Chicken Diseases Detection and Classification Based on Fecal Images Using EfficientNetB7 Model

Vandana
Department of Computer Science and Engineering, Banas thali Vidyapith

Kuldeep Kumar Yogi
Department of Computer Science and Engineering, Banas thali Vidyapith

Satya Prakash Yadav
Department of Computer Science and Engineering, G L Bajaj Institute of Technology and Management

https://doi.org/10.5109/7172288

出版情報：Evergreen. 11 (1), pp.314-330, 2024-03. 九州大学グリーンテクノロジー研究教育センター
バージョン：

Chicken Diseases Detection and Classification Based on Fecal Images Using EfficientNetB7 Model

Vandana[1*], Kuldeep Kumar Yogi[2], Satya Prakash Yadav[3]

[1,2]Department of Computer Science and Engineering, Banas thali Vidyapith, Banasthali, Rajasthan, India

[1]JIMS Engineering Management Technical Campus, Greater Noida, India

[3]Department of Computer Science and Engineering, G L Bajaj Institute of Technology and Management, Greater Noida, India

*Author to whom correspondence should be addressed:
E-mail: vandanabharti233@gmail.com

(Received October 15, 2023; Revised February 19, 2024; Accepted February 27, 2024).

Abstract: The agriculture sector, particularly the chicken and poultry industries, is under pressure to produce more due to the increased demand for livestock products among consumers. Increased poultry production can lead to the enhanced spread of many infectious diseases in chickens, which can result in high bird fatality rates and significant financial losses. A shortage of trustworthy professionals or delayed diagnosis cause farmers to be losing an extensive number of domestic chickens. Deep learning algorithms can help the early detection of illnesses. This paper proposes a system based on convolutional neural networks to categorize chicken illnesses by identifying healthy and harmful fecal images. Unhealthy images may indicate a poultry illness. Through the use of deep learning algorithms and image analysis of chicken feces, the most common illnesses that affect chickens may be rapidly identified. With the use of a convolutional neural network (CNN) architecture, this research developed a model to identify different chicken ailments by classifying fecal images into two groups: those representing symptoms associated with healthy conditions and those representing symptoms associated with potentially dangerous conditions like Newcastle diseases, Coccidiosis, or Salmonella. To determine if chicken feces fell into one of four categories with the least amount of loss utilized the EfficientNetB7 model with additional layers that extracted the most appropriate features from the fecal images and achieved the highest accuracy. With an accuracy of 97.07%, the new proposed model generated the greatest results when compared to the aforementioned models.

Keywords: Chicken Disease; Image Classification; Fecal Images; EfficientNetB7; CNN; Transfer Learning.

1. Introduction

Chicken poultry industry is essential in providing nutrient-rich food for the world's growing population. Poultry farming, specifically, is recognized for its valuable protein source and significant contributions to the socio-economic development of developing countries. It ensures food and nutrition security, generates massive income, and able to boosts the gross domestic product. However, as demand for poultry products rises, the industry must improve its efficiency and production[1)]. Farms with more chickens may have increased rates of infectious disease transmission, which might result in significant poultry mortality and financial losses from disease outbreaks. Every year, millions of chickens are died at slaughterhouses due to various health issues that cause significant financial losses for farmers. As demonstrated in Fig. 1, several prominent chicken diseases, including infectious respiratory diseases, bacterial diseases, viral diseases, parasitic diseases, neoplastic diseases and viral diseases. Infectious respiratory diseases which include bronchitis, avian influenza, Newcastle disease and many more. Bacterial diseases include fowl cholera, typhoid, salmonellosis, and many more. The parasitic diseases include coccidiosis, red mites, blackheads and worms. These poultry chicken diseases could be associated with issues with inadequate biosecurity, low vaccination rates, and poor poultry servicing practices[2)]. Addressing these challenges is crucial to ensure sustainable and safe poultry production and meet the growing global demand for animal proteins.

Poultry farms are essential to fulfilling the rising demand for animal protein. However, the poultry industry faces significant challenges due to the prevalence of various diseases, with Coccidiosis, salmonella and Newcastle disease being the most common and severe poultry ailments. These diseases have far-reaching economic consequences and can cause immense suffering for the birds. Understanding the causes, symptoms, and preventive measures for these diseases is crucial for ensuring the health and productivity of poultry flocks worldwide.

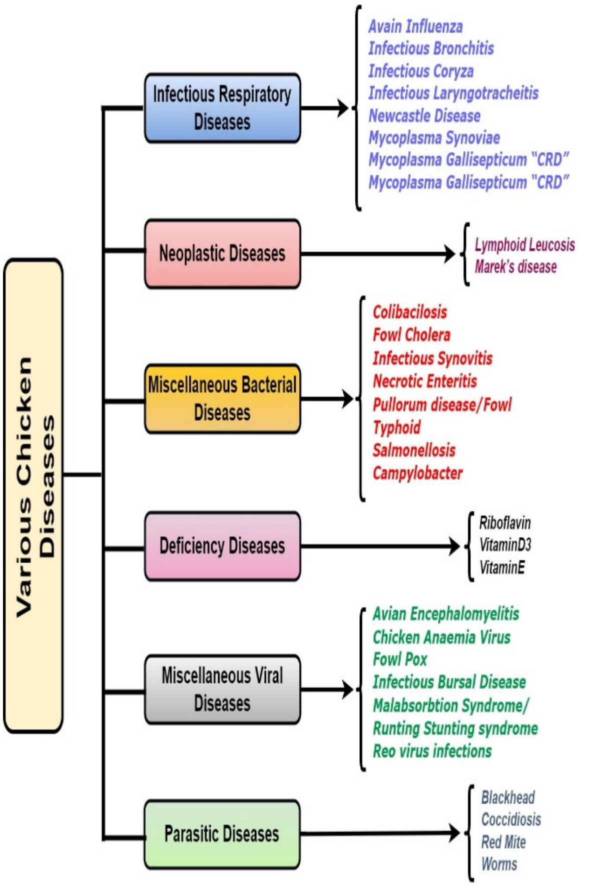


Fig. 1: Various Types of Disease that Affect the Chicken Health

Coccidiosis is a parasitic disease caused by Eimeria species protozoa residing in the intestines of chickens. It is highly contagious and can spread rapidly within a flock. When chickens are left unchecked, Coccidiosis leads to reduced appetite, diarrhea, weight loss, and an inability to absorb nutrients effectively due to damage to the gut walls. Such symptoms can severely impact the growth and development of birds, resulting in significant economic losses for poultry farmers. Preventing Coccidiosis begins with maintaining strict biosecurity measures on poultry farms. This involves controlling the entry of new birds, ensuring proper sanitation practices, and minimizing exposure to contaminated materials or wild birds. Additionally, using coccidiostats, medications that control coccidian growth, in feed formulations can help manage the disease. Regular monitoring of flocks and seeking veterinary advice at the first sign of infection are essential for effective control.

The cause of Newcastle disease, which affects both domestic and wild birds, is the avian paramyxovirus serotype 1 virus. The disease spreads through aerosols from infected bird feces and respiratory droplets, making it highly transmissible among flocks. Respiratory symptoms such as gasping, coughing, sneezing, and rales are common signs of Newcastle disease. Preventing Newcastle disease hinges on vaccination and strict biosecurity practices. Regular vaccination of poultry flocks, along with the isolation of new birds and monitoring of their health status, are essential to prevent outbreaks. Ensuring proper disinfection of equipment and facilities, as well as limiting access to visitors and wild birds, can significantly reduce the risk of disease spread. Combating poultry diseases like Coccidiosis and Newcastle disease requires a collaborative effort from governments, poultry producers, veterinarians, and researchers worldwide. Sharing knowledge, best practices and technology can enhance disease surveillance, early detection, and effective control strategies. Investments in research and production of new vaccines and treatments can further strengthen the industry's resilience against these diseases. A gastro-intestinal ailment is salmonella. While some birds with the infection heal after some time, others keep on excreting germs for months at a time. A gastro-intestinal ailment is salmonella. While some birds with the infection heal after a period of time, others keep on excreting germs for months at a time.

Computer vision has a vital role to play in research, deep learning, machine Learning[3,4]. Now days, the diagnosis, classification and localization of disease is increasingly being carried out using computer vision and deep learning[5] in healthcare applications. Due to the increased availability of data thanks to modern technology, it is now feasible to anticipate infectious diseases in poultry. Over the period, there are many CNN models like MobileMe, InceptionV3, ResNet and Denseness are used to classify chicken diseases.

EfficientNetB7 is an efficient CNN model that designed with a compound scaling method, allowing easy scaling up or down of model size depending on the requirements of the task. The combination of the EfficientNetB7-CNN Model with sophisticated computer vision methods presents a promising avenue for non-invasive health evaluations in the poultry sector. Examining poultry health through fecal analysis offers valuable insights, as changes in texture and color can indicate the presence of serious and contagious diseases. In contrast to earlier studies that typically utilized simplistic binary or limited multi-class classification approaches, this research employs image processing techniques with EfficientNetB7-CNN algorithms. The findings suggest that our methodology has the potential to effectively diagnose and detect diseases in chickens with high accuracy.

The purpose of this paper is to implement a CNN model that is capable of detecting chicken disease from fecal images. To achieve this aim, by using an EfficientNetB7 deep learning model with additional layers that extract important features from fecal images which are capable of detecting chicken disease and also improving the performance of the model because of its compound scaling feature. This research's primary contributions are outlined in the following order:

- An enhanced version of the EfficientNetB7 model is proposed for classifying chicken diseases based on images of chicken feces.
- The performance of the enhanced EfficientNetB7 model has been compared with previously published work on chicken disease classification based on the same the dataset.

Following is how the paper is structured. Section delves into the existing literature and related works, offering insights into the background and context of the research topic, Section 3 the methodology, data collection process, and the proposed model are discussed in detail. Section 4 focuses on presenting and analyzing the experimental results and outcomes compared with the previously published work. Section 5 Concludes the proposed work and Section 6 contains List of references.

2. Literature Review

The increasing demand for poultry products underscores the necessity of prioritizing poultry welfare. The quality of poultry products is intricately linked to the well-being of the poultry themselves. However, conducting a comprehensive assessment of poultry welfare poses challenges as various criteria may conflict, leading to a complex and time-consuming evaluation process. Technological advancements play a pivotal role in aiding poultry farmers in ensuring good poultry welfare[6]. Deep learning algorithms analyze visual input together with associated class labels, revealing a world of varied patterns in the process[9,10]. A comprehensive previous study for chicken health is described in the following section based on chicken sound and image analysis.

2.1. A Comprehensive Chicken Poultry Study Based on Sound Analysis

The vocalization of poultry serves as a vital physiological characteristic, serving as a reliable indicator of their health and overall well-being[31]. This vocalization not only aids in predicting poultry weight but has also proven effective in analyzing pecking activity, providing indirect insights into the chickens' health status[32]. Vocalization, stemming from specific organs, serves as an outward expression of physiological signals affected by both internal and external factors[33]. The respiratory system's well-being is closely related to these signals[34]. Variations in chicken vocalization[40] can serve as an early warning system for breeders, signaling potential concerns such as poor environmental conditions or the onset of disease. Therefore, recognizing sound as an early indicator of animal health is a logical approach. Table 1 provides a compilation of diverse research efforts focusing on sound analysis as a method to monitor the health of chickens across different poultry farms.

In contrast to the controlled settings of closed environments in previous studies, real-world conditions in commercial farms introduce various ambient noises[41]. Recognizing sneezing as a clinical indicator of respiratory diseases, an algorithm was devised and implemented to identify sneezing sounds amidst multiple noise sources. With an accuracy of 88.4%, this algorithm presented the potential benefits of an automated voice recognition-based chicken health tracking platform[54]. Five acoustic characteristics were taken from the noises made by healthy and ill hens in research conducted by Mahdavian et al.[62] to be classified. The findings revealed that MFCCs and wavelet energy could effectively identify Newcastle disease, achieving accuracies of 80% and 78%, respectively. Despite their comparable accuracy, wavelet energy outperformed MFCCs in the early detection of healthy and sick states. In distinguishing between healthy and challenged birds, it was observed that MFCCs excelled, while wavelet energy demonstrated superior performance in detecting diseases among chickens[51]. In an analysis of vocal sound for disease detection (Clostridium perfringens type A), M. Sadeghi et al.[42] used Fisher Discriminate Analysis (FDA), Neural Network Pattern Recognition (NNPR) structure by which the model achieved accuracy between 66.6 and 100%. By analysis of sound vibration, to identify Newcastle, Bronchitis virus, Avian Influenza disease A. Banakar et al.[43] used dempster-shafer evidence theory (D-S) and SVM algorithm by which the model achieved an accuracy of 91.15%.

Rales are a common sign of respiratory disorders in poultry. Rales are an extra sound that differs from regular breathing. In the study conducted by Carroll et al.[55], 6-15day-old chickens were deliberately infected with the infectious bronchitis virus. Subsequently, the researchers recorded the sounds produced by both healthy and infected chickens using a microphone. D. Cheng et al.[8] used recurrent neural network (RNN) and CNN model to analyze the voices of sick chickens for identification of respiratory issues in poultry and achieved 97.4% accuracy. M. Rizwan et al.[68] used support vector machine (SVM) and extreme learning machine (ELM) classifiers, achieving 97.6% accuracy. The research conducted by Cuan et al.[56], early detection of Newcastle disease (ND) was successfully accomplished through the analysis of chicken sounds. To diagnose respiratory problems in poultry J. Huang et al.[60], used SVM classifier and achieved 90% accuracy on the sound vibrations of chickens. Comparatively speaking, using auditory signals to diagnose animal illnesses is not very cost-effective. presenting broad application prospects that are yet to reach full maturity. However, two primary challenges need to be addressed. Firstly, denoising poses a significant hurdle. In the living environment of animals, activities such as fan rotation and conveyor belt operation generate

Table 1. Sound Based Analysis on Chicken Behavior and Disease Detection

References	Analysis	Objective	Limitation	Algorithm	Assessment
J. Huang et al.[31], 2019	Sound Vibrations	Avian Influenza Diagnosis	The interference caused by the convergence of sound vibrations posed a challenge in accurately diagnosing Avian Influenza among poultry chickens in extensive poultry farming settings.	MFCC and SVM	Accuracy range of 84% and 90%
A. Aydin et al. [32], 2016	Pecking Sound Assessment	Feed Consumption and Growth Monitoring	Lacks the capability to assess the well-being of chickens and is not suitable for use in the poultry sector.	Linear Regression	Accuracy was 93%
A. Aydin et al. [33], 2014	Pecking Sound Analysis	The number of pecking and feed intake were computed.	Lacks the capability to assess the well-being of chickens and is not suitable for use in the poultry sector.	Linear Regression	Accuracy was 93%
A. Aydin et al. [34], 2015	Pecking sound, look, and intake of meal	Keep an eye on your meal intake.	Lacks the capability to assess the well-being of chickens and is not suitable for use in the poultry sector.	Linear Regression	Accuracy was 86.00%
I. Fontana et al. [40], 2015	Peak Frequencies	Growth Detection	It is consequently unfeasible for the poultry sector since the humming vibrations of sound interfere.	Statistical analysis of sound	--
I. Fontana et al.[41], 2016	Peak Frequencies	Growth Detection	It is consequently unfeasible for the poultry sector since the humming vibrations of sound interfere.	Statistical analysis of sound	--
M. Sadeghi et al.[42], 2015	Analysis of Vocal Sound	Disease Detection (Clostridium perfringens type A)	A challenge to implement in sizable chicken farms due to the complexity of voice analysis resulting from hundreds of chicks' vocal vibrations overlapping.	FDA NNPR	Accuracy was 66.6 and 100%
A. Banakar et al.[43], 2016	Sound Vibrations	Newcastle, Bronchitis virus, Avian Influenza Diagnosis	In vast poultry farms, it is difficult to hear every fowl in the flock. As such, it is challenging to implement across big chicken farms.	Dempster-Shafer evidence theory (D-S) and SVM	Accuracy 91.15%.
K. Cuan et al. [51], 2020	Chicken sound convolutional neural network (CSCNN),	Avian influenza	In vast poultry farms, it is difficult to hear every fowl in the flock. As such, it is challenging to implement across big chicken farms.	MFCC, MFCC Delta and MFCC Delta-Delta, CNN	Accuracy 95.84%,
L. Carpentier et al. [54], 2019	Sneezing sounds	Detect sneezing in chickens	In vast poultry farms, it is difficult to hear every fowl in the flock. As such, it is challenging to implement across big chicken farms.	Linear Discriminant	Accuracy 88.4%
B. Carroll et al. [55], 2014	Sound Vibrations	Detect rales	In vast poultry farms, it is difficult to hear every fowl in the flock. As such, it is challenging to implement across big chicken farms.	Decision Trees	Accuracy 73.4%
D. Cheng et al.[8], 2020	Sound, swab samples	Identify and assess respiratory issues	In vast poultry farms, it is difficult to hear every fowl in the flock. As such, it is challenging to implement across big chicken farms.	RNN, CNN	Accuracy 97.4%
A. Mahdavian et al.[62], 2021	Bronchitis, and Newcastle disease	Diagnose respiratory problems	In vast poultry farms, it is difficult to hear every fowl in the flock. As such, it is challenging to implement across big chicken farms.	Mel cepstral coefficients (MFCC), SVM	Accuracy 83%
M. Rizwan et al. [68], 2016	Chicken sound analysis	Detect an unusual sound that happens while you breathe normally called rale	In vast poultry farms, it is difficult to hear every fowl in the flock. As such, it is challenging to implement across big chicken farms.	SVM, ELM	Accuracy was 97.6%
K. Cuan et al. [56], 2022	Chicken sound analysis	To identify Newcastle disease diseased chicken	It is challenging to implement across big chicken farms.	DNN	Precision 96.54%

J. Huang et al. [60], 2019	Chicken sound analysis	Diagnose respiratory problems	In vast poultry farms, it is difficult to hear every fowl in the flock. As such, it is challenging to implement across big chicken farms.	SVM	Accuracy was 90.00%

substantial ambient noises, potentially impacting audio preprocessing and final outcomes. Another difficulty is the extreme rarity of aberrant noises. The data on chicken voices are continuous, but the anomalous noises that are suggestive of a problem usually only take up a small portion of the longer recording times, randomly. Consequently, future jobs will require developing and putting into practice algorithms to improve identification efficiency and accuracy in such complicated contexts. Moreover, if spatial localization of abnormal sounds within the chicken house becomes possible, it could elevate the management standards in modern poultry farming, alleviating the burden on farmers.

2.2. A Comprehensive Chicken Poultry Study Based on Image Analysis

Utilizing image processing offers a budget-friendly and efficient means of autonomously analyzing poultry behavior, encompassing health condition detection, weight prediction, tracking, and monitoring. This technology allows for the economical and autonomous examination of poultry behavior, providing insights into various aspects such as health status, weight estimation, and activity tracking as described in Table 2. The recorded activities of chickens within a flock can be further scrutinized later to identify distinct patterns and behaviors.

Image processing[24] proves to be a cost-effective tool for monitoring poultry behavior, enabling the comparison of adjacent sets of pixels to achieve accurate detection and analysis of flock activities[27]. This approach not only streamlines the evaluation of health conditions but also enhances the overall management of poultry through predictive weight assessments and continuous tracking and monitoring.

A flock's unusual eating behavior might be used as a warning sign for the health of the hens. Monitoring poultry behavior and the timely identification of infections can be achieved through the analysis of poultry feces. According to the study, this monitoring and classification system works better than conventional on-farm microbiological techniques in identifying flocks of chickens clear of Campylobacter[46]. The claimed advantage is the ability to provide monitoring results within a relatively short timeframe of 7 to 10 days. In 2012 P. J. Hepworth et al.[59] analyzed average weight, death rates, and density of stocking of chickens to diagnose hock burn in chickens and using SVM classifier achieved 78% accuracy.

Monitoring several chicken behavioral traits, such as eating, sleeping, and walking, as well as pose estimation activities are analyzed by Y. Liu et al.[30], Hemalatha et al.[12], F. M. Colles et al.[46], X. Zhuang et al.[44] C. Okinda et al.[50], X. Zhuang et al.[70], C. Fang et al.[52], A. Nasiri et al.[75], and M. Campbell et al.[38] and successfully identified various types of chicken diseases by leveraging advanced imaging and machine learning techniques, the study demonstrates the potential for accurate and efficient monitoring of poultry health and population dynamics in controlled environments.To observe unusual activities of chickens by G. A. Fraess et al.[45], H. Pu et al.[47], X. Yang et al.[73], S. Neethirajan et al.[74] by employing a variety of machine learning and deep learning approaches, leading to improved performance outcomes.

According to A. A. G. Raj et al.[64] the study of climate changes, encompassing variations in temperature and humidity, significantly impacts various aspects of chicken physiology, including reduced feed intake, growth, weight, semen quality, and fertility. To comprehensively monitor and analyze chicken health, the study employs a thermal camera for video monitoring to categorize the information, and a depth camera to simulate the chickens' health. For feature investigations, mobility features—walk speed in particular—are retrieved and statistical analysis are carried out. The analysis of desired weight goal, quantity of feed consumed, and weight in real-time J. You et al.[37] used DNN to Identify non-laying birds. S. Amraei et al.[48] used ANN model to implement an automatic weight estimation approach. Through the analysis of diverse chicken images, researchers such as Z. Xu et al.[69], T. Fang et al. [66], X. Qiang et al. [63], A. G. R et al.[67], P. He et al.[39], A. A. A. Bakar et al.[65], and J. A. Orandi et al.[57] showcase how cutting-edge technology significantly enhances the accuracy and effectiveness of monitoring procedures in chicken production. This advanced technology is instrumental in detecting various harmful chicken diseases prevalent in poultry farms.

To address heat stress in poultry chickens, a thermal camera is recommended[49]. Using the temperature dataset that was gathered, a Support Vector Machine (SVM) classification model is used to estimate the health of the hens. Thermal cameras are utilized within the controlled environment of poultry farms to gather the chickens' temperature dataset. This integration of computer vision and thermal monitoring showcases the potential for advanced technologies to enhance precision in predicting weight and managing health factors in poultry farming[25]. The study asserts that the authors have achieved the quickest turnaround time for the identification of infections on the fourth day. This is depending on the observation of changes in the elongation and variance of certain visual cues, such as circles, suggesting that these features can serve as early indicators of infection in chickens. This approach showcases the integration of climate-related factors, advanced imaging technologies, and mobility features to enhance the overall monitoring and early detection capabilities in poultry health management.

SVM stands out as a powerful generalized linear classifier in the realm of binary data classification through supervised learning. The first group to use SVM in conjunction with the exterior features of chicken feces to diagnose poultry diseases was Aziz et al.[28]. Their approach involved leveraging the grey-level cooccurrence matrix, a texture descriptor renowned for statistical measurements of grey-level coexistence in images. Extracting 19 texture features, they fed this set into SVM to distinguish between healthy and diseased chicken feces, achieving an impressive accuracy of 93.75%. However, the study's limitation lies in its sample size of 20, raising questions about representativeness. Moving beyond mere

Table 2. Identifying Chicken Behavior and Chicken Diseases Based on Image Analysis

References	Analysis	Objective	Limitation	Algorithm	Assessment
Y. Liu et al.[30], 2003	Examination of the skin and fecal classes' categorization	Organize the visible/near-infrared (NIR) spectra of clean chicken skins and clean chicken excrement along with the hyperspectral imaging data that shows the spectra of infected chicken skins	In vast poultry farms, it is difficult to hear every fowl in the flock. As such, it is challenging to implement across big chicken farms.	Subtraction algorithm and a ratio algorithm, Principal Component Analysis (PCA) model	--
P. J. Hepworth et al. [59], 2012	Average weight, death rates, and Density of stocking	Diagnose Hock burn	Certain obstacles lie ahead in enabling epidemiologists by using SVM. These challenges encompass the understanding of coefficients in relation to odds ratios and p-values, as well as the incorporation of methods to address hierarchical data	SVM and Logistic	Accuracy was 78%
Hemalatha et al.[12], 2014	Postures and activities	Avian pox disease recognition	In vast poultry farms, it is difficult to hear every fowl in the flock. As such, it is challenging to implement across big chicken farms.	SVM with Gaussian Radial Basis Function (GRBF), Extreme Learning Machines	Accuracy was 96.6
G. A. Fraess et al.[45], 2016	Behavioural assessment	Unusual Feeding Observation	When a bigger size of poultry fowl is noticed, there is conflict between the nearby pixels.	Statistical analysis	--
F. M. Colles et al.[46], 2016	Behavioural assessment	Early Disease Identification and Monitoring of Unusual Feeding	In order to examine unusual feeding behavior with a limited number of poultry hens, light controlling must be stabilized.	Statistical analysis	--
N. A. Aziz et al.[28], 2017	Image based analysis	Chicken disease detection	The identification and categorization of diseases required highly sophisticated computation.	SVM	Accuracy was 93.80%
S. Amraei et al.[48], (2017)	Automatic weight estimation	Chicken weight estimation	Predicting weight is impractical for extensive poultry farms.	ANN	--
Z. Xu et al.[35], 2017	Avian Influenza	To identify diseased chicken	Indeed, the system lacks the ability to explain the underlying processes responsible for the observed and projected spread, as well as the optimal methods for control.	Association rule, Sequential Pattern Mining (SPM)	--

H. Pu et al.[47], 2018	Behavioural assessment	Observing Crowds	Lacks the capability to assess the well-being of chickens and is not suitable for use in the poultry sector.	CNN	Accuracy was 99.17%.
A. Nawab et al. [49], 2018	Heat stress	The influence of heat stress on poultry production	Offers a simplistic method for disease diagnosis in poultry farms relying on temperature.	Statistical analysis	--
A. A. G. Raj et al. [64], 2018	Temperature and walking	To identify diseased chicken	It is challenging to implement across big chicken farms.	kNN	--
X. Zhuang et al.[44], 2018	Behavioural assessment	To identify diseased chicken using posture feature Modelling	Disease Detection and Classification techniques required high computations as the proposed technique implements the SVM Model for classification.	SVM	Accuracy was 99.469%
J. Wang et al.[29], 2019	Image based analysis	Chicken disease detection	Model is not able to detect which type of disease chicken have.	Faster R-CNN and YOLO-V3	99.1% recall and 93.3% mean average precision
T. Fang et al. [66], 2019	Chicken disease Detection	Infectious bursal disease (IBD) diagnoses	It provides the study of previous work of quick, accurate, and targeted diagnostic instrument only.	Ribonucleic acid (RNA) microarray	--
C. E Golden et al.[58], 2019	Fecal and soil sample analysis	To detect the Listeria spp prevalence	It is challenging to implement across big chicken farms.	RF, GBM	AUC 0.91
C. Okinda et al. [50], 2019	Behavioural assessment	Identifying sick chicken based on walk speed behavior classification	Challenging to track and observe the individual chickens' moving speed in large poultry farms.	ANN, Logistic, SVM	Accuracy was 98.80%
X. Qiang et al. [63], 2019	Chicken disease Detection	To identify Avian Influenza chicken-diseased	It is challenging to implement across big chicken farms.	SVM, Bayesian Network (BN), KNN	AUC 0.99
X. Zhuang et al.[70], 2019	Feather texture, and poses of chickens	To identify diseased chicken	It is challenging to implement across big chicken farms.	CNN	Precision was 99.70
A. G. R. Alex et al. [67], 2019	Image and sound	To identify diseased chicken	It is challenging to implement across big chicken farms.	kNN, SVM, Logistic, DT	Accuracy was 95.10%
C. Fang et al. [52], 2020	Behavioral assessment	Identifying sick chicken based on pose estimation	Lacks the capability to assess the well-being of chickens and is not suitable for use in the poultry sector.	DNN and Naive Bayesian model (NBM)	Precision is 0.7511 (standing), 0.5135 (walking), 0.6270 (running), 0.9361 (eating), 0.9623 (resting), and 0.9258 (preening).
D. Hwang et al. [61], 2020	Fecal Analysis	To identify Salmonella chicken disease	Few data points used in this research	Random Forest	AUC 0.88
J. You et al.[37], 2021	Desired weight goal, quantity of feed consumed, weight in real-time and time	Identify non-laying birds	Its applicability was limited to recognizing egg-laying events occurring on the following day and the binary-label predictions lacked the capacity to differentiate further details among outputs sharing the same label.	DNN	AUC 0.94

H. Mbelwa et al.[1], 2021	Chicken fecal images	Classification of healthy and unhealthy chicken	Limited dataset and performance issue	XceptionNet deep learning framework	Accuracy was 94%
D. Machuve et al.[13], 2022	Coccidiosis, Salmonella, and Newcastle disease classification	To identify diseased chicken	The dataset is much less	DNN - MobileNetV2	Accuracy was 98.02%
Y. Guo et al. [71], 2022	Behavioural assessment	To monitor chicken behaviours (i.e., feeding, drinking, standing, and resting)	It is challenging to implement across big chicken farms.	CNN-DenseNet-264	Accuracy rates: 85%, 95%, 92%, 89.5
X. Yang et al.[73], 2022	Behavioural assessment	To observe and track the behaviours of hens in cage-free facilities.	Error detections resulted from factors such as extensively overlapping stock, uneven light intensity, and images being obstructed by equipment, such as drinking lines and feeders.	Deep learning model (YOLOv5x-hens)	Accuracy more than 95%
S. Neethirajan et al.[74], 2022	Behavioural assessment	Detect anomalies in chicken behaviour.	Limited dataset	You Only Look Once (Yolov5)	--
A. Nasiri et al. [75], 2022	Pose estimation-based mode	Lameness detection	It is challenging to implement across big chicken farms.	CNN-LSTM network, ResNet50	Accuracy was 97.5%.
P. He et al.[39], 2023	Disease detection	Chicken Eimeria classification	Optimization issue	CNN named Residual-Transformer-Fine-Grained (ResTFG)	Accuracy was 96.9%
S. Sudhagar et al.[2], 2023	Chicken fecal images	Healthy chicken, Coccidiosis, Salmonella and Newcastle image	Limited dataset	DenseNet method	Accuracy was 97%.
M. K. Gourisaria et. al.[7], 2023	Chicken fecal images	healthy chicken, Coccidiosis, Salmonella and Newcastle image	Performance issue	ChicNetV6	Accuracy was 94.49%
M. Zhou et al.[72], 2023	Abnormal chicken dropping	identification of healthy chicken	It is challenging to implement across big chicken farms.	Faster R-CNN	Accuracy was 98.8%
Z. D. Mizanu et al. [69], 2023	Chicken fecal images	Classification of healthy and unhealthy chicken	It is challenging to implement across big chicken farms.	ResNet50 and YOLO-V3	Accuracy was 98.7%.
A. A. A. Bakar et al.[65], 2023	Detect bacteria- or virus-infected chickens	To identify chickens that may be infected with bacteria or viruses by analysing the optical chromaticity of the chicken comb.	It works on only a single chromaticity feature. The multi-feature approach is needed to detect diseases.	Logistic Regression, SVM, K-Nearest Neighbours (KNN)	Accuracy was 99.469%
J. A. Orandi et al.[57], 2023	Disease detection	Disease detection	The author is not sure whether the harris Corner is a better feature detector or not.	CNN (features extracted (Ridges, edges, and Harris corners)	Accuracy was 94.14%
M. Campbell et al.[38], 2023	Behavioural assessment	To monitor broiler activity by using trekking behaviour	Behaviours such as feeding and drinking events are not analysed by model	Clustering algorithm	precision, recall and f score of 0.98, 0.90 and 0.94

K. Srivastava et al. [14], 2023	Chicken fecal images	Classification of healthy and unhealthy chicken	Limited dataset	CNN	Accuracy on testing set 93.23%
Akbudak et al. [15], 2023	Chicken fecal images	Classification of healthy and unhealthy chicken	Limited dataset and performance issue	MobileNetV2 model	Accuracy was 82%
A. E. Ifuchenwuwa et al.[53], 2023	Chicken fecal images	The healthy and the unhealthy are infected with coccidiosis	Able to detect only one disease	CNN	Accuracy was 91%

abnormal feces in images laden with diverse samples.

The advent of deep learning algorithms has opened doors to handling larger datasets. J. Wang et al.[29] expanded the horizon by collecting 10,000 images of Ross broiler feces, employing manual categorization into five types Based on the test dataset, the results showed that the Faster R-CNN network worked more effectively, with 99.1% recall and 93.3% average mean accuracy. C. E. Golden et al.[58] analyzed fecal and soil samples to detect the prevalence of Listeria spp. and utilized the Random Forest (RF) and Gradient Boosting Machine (GBM) algorithms, achieving an impressive Area Under the Curve (AUC) score of 0.91. D. Hwang et al.[61] analyzed fecal images to identify Salmonella chicken disease and employed the Random Forest (RF) algorithm, achieving AUC score of 0.94. H. Mbelwa et al.[1], D. Machuve et al.[13], S. Sudhagar et al.[2], Gourisaria et. al.[7], M. Zhou et al.[72], Z. D. Mizanu et al.[69], Srivastava et al.[14], Akbudak et al.[15], A. E. Ifuchenwuwa et al.[53] analyzed fecal images to identify various chicken diseases, including Coccidiosis, Salmonella, Newcastle disease, Avian influenza, and others and utilized a range of CNN pre-trained models, such as XceptionNet, DNN - MobileNetV2, Faster R-CNN, ResNet50, and YOLO-V3. Through this approach, they achieved optimal performances in disease detection, proving to be particularly beneficial for poultry farms.

Over the period, there are many CNN models used to classify chicken diseases. The DenseNet model, which performed better in diagnosing illnesses in chickens, was employed. The drawback of DenseNet's dependency on intermediate feature map storage is that it may result in memory limitations, which may reduce the maximum image size that can be processed effectively. Eight CNN[16] model used, to classify the fecal images and achieved high accuracy. It is crucial to balance network width, depth, and resolution in all dimensions while CNN model scaling in order to achieve higher accuracy and efficiency. Y. Yao et al.[11] used VGG-19 to classify the hen's gender. VGG-19 has a large number of parameters, leading to high memory usage during training and inference, which can be impractical for deployment on memory-constrained devices. IFSSD model used to detect respiratory problems in chickens[70]. Implementing and training FSSD can be complex due to its intricate architecture, involving multiple feature fusion stages and auxiliary prediction heads. To detect diseases, D. Machuve[13] developed the deep learning model InceptionV3 which has given the better accuracy lack to provide the best performance because to achieve improved accuracy and efficiency, it's essential to carefully balance all aspects of network width, depth, and resolution during scaling. ResNet50 CNN[85] model used to detect day wise age of chickens and achieved the highest performance by modifying the network depth, i.e., the number of layers. To track and record poultry behaviour, an AlexNet[26] model was used. The capacity to capture intricate hierarchical characteristics is limited in AlexNet. Model compression is a widely used method to decrease the size of a model, typically by sacrificing some degree of accuracy in exchange for improved efficiency. MobileNets surpass the efficiency of manually crafted mobile ConvNets by extensively optimizing parameters such as network width, depth, convolution kernel types, and sizes. Yet, the application of these optimization techniques for larger models with significantly larger design spaces and higher tuning costs remains unclear. Various methods exist to scale a convolutional neural network (CNN) to accommodate different resource constraints. MobileNets[19] can be scaled by adjusting the network width, specifically by modifying the number of channels. Although research has shown that network width and depth are important for CNN expressiveness, the topic of how to scale a CNN to achieve optimal accuracy and efficiency has not yet been addressed. EfficientNetB7 is an efficient CNN model that designed with a compound scaling method, allowing easy scaling up or down of model size depending on the requirements of the task.

Parasite counting and species identification within feces constitute another crucial facet of intestinal disease detection in poultry. Scholarly efforts have yielded high-accuracy methods for this task. While biochemical methods excel in precise disease identification, their complexity limits early disease warnings. Conversely, relying solely on external feces characteristics offers valuable insights for prompt disease prevention measures. Future research should delve into various diseases' fecal characteristics across infection stages, focusing on early-stage analysis for effective disease early warning.

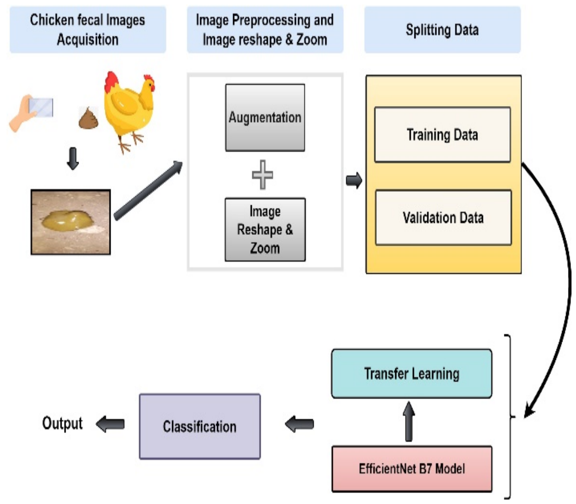


Fig. 2: Flowchart illustrating the Process of the proposed Model

3. Methodology

This research paper, introduced an approach to detect chicken diseases through a comprehensive classification process. The suggested approach uses chicken fecal image analysis of chicken excrement to precisely identify the presence of three common poultry diseases: Salmonella, Coccidiosis, and Newcastle and healthy chicken image. The proposed model encompasses a multi-faceted process, encompassing data collection, meticulous image preprocessing, strategic augmentation of dataset images, splitting the dataset into train data and validation data, the intricate training and validation of a cutting-edge image classification deep learning model, culminating in the creation of an intuitive mobile application interface. A succinct overview of our research journey is depicted in Fig. 2, encapsulating the distinct steps that were undertaken to achieve an innovative disease detection system. The process of the proposed model is described into the following stages: image acquisition, image preprocessing and augmentation, division of data into training and testing, transfer learning and classification.

3.1 Dataset

In this research a distinctive assemblage: a collection of annotated poultry fecal images that serve as the bedrock for diagnosing poultry diseases. The dataset was collected through an expansive online search, encompassing diverse languages, to identify relevant images. In this research, the dataset was taken online from zenodo.org[36]. There are four categories of fecal images used that are Salmonella claims 2276 images, while Coccidiosis holds sway over 2103 images. Marching alongside, the Healthy class contributes 2057 images, while the New Castle disease class, though the smallest contingent, valiantly contributes 376 images. A total 6,812 fecal images are labeled. The proposed model identifies three chicken diseases along with healthy chicken images. The fecalimages of three diseases and healthy chickens are shown in the Fig. 3.

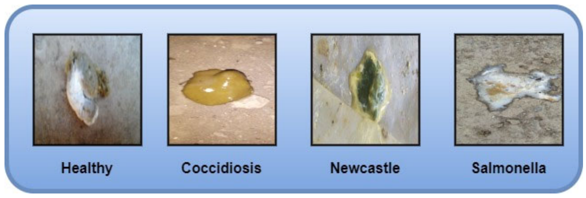


Fig. 3: Chicken Fecal Images Used in Proposed Model

3.2 Image Processing and Data Augmentation

The pre-processing was done on the fecal images to ensure uniformity and enhance features[22]. Noise in the fecal images has been reduced using a variety of filters, including mean, median, and anisotropic diffusion approaches. Image augmentation serves as a dynamic tool in the realm of training datasets, enriching them through the creation of modified image variants within the repository. The principal aim of this augmentation is to bolster the dataset's volume while subtly reshaping the images, effectively mitigating congestion during the training phase.

In image preprocessing, data augmentation is used to prevent learning irrelevant features in CNN. For augmentation of data some operations such as flipping horizontally rotation range-+20 is taken, width shift and height shifting is 0.2, and the orchestration of zoom is 0.2 has been used in this paper. The targeted input size of each image is taken 224x224 pixels as shown in Table 3.

3.3 Transfer Learning

A deep learning model must be trained from scratch using a huge number of images[21]. Through modification, retraining, and the fulfilment of a new use case, transfer learning methodologies enable the leveraging of an existing model. Traditional CNN models are typically constructed within a restricted resource budget, and if additional resources become available, then it may be scaled up for improved accuracy. EfficientNet scales up models in a straightforward yet efficient way by using a method known as compound coefficient. Compound scaling consistently applies on a given set of scaling coefficients to each dimension, rather than enlarging width at random, depth, or resolution. EfficientNetB7 is a deep learning model that has achieved better performance on image classification and recognition work. The model is frequently scaled by arbitrarily increasing the CNN[20] width, depth, or input image resolution. Even though manual modification is time-consuming and labor-intensive, this method occasionally yields poor performance. EfficientNetB0, the initial architecture, was first created, and then it was built up to produce the EfficientNet series using the compound scaling approach. There are eight EfficientNets versions, numbered EfficientNetB0 to EfficientNetB7, that are supported by this methodology. Mobile inverted bottleneck convolution (MBConv) with compression and excitation optimization is the fundamental building component of the EfficientNet architecture[17,18]. Fig. 4 shows how EfficientNetB7's network architecture is structured.

Table 3. Parameters Set for Data Augmentation

Image Size	224x224x3
Data Augmentation	Horizontal flip=True Rotation value = +20 Width shift = 0.2 Height shift =0.2 Zoom = 0.2

3.4 Performance Evaluation Matrix

The F1 score, as well as measures for accuracy, precision, and recall, were used to evaluate the models' performance. As shown in Eq. 1-4, the metrics were generated from the confusion matrix of the model using the values of TP (True Positive), TN (True Negative), FP (False Positive), and FN (False Negative).

$$Precision = \frac{TN}{(TN+FP)} \quad (1)$$

$$Accuracy = \frac{TP+TN}{(TP+TN+FN+FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

3.5 The Proposed Model

Training a deep learning model from scratch necessitates a substantial quantity of images and a

powerful processor. To mitigate this challenge, transfer learning techniques enable the adaptation of an existing model to suit a new task by adjusting and retraining it. In this research, a pre-trained EfficientNetB7 model was utilized for feature extraction. EfficientNetB7 is a convolutional neural network model that employs an effective compound scaling approach, uniformly adjusting the network's width, depth, and resolution.

This research used a pre-trained EfficientNetB7 network to extract the important features based on the transfer learning approach. When features are extracted by EfficientNetB7 then those features are passed through the batch normalization layer which is used to make faster and more stable training and then a sequence of dense layers, and dropout layers are added for classifying diseases. Dropout layers were applied to avoid overfitting in the model. While training the classifier model, an early stopping technique is applied which is also used to reduce the overfitting problem. The complete classifier model used in this research is shown Fig. 5. Salmonella, coccidiosis, new castle disease, and healthy are the four output units in the last layer that correspond to the four

health statuses of chickens. Every convolutional layer makes use of the ReLU activation function in order to remove negative bias and for final classification of diseases softmax activation functions used in last layer. The suggested model was optimized using the adamax optimizer.

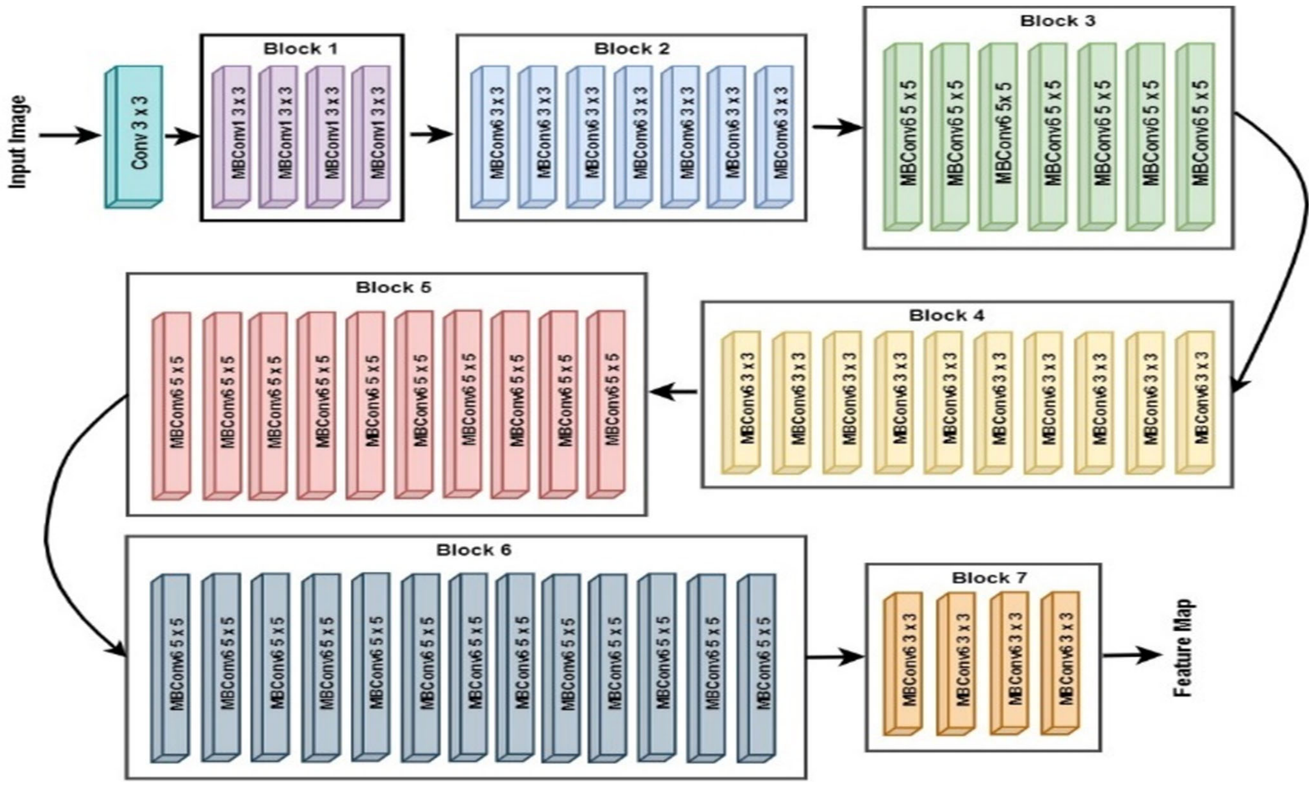
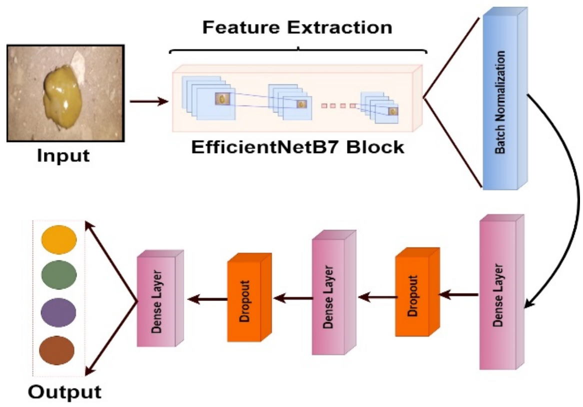


Fig. 4: Architecture of EfficientNetB7 Model



.**Fig. 5:** The Proposed Model for Chicken Disease Classification

ReLU activation function given in Eq. 5. The function returns zero if the resultant value is negative, while the function returns the same result if the resultant value is positive.

$$ReLU(x) = \max(0, x) \qquad (5)$$

Here x is the input value. In the proposed work, Adamax is utilized because it employs adaptive learning rates to expedite the training process, facilitating more efficient updates to the network weights. Adamax optimizer function presented as through the Eq.6, Eq. 7, Eq. 8, Eq. 9, Eq. 10 and Eq. 11.

$$\omega_t^i = \omega_{t-1}^i - \frac{\eta}{v_t + \epsilon} * \widehat{m}_t \qquad (6)$$

$$\widehat{m}_t = \frac{\widehat{m}_t}{1-\beta_1^t} \qquad (7)$$

$$v_t = max(\beta_2 * v_{t-1}, |G|) \qquad (8)$$

$$m_t = \beta_1 * v_{t-1} + (1 - \beta_1)G \qquad (9)$$

$$G = \nabla_\omega C(\omega_t) \qquad (10)$$

where ω_t is the weights at step t, η learning rate, m_t is running average of the gradient also called first moment, $\beta_i \mathcal{E}\, [0,1]$ is called decay factor, v_t Second moment at step t, $C(\omega_t)$ is the cost function with respect to weight at step t and G is the gradient descent.

Softmax function is generally used in the output layer. For identifying and detecting four categories of diseases by using softmax activation function in the proposed model. Softmax function presented in Eq. 11.

$$S(x_i) = \frac{e^{x_i}}{\sum_{k=1}^{K} e^{x_k}} \qquad (11)$$

where, i=1,2,3….., K, K is the number of classes and x_i is the i-th input vector, exponential function e^{x_i} for input vector, exponential function e^{x_k} for output vector.

4. Experiment and Results

The developed suggested classifier model was trained to utilize an 80/20 train-test split ratio with 200 epochs on a huge number of labelled fecal images.

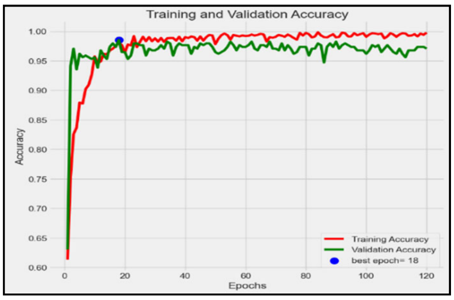
4.1 Hyperparameter Configuration

The proposed CNN model is tuned using various hyperparameter[23)] settings during training. The details of the hyperparameters employed are shown in Table 4. The early stopping technique has been implemented in this model to prevent overfitting. As a result, the model halted its learning process after 120 epochs.

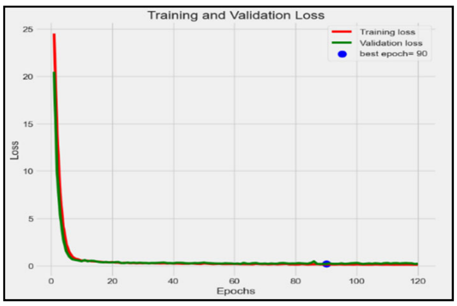
Table 4. To Train the Model Various Hyperparameter Used in the Proposed Model

Hyperparameters	Value
Epocs used	120
Learning rate	0.001
Optimizer used	Adamax
Input Size	224x224x3
Batch Size	128
Loss Function	Relu, Softmax
Loss	Categorical_crossentropy

On training data, the model's accuracy was determined to be 99.78%, while on validation data, it was 97.07%. The model's accuracy and loss history throughout training and validation are shown in Fig. 6 and Fig. 7 depicts the classifier's confusion matrix. The confusion matrix's x-axis displays the classifier's predicted value, while the y-axis displays the classifier's actual value. The diagonals show the model's actual positive count, and the expected and actual values are represented graphically.



(a)



(b)

Fig. 6: Curve for Training and Validation of Proposed Model (a) Accuracy; (b) Loss

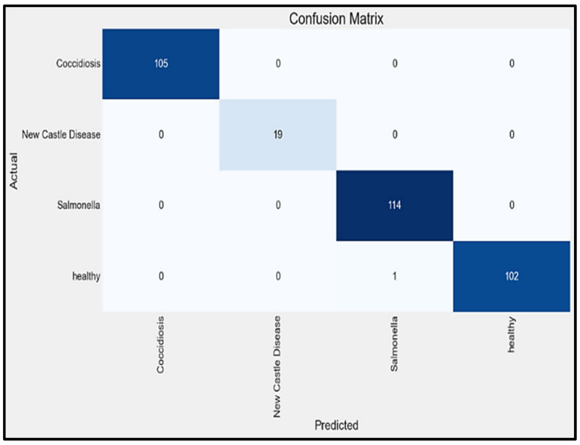


Fig. 7: Confusion Matrix of Proposed Classifier

4.2 Classification Report of Proposed Classifier

Performance evaluation testing for the deep learning model is defined by the classification report. This report serves as a showing of the accuracy, recall, F1 score, and support levels of the classification model. It aids in understanding the proposed classifier's overall performance, which is shown in Table 5.

Table 5. Classification Report for The Proposed Classifier

	Precision	Recall	F1-Score
Coccidiosis	1.0000	1.0000	1.0000
Healthy	1.0000	0.9903	0.9951
NewCastle	1.0000	1.0000	1.0000
Salmonella	0.9971	1.0000	0.9956
accuracy			0.9971

Through the evaluation of the proposed study, the proposed classifier performed admirably and successfully classified the illnesses affecting poultry. As demonstrated in Table 6, the proposed classifier performs better than previous published models.

Table 6. Results Comparison of with Previous Published Models

Reference	Model Used	Accuracy Achieved (%)
S. Sudhagar et al. [2], 2023	DenseNet 121	97%
Akbudak et al. [15], 2022	XceptionNet	88%
D. Machuve et al. [13], 2022	XceptionNet	94%
M. S. Hossain et al. [16], 2023	CNN	93.2%
M.K. Gourisaria et al.[7], 2023	ChicNetV6	94.49%
K. Srivastava et al. [14] ,2023	CNN	96.04%
Our Proposed Model, 2023	EfficientNetB7	97.07%

5. Conclusion

The proposed work created a method for categorizing chicken illnesses based on CNN. The use of deep learning approaches and datasets are two crucial elements that can improve poultry farmers' efficiency in the detection of chicken disease at early stages.

This research proposed a CNN model using transfer learning techniques, which analyses the fecal images in our dataset to uncover an invisible pattern. EfficientNetB7 achieves an improved performance on the fecal images because it is used to maintain the compound scaling in the network. Hence our proposed model predicts the four groupings as follows: Healthy chickens, Salmonella, Newcastle and Coccidiosis diseases. This new proposed model achieved 97.07% accuracy in classifying the diseases. This new suggested model recognized that diseases may be discovered early on before these diseases kill poultry chickens, and these procedures help reduce losses and increase output. The research findings indicate that our method have the potential to diagnose and detect diseases in chickens accurately, even at early stages. In the future, this research can be extended with more datasets to diagnose more diseases. Furthermore, The scope of this research could be broadened to enhance convergence rates and optimize accuracy by applying metaheuristic algorithms.

References

1) H. Mbelwa, J. Mbelwa and D. Machuve, "Deep Convolutional Neural Network for Chicken Diseases Detection" *International Journal of Advanced Computer Science and Applications (IJACSA)*,12(2), (2022) doi: 10.14569/IJACSA.2021.0120295.
2) S. Suthagar, G. Mageshkumar, M. Ayyadurai, C. Snegha, M. Sureka, and S. Velmurugan, "Faecal Image-Based Chicken Disease Classification Using Deep Learning Techniques," *Inventive Computation and Information Technologies. Lecture Notes in Networks and Systems, Springer, Singapore*, 563, (2023), doi: 10.1007/978-981-19-7402-1_64.
3) R.H. Soto, F. Feancis, M. A. Lopez, J. P. Ramiez "Implementation of Machine Learning in Supply Chain Management process for Sustainable Development by Multiple Regression Analysis Approach (MRAA)", Evergreen. 10(02), 1113-1119 (2023), doi: 10.5109/6793671.
4) M.S. Sumathi, J Shruthi, V. Jain, G.K. Kumar and Z.Z. Khan " Using Artificial Intelligence (AI) and Internet of Things (IoT) for Improving Network Security by Hybrid Cryptography Approach", Evergreen. 10(02), 1133-1139 (2023), doi: 10.5109/6793674.
5) V. Aggrawal, A. Ranjan, S. Shaurya and S.K. Garg " To Determine the Futures pricing of Metal Commodities using Deep Learning", Evergreen. 10(2), 1027-1033 (2022) doi:10.5109/6793658.
6) N. Luna, M.A. Moustafa, S. Agung and A. M.

Prasetyo, "Exploratory Study of Drone Data Stabilization with Implications in Vibration-based Structural Health Monitoring", *Evergreen.* 10(03), 1776-1783 (2023), doi: 10.5109/7151727.

7) M.K. Gourisaria, A. Arora,S. Bilgaiyan, and M. Sahni, “Chicken Disease Multiclass Classification Using Deep Learning,” *Proceedings of International Conference on Information Technology and Applications Springer, Singapore*, 614, 225–238, (2023), doi: 10.1007/978-981-19-9331-2_19

8) D. Cheng, T. Rong, and G. Cao, "Density map estimation for crowded chicken", *Image and Graphics. ICIG 2019. Lecture Notes in Computer Science (p. 11903). Springer, Cham,* 432-441, (2019), doi: 10.1007/978-3-030-34113-8_36.

9) Dief, Tarek N and Yoshida Shigeo, “System Identification for Quad-rotor Parameters Using Neural Network”, Evergreen. 3 (1), 6-11 (2016), doi.org:10.5109/1657380.

10) P. Saraswat, R. Agrawal, "Artificial Intelligence as Key Enabler for Sustainable Maintenance in the Manufacturing Industry: Scope & Challenges" *Evergreen.* 10(04), 2490-2497 (2023), doi: 10.5109/7162012.

11) Y. Yao, H. Yu, J. Mu, J. Li, and H. Pu, “Estimation of the Gender Ratio of Chickens Based on Computer Vision: Dataset and Exploration,” Entropy. 22(7), 719, (2020), doi: 10.3390/e22070719.

12) Hemalatha, S. Muruganandand, and R. Maheswaran, "Recognition of poultry disease in real-time using extreme learning machine. *in Proceedings of international Conference on inter Disciplinary Research in Engineering and Technology,* (2014). https://api.semanticscholar.org/CorpusID:49672832

13) D. Machuve, E. Nwankwo, N. Mduma, and J. Mbelwa, “Poultry diseases diagnostics models using deep learning,” *Front Artif Intell.* 5, (2022), doi: 10.3389/frai.2022.733345.

14) K. Srivastava, and P. Pandey, “Deep Learning Based Classification of Poultry Disease” Int. j. autom. smart technol. 13(1), 2439--2439(2023), doi: 10.5875/ausmt.v13i1.2439.

15) Akbudak, B. Sina and Turkey “Disease Detection from Chicken Feces on A Mobile Platform Using Deep Learning Methods”, *Young Scientist Research.* 6(1), 17-23 (2022).

16) M. S. Hossain, U. S. Salsabil, M. M. M. Syeed, M. M. Rahman, K. Fatema and M. F. Uddin, "SmartPoultry: Early Detection of Poultry Disease from Smartphone Captured Fecal Image," *JCSSE. Phitsanulok, Thailand*, 345-350(2023),doi: 10.1109/JCSSE58229.2023.10202054, doi:

17) M. Sandler, A. G. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, “Mobilenetv2: Inverted residuals and linear bottlenecks,” *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 4510–4520 (2018), doi: 10.1109/CVPR.2018.00474.

18) A. Chaoudhary and P. Verma "Road Surface Quality Detection Using Light Weight Neural Network for Visually Impaired Pedestrian", Evergreen. 10(2), pp. 706-714 (2023), doi: 0.5109/6792818.

19) A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand,M. Andreetto, and H. Adam,”Mobilenets: Efficient convolutional neural networks for mobile vision Applications”, *arXiv (Cornell University)*, (2017), doi: http://export.arxiv.org/pdf/1704.04861.

20) L. Ngeljaratan, M.A. Moustafa, A. Sumarno, A. M. Prasetyo, D. P. Sari and Maidina, "Exploratory Study of Drone Data Stabilization with Implications in Vibration-based Structural Health Monitoring", Evergreen. 10(3), 1776-1783(2023).

21) J. F. Fatriansyah, S. N. Surip, and F. Hartoyo, "Mechanical Property Prediction of Poly(Lactic Acid) Blends Using Deep Neural Network", Evergreen. 09(1), 141-144 (2022), doi: 10.5109/4774229, doi: 10.5109/4774229.

22) T. G. Patil and S.P. Shekhawat " Artificial Neural Network based Quality assessment of Guava fruit", Evergreen. 09(2), 389-395(2022) doi: 10.5109/4794164.

23) P. Ranjan, S. Yadav, H. Gupta and A. Bage " Design and Development of Machine Learning Assisted Cylindrical Dielectric Resonator Antenna", Evergreen. 10(1), 308-316 (2023). doi: 10.5109/6781085.

24) A. Sharma, H. Chawla and K. Srinivas "Prediction of Surface Roughness of Mild Steel finished with Viscoelastic Magnetic Abrasive Medium", Evergreen. 10(02), 1061-1067 (2023), doi: 10.5109/6793663.

25) H.K. Choudhary, K. Sarswat, H. Yadav, H. Puri, A. R. Mishra and S. S. Chauhan " A Real Time Dynamic Approach for Management of Vehicle Generated Traffic", Evergreen. 10(01), 289-299 (2023), doi: 10.5109/6781078.

26) C. Fang, J. Huang, K. Cuan, X. Zhuang, and T. Zhang, "Comparative study on poultry target tracking algorithms based on a deep regression network"’, Biosystems Engineering, 190, 176-183 (2020), doi: https://doi.org/10.1016/j.biosystemseng.2019.12.002

27) R.C. Meena, P. Meena, A. Meena K. Meena and S. Meena, "Sustainability and Reachability of Healthcare through Artificial Intelligence", *Evergreen.* 10(04), 2506-2511 (2023), doi: 10.5109/7162014.

28) Aziz, N. Abdul and Md. F. B. Othman, “Binary classification using SVM for sick and healthy chicken based on chicken’s excrement image.” *Semantic Scholar*.(2017), https://api.semanticscholar.org/CorpusID:69480537

29) J. Wang, M. Shen, L. Liu, Yi Xu and C. Okinda," Recognition and Classification of Broiler Droppings Based on Deep Convolutional Neural Network", *Journal of Sensors,* 2019, 1–10, (2019)

doi:10.1155/2019/3823515.

30) Y. Liu, W. R. Windham, K.C. Lawrence, and B. Park, "Simple algorithms for the classification of Visible/Near-Infrared and hyperspectral imaging spectra of chicken skins, feces, and fecal contaminated skins", *Applied Spectroscopy,* 57(12), 1609–1612, doi: 10.1366/000370203322640260.
31) J. Huang, W. Wang, T. Zhang, "Method for detecting avian influenza disease of chickens based on sound analysis" *Biosyst. Eng.,* (180), 16–24, (2019). doi: 10.1016/j.biosystemseng.2019.01.015
32) A. Aydin, and D. Berckmans, "Using sound technology to automatically detect the short-term feeding behaviours of broiler chickens", *Computers and Electronics in Agriculture*, (121), 25–31, (2016). doi: 10.1016/j.compag.2015.11.010.
33) A. Aydin, C. Bahr, S. Viazzi, V. Exadaktylos, J. Buyse, and D. Berckmans, "A novel method to automatically measure the feed intake of broiler chickens by sound technology," *Computers and Electronics in Agriculture*, (101), 17–23. (2014). doi: 10. 016/j.compag.2013.11.012.
34) A. Aydin, C. Bahr, and D. Berckmans, "A real-time monitoring tool to automatically measure the feed intakes of multiple broiler chickens by sound analysis," *Computers and Electronics in Agriculture*, (114), 1–6,(2015), doi: 10.1016/j.compag.2015.03.010.
35) Z. Xu, J.-U. Lee, J. Park, and Y. Chung, "Multidimensional analysis model for highly pathogenic avian influenza using data cube and data mining techniques," *Biosystems Engineering*, 157, 109–121, (2017). doi: 10.1016/j.biosystemseng.2017.03.004.
36) Farm-labeled dataset https://zenodo.org/record/4628934#.YtDNzOxBy1u
37) J. You, E. Lou, Md. Afrouziyeh, N. M. Zukiwsky, M. J. Zuidhof , "Using an artificial neural network to predict the probability of oviposition events of precision-fed broiler breeder hens", *Poultry Scienc*e, 100(8), 101187, (2021). doi: 10.1016/j.psj.2021.101187.
38) M. Campbell, P. Miller, K. Díaz-Chito, X. Hong, N. McLaughlin, E.Parvinzamir, J. Martínez Del Rincón and N. O'Connell, "A computer vision approach to monitor activity in commercial broiler chickens using trajectory-based clustering analysis", *Computers and Electronics in Agriculture,* 217, 108591, (2024). doi: 10.1016/j.compag.2023.108591.
39) P. He et al., "A reliable and low-cost deep learning model integrating convolutional neural network and transformer structure for fine-grained classification of chicken Eimeria species," *Poultry Science*, vol. 102(3), 102459,(2023). doi: 10.1016/j.psj.2022.102459.
40) I. Fontana, E. Tullo, A. Butterworth, and M. Guarino, "An innovative approach to predict the growth in intensive poultry farming," *Computers and Electronics in Agriculture,* (119), 178–183, (2015). doi: 10.1016/j.compag.2015.10.001.
41) I. Fontana, E. Tullo, A. Scrase, and A. Butterworth, "Vocalisation sound pattern identification in young broiler chickens," *animal*, 10(9), 1567–1574, (2015), doi: 10.1017/s1751731115001408.
42) M. Sadeghi, A. Banakar, M. Khazaee, and M. Soleimani, "An Intelligent Procedure for the Detection and Classification of Chickens Infected by Clostridium Perfringens Based on their Vocalization," *Revista Brasileira de Ciência Avícola*, 17(4), 537–544, (2015). doi: 10.1590/1516-635x1704537-544.
43) A. Banakar, Md. R. Sadeghi, and A. Shushtari, "An intelligent device for diagnosing avian diseases: Newcastle, infectious bronchitis, avian influenza," *Computers and Electronics in Agriculture,* 127, 744–753, (2016). doi: 10.1016/j.compag.2016.08.006.
44) X. Zhuang, M. Bi, J. Guo, S. Wu, and T. Zhang, "Development of an early warning algorithm to detect sick broilers," *Computers and Electronics in Agriculture*, 144, 102–113, (2018). doi: 10.1016/j.compag.2017.11.032.
45) G. A. Fraess, C. J. Bench, and K. B. Tierney, "Automated behavioural response assessment to a feeding event in two heritage chicken breeds," *Applied Animal Behaviour Science*, 179, 74–81, (2016), doi: 10.1016/j.applanim.2016.03.002.
46) F. M. Colles et al., "Monitoring chicken flock behaviour provides early warning of infection by human pathogenCampylobacter," *Proceedings of the Royal Society B: Biological Sciences*, 283(1822), 20152323, (2016), doi: 10.1098/rspb.2015.2323.
47) H. Pu, J. Lian, and M. Fan, "Automatic Recognition of Flock Behavior of Chickens with Convolutional Neural Network and Kinect Sensor," *International Journal of Pattern Recognition and Artificial Intelligence*, 32(07), 1850023, (2018), doi: 10.1142/s0218001418500234.
48) S. Amraei, S. Abdanan Mehdizadeh, and S. Salari, "Broiler weight estimation based on machine vision and artificial neural network," *British Poultry Science*, 58(2), 200–205, (2017), doi: 10.1080/00071668.2016.1259530.
49) A. Nawab, F. Ibtisham, G. Li, B. Kieser, J. Wu,W. Liu, Y. Zhao, Y. Nawab, K. Li, M. Xiao, et al., "Heat stress in poultry production: Mitigation strategies to overcome the future challenges facing the global poultry industry," *Journal of Thermal Biology*, 78, 131–139, (2018), doi: 10.1016/j.jtherbio.2018.08.010.
50) C. Okinda et al., "A machine vision system for early detection and prediction of sick birds: A broiler chicken model," *Biosystems Engineering*, 188, 229–242, (2019). doi: 10.1016/j.biosystemseng.2019.09.015.
51) K. Cuan, T. Zhang, J. Huang, C. Fang, and Y. Guan, "Detection of avian influenza-infected chickens

based on a chicken sound convolutional neural network," *Computers and Electronics in Agriculture*, 178, 105688, (2020). doi: https: 10.1016/j.compag.2020.105688.

52) C. Fang, T. Zhang, H. Zheng, J. Huang, and K. Cuan, "Pose estimation and behavior classification of broiler chickens based on deep neural networks," *Computers and Electronics in Agriculture*, 180, p. 105863,(2021). doi: 10.1016/j.compag.2020.105863.

53) A. E. Ifuchenwuwa, E. Osaghae, and F. Basaky, "Deep Learning Implementation for Poultry Disease Detection and Control," *Zenodo (CERN European Organization for Nuclear Research)*, (2023). doi: 10.5281/zenodo.8150171

54) L. Carpentier, E. Vranken, D. Berckmans, J. Paeshuyse, and T. Norton, "Development of sound-based poultry health monitoring tool for automated sneeze detection," *Computers and Electronics in Agriculture*, 162, 573–581, (2019). doi: 10.1016/j.compag.2019.05.013.

55) B. Carroll, D. E. Anderson, W. Daley, S. D. Harbert, D. F. Britton, and M. W. Jackwood, "Detecting symptoms of diseases in poultry through audio signal processing," *IEEE Global Conference on Signal and Information Processing*, (2014). doi: 10.1109/globalsip.2014.7032298.

56) K. Cuan, T. Zhang, Z. Li, J. Huang, Y. Ding, and C. Fang, "Automatic Newcastle disease detection using sound technology and deep learning method," *Computers and Electronics in Agriculture*, 194, 106740, (2022). doi: 10.1016/j.compag.2022.106740.

57) J. A. Orandi, and K. Christopher, "A computer Vision System for Early Detection of Sick Birds in a Poultry Farm Using Convolution Neural Network on Shape and Edge Information", *Thesis for: Master, University of Nairobi*, (2023) doi: 10.37839/RG.0.0.1.2023.

58) C. E. Golden, M. J. Rothrock, and A. Mishra, "Comparison between random forest and gradient boosting machine methods for predicting Listeria spp. prevalence in the environment of pastured poultry farms," *Food Research International,* 122, 47–55, (2019), doi: 10.1016/j.foodres.2019.03.062.

59) P. J. Hepworth, A. V. Nefedov, I. B. Muchnik, and K. L. Morgan, "Broiler chickens can benefit from machine learning: support vector machine analysis of observational epidemiological data," *Journal of The Royal Society Interface*, 9(73), 1934–1942, (2012). doi: 10.1098/rsif.2011.0852.

60) J. Huang, W. Wang, and T. Zhang, "Method for detecting avian influenza disease of chickens based on sound analysis," *Biosystems Engineering,* 180, 16–24, (2019). doi: 10.1016/j.biosystemseng.2019.01.015.

61) D. Hwang, M. J. Rothrock, H. Pang, M. Guo, and A. Mishra, "Predicting Salmonella prevalence associated with meteorological factors in pastured poultry farms in southeastern United States," *Science of The Total Environment*, 713, 136359, (2020). doi: 10.1016/j.scitotenv.2019.136359.

62) A. Mahdavian, S. Minaei, P. M. Marchetto, F. Almasganj, S. Rahimi, and C. Yang, "Acoustic features of vocalization signal in poultry health monitoring," *Applied Acoustics*, 175,107756, (2021). doi: 10.1016/j.apacoust.2020.107756.

63) X. Qiang and Z. Kou, "Predicting interspecies transmission of avian influenza virus based on wavelet packet decomposition," *Computational Biology and Chemistry*, 78, 455–459, (2019). doi: 10.1016/j.compbiolchem.2018.11.029.

64) A. A. G. Raj and J. G. Jayanthi, "IoT-based real-time poultry monitoring and health status identification," *2018 11th IEEE International Symposium on Mechatronics and its Applications (ISMA),* 1-7, (2018). doi: 10.1109/isma.2018.8330139.

65) Mohd, Pin Jern Ker, Shirley, Mohd Zafri Baharuddin, Hui Jing Lee, and Abdul Rahman Omar, "Translating conventional wisdom on chicken comb color into automated monitoring of disease-infected chicken using chromaticity-based machine learning models," *Frontiers in Veterinary Science*, 10, (2023). doi: 10.3389/fvets.2023.1174700.

66) T. Fang, "Rapid diagnosis of infectious bursal disease with RNA microarray and machine learning", *International Conference of Bioinformatics and Computational Biology* , 67–73, (2019).

67) A. G. R. Alex and G. J. Joseph, "Real-Time Poultry Health Identification Using IoT Test Setup, Optimization and Results," *Communications in Computer and Information Science*, 30–40, (2019). doi: 10.1007/978-981-13-5758-9_3.

68) M. Rizwan, B. Caroll, D. Anderson, W. Daley, S. Harbert, D. Britton, M. Jackwood, "Identifying rale sounds in chickens using audio signals for early disease detection in poultry," *2016 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, 55-59,(2016). doi: 10.1109/GlobalSIP.2016.7905802.

69) M. Z. Degu and G. L. Simegn, "Smartphone based detection and classification of poultry diseases from chicken fecal images using deep learning techniques," *Smart Agricultural Technology*, 4, 100221, (2023). doi: 10.1016/j.atech.2023.100221.

70) X. Zhuang and T. Zhang, "Detection of sick broilers by digital image processing and deep learning," *Biosystems Engineering*, 179, 106–116, (2019), doi: 10.1016/j.biosystemseng.2019.01.003.

71) Y. Guo, S. E. Aggrey, P. Wang, A. Oladeinde, and L. Chai, "Monitoring Behaviors of Broiler Chickens at Different Ages with Deep Learning," *Animals*, 12(23), 3390–3390, (2022). doi: 10.3390/ani12233390.

72) M. Zhou, J. Zhu, Z. Cui, H. Wang, and X. Sun, "Detection of abnormal chicken droppings based on improved Faster R-CNN," *International Journal of*

Agricultural and Biological Engineering, 16(1), 243–249, (2023). doi: 10.25165/j.ijabe.20231601.7732.
73) X. Yang, L. Chai, R. B. Bist, S. Subedi, and Z. Wu, "A Deep Learning Model for Detecting Cage-Free Hens on the Litter Floor," *Animals*, 12(15), 1983, (2022). doi: 10.3390/ani12151983.
74) S. Neethirajan, "ChickTrack – A quantitative tracking tool for measuring chicken activity," *Measurement*, 191, 110819, (2022), doi: 10.1016/j.measurement.2022.110819.
75) A. Nasiri, J. Yoder, Y. Zhao, S. Hawkins, M. Prado, and H. Gan, "Pose estimation-based lameness recognition in broiler using CNN-LSTM network," *Computers and Electronics in Agriculture*, 197, 106931, (2022). doi: 10.1016/j.compag.2022.106931.