learning Algorithm" Sensors 21, no. 11: 3579. https://doi.org/10.3390/s21113579

[28] Ahmed, Ghufran, Rauf Ahmed Shams Malick, Adnan Akhunzada, Sumaiyah Zahid, Muhammad Rabeet Sagri, and Abdullah Gani. 2021. "An Approach towards IoT-Based Predictive Service for Early Detection of Diseases in Poultry Chickens" Sustainability 13, no. 23: 13396. https://doi.org/10.3390/su132313396

[29] Astill, J.; Rozita, A.; Evan, D.; Fraser, D.G.; Roberts, B.; Sharif, S. Smart poultry management: Smart sensors, big data, and the internet of things. Comput. Electron. Agric. 2020, 170, 105291.

[30] Yang, J., Sun, R., Jin, C., Yin, B.: Research on the identification method of intestinal diseases in laying hens based on multi-scale convolution. China Agric. Inform. 34, 14–26 (2022).

[31] Pang, B.: Classification of images using EfficientNet CNN model with convolutional block attention module (CBAM) and spatial group-wise enhance module (SGE). In: Agyeman, M.O., Sirkemaa, S. (eds.) International Conference on Image, Signal Processing, and Pattern Recognition (ISPP 2022), vol. 12247, p. 1224707. International Society for Optics and Photonics, SPIE (2022).

[32] Wei, F., Zhang, Z., Liang, G.: Research on application of insect species image recognition based on convolutional neural network. J. Henan Normal Univ. (Nat. Sci. Ed.) 50, 96–105 (2022).

[33] Tan, Mingxing & Le, Quoc. (2019). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks.

[34] Alhichri, Haikel & Alsuwayed, Asma & Bazi, Yakoub & Ammour, Nassim & Alajlan, Naif. (2021). Classification of Remote Sensing Images Using EfficientNet-B3 CNN Model with Attention. IEEE Access. PP. 1-1. 10.1109/ACCESS.2021.3051085.

[35] Machuve, D., Nwankwo, E., Mduma, N., Mbelwa, H., Maguo, E., & Munisi, C. (2021). Machine Learning Dataset for Poultry Diseases Diagnostics (Version 2) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.4628934

[36] Barsagade A. G., & Rumale, A. S. (2024). Internet of Things Based Intelligent monitoring and controlling of Poultry System on using Artificial Intelligence. International Journal of Intelligent Systems and Applications in Engineering, 12(10s), 456–467.