DISEASE DETECTION FROM CHICKEN FECES ON A MOBILE PLATFORM USING DEEP LEARNING METHODS

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ABSTRACT

The demand for poultry, which has been an important economic activity for humanity for thousands of years, is increasing due to many reasons . One of the most important factors that negatively affect poultry farming is pathogenic animal diseases. The detection of diseases in poultry is usually done through laboratory tests, the disease progresses and causes mortality in the time required for laboratory examinations. In this study, a mobile application was developed to minimize the mentioned problems and to enable poultry producers to obtain fast and reliable information about diseases that occur in their animals.

Keywords : *Chicken diseases, Deep learning, Mobile application.*

1. Introduction

In this study, a mobile application was developed to minimize the mentioned problems and to enable poultry producers to obtain fast and reliable information about diseases that occur in their animals. To be used in this mobile application, a deep learning model has been developed that can distinguish pseudo-plague (Newcastle strain), salmonella, and coccidiosis diseases in chicken feces through the data collected by processing the photographs taken from the feces of chickens with the help of tools such as artificial intelligence, machine learning, and image processing, which are widely used today. To train the deep learning model used, a dataset of 6812 photos consisting of chicken droppings was prepared for training deep learning models and models previously used for various purposes were trained through transfer learning. After the training, the models were evaluated comparatively and the model with the highest accuracy and efficiency ratio was selected for use in the mobile application. In addition, a panel has been developed in which users can get information about possible diseases that may be found in their chickens as a result of answering questions about the symptoms that can be observed in their chickens.

Poultry farming, which has been shown as one of the main economic activities of humanity for thousands of years, gains importance every year due to the advantages it provides for producers and consumers, and as a rapidly growing economic sector on a global scale, it is closely related to a large part of the world's population. Poultry farming, which stands out as an economic activity with a high-profit margin due to the competitive advantage that can be achieved even at local scales due to the low opportunity cost for the producers, is also frequently preferred by consumers due to its high nutritional value and relatively more economical conditions. Considering these reasons, it is seen that the demand for poultry farming is already increasing at exponential levels all over the world, and it is predicted that this trend will gradually accelerate in the future as well. So much so that since 1995, the demand for chicken meat in the world has doubled every 10 years; the egg and other poultry products market has achieved a growth of around one hundred and fifty percent on a global scale [2]. At the same time, the waste and other by-products generated after production are rich in elements such as nitrogen, phosphorus, calcium, and potassium that are necessary for soil quality and will increase product yield, a chicken produces 5 kilograms of waste that can be used as fertilizer annually, chemical agents rapidly pollute the currently limited resources. and due to reasons such as commercial fertilizers do not produce sustainable solutions for ecological balance, the poultry farming sector; gains a position that directly or indirectly affects the basic economic activities in many countries. In particular, the use of chicken manure in agricultural activities is expanding in Asia Minor and many African countries such as Pakistan, and Iran, where access to chemical fertilizers and reinforcing agents is limited [3].

As a sector that affects the entire food web in the ecosystem, poultry farming, like all other livestock sectors, is critically adversely affected by emerging animal diseases. As in many countries of the world, these diseases are viewed as the most important obstacle to sectoral development and competitiveness for Turkey. Although the breeders in Turkey do not have difficulty in reaching a certain quality in the final products to be exported, they lose their potential export opportunities due to widespread zoonosis and animal diseases and there are economic losses that will deeply affect the sector [1]. In addition, poultry diseases transmitted to other foods and water sources through agricultural processes in which the wastes produced by chickens are used as fertilizer pose a high danger to public health, especially to the people living in rural areas. Considering that poultry farming is in a more complex relationship with other economic activities, especially in developing countries where access to health services and protective measures is relatively inadequate, it is seen that this situation constitutes a major deficiency in terms of preventing epidemics that are currently on the agenda of the whole world. So much so that typhoid fever, which is a common chicken disease and a disease caused by Salmonella bacteria, has lost its power in countries such as the USA, Denmark, and Turkey, where the sanitary infrastructure has developed since the 2000s, but only in the border regions of Pakistan and Iran in 2017-2018. It has caused the death of hundreds of people by developing new mutations with a high mortality rate and antibiotic resistance even within the range [4].

In addition to diseases caused by bacteria, viral infections transmitted from poultry to humans also cause major problems both locally and globally. Avian Influenza, which is known as "bird flu" among people, has deeply affected many countries, including Turkey, in the 2000s. In addition to new viruses such as H7N9, which are currently circulating in countries such as China, Vietnam, and Thailand and can be transmitted from person to person [5], studies conducted in Western and Sub-Saharan Africa regions draw attention to a new H5N1 danger [6]. Considering the incurable viruses such as HIV, which can transmit from other vertebrates to humans through mutations, and SARS-CoV-2, which has been affecting the whole world for more than 2 years, biosecurity is of high importance today, and solutions that can detect pathogenic diseases of poultry origin at the earliest and the lowest cost are considered. It is seen that the need is increasing day by day. Considering the damage caused by many poultry diseases to the intestinal and digestive tracts, it is thought that chicken droppings may be a good indicator for the most common poultry diseases such as coccidiosis (coccidiosis), pseudo-plague (Newcastle strain) and Salmonella-related diseases.

Coccidiosis, which is a deadly disease seen in many vertebrates due to protozoa of the Eimeria genus, adversely affects the intestinal tract of the infected creature and causes problems such as tissue damage, diarrhea, decreased resistance to other diseases, and in some cases death [7]. Coccidiosis disease causes great harm to the poultry industry, considering the negative effects on animals that die due to the disease and producers who come into contact with live, feces, and other wastes. So much so that, according to 2016 data, coccidiosis caused a loss of over £100 million in the UK alone; It has been found to cause damage to the poultry farming industry in developing countries such as Brazil, Egypt, Guatemala, India, and Nigeria at a level of over £10 billion that could be classified as devastating [8].

Although drugs and vaccines have been developed for the prevention and early diagnosis of coccidiosis disease, due to the high cost of drugs and the logistical barriers to establishing the necessary infrastructure for widespread vaccination in developing countries, they could not be easily made available to poultry producers, prompting the producers to seek more natural, economical and effective solutions. [9].

Newcastle strain (false plague), another common poultry disease in the world, is reported as a deadly and contagious disease affecting many domestic and wild animal species. The only known diagnostic method for the diagnosis of this disease, which is seen in Asia, Africa, and parts of North and South America, is high-cost and long-term laboratory tests. Many producers do not seek medical help except in very urgent cases due to the high cost, even though symptoms are observed and the disease is suspected, and this situation endangers public health as well as causes financial damage. Another dangerous situation related to pseudo-plague is that it is a disease with a high ability to cross-transmission between species. For this reason, vaccine makers and laboratory workers are the most affected by the Newcastle strain, which can infect bird species as well as spread among humans, and resistant mutations that are more difficult to treat can be seen. [10]

Salmonella-based diseases have been followed as an international public health threat since the 2000s, as a disease with high mortality. According to 2015 data, Salmonella bacteria, which causes 93.8 million food-borne diseases and 155,000 annual deaths [11], continues to be effective in many countries, especially in African countries, East Asia, and Asia Minor, although it has lost its effect in countries such as Turkey and European countries [12]. Salmonella Enterica, one of more than 2000 different serotypes, tends to cause systemic diseases in humans. Although progress has been made in the fight against Salmonella with today's technology, the immunity of pathogens against the substances used and the fact that it is a pathogen that can be transmitted to humans through food makes a full-scale control in poultry difficult without effective early diagnosis methods [13]. This situation causes great economic damage to the chicken farming sector.

As one of the biggest common points of poultry diseases, which are pregnant with such great economic problems and cause harm to the ecological balance, changes in the appearance of chicken droppings can be shown due to the effects of diseases on the digestive system [14]. In particular, detecting the apparent differences in stools with the help of computer vision algorithms, which have recently played a role in the detection of many diseases and problems, will be able to eliminate the logistical impossibilities and cost problems, which are one of the most fundamental problems in the diagnosis of diseases. Today, computer vision technologies are used in quite different fields such as health [15], agriculture [16], and livestock [17]; It is used for purposes such as image classification, image recognition, and image segmentation. To perform the image classification process used in this study, firstly, the images to be classified are named with appropriate classes, and a data set is created. Then, a deep learning model, which is thought to be suitable, is trained with this data set and a model trained on that data set is obtained. This model is tested by using the test set separated from the data set before the training process and the accuracy of the model is obtained. For example, the working group led by Ranjbarzadeh [18] developed a deep learning model that can segment brain tumor images with an accuracy of 92%, and Konstantinos P. Ferentinos [19] identified 58 different plant diseases with an accuracy of 99.53%. has developed a deep-learning model that can diagnose.

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2. Method

Deep learning algorithms, which are a sub-field of machine learning algorithms, can reach very high accuracy rates in areas of use such as classification, object detection, and segmentation in computer vision. Deep learning algorithms, which use artificial neural networks created by imitating the cognitive process of humans, are widely used in the construction of autonomous vehicles, the development of chatbots, and image processing. Although artificial intelligence networks used in deep learning have a convolutional neural network (CNN), generative contentious network (GAN), recursive neural network (RNN), and similar network structures, each is used by researchers in line with different requirements. In this study, we have used the CNN structure, which enables deep learning to transform images into digital matrices.

In line with the aforementioned purposes, (i) a suitable development environment has been established in the computer environment, (ii) operations have been made on the dataset, (iii) appropriate deep learning models have been trained, and (iv) a mobile application has been developed to ensure that the work done is accessible to all segments.

A. Creating the Development Environment

One of the issues that the researcher should decide before starting any artificial intelligence study is to choose the artificial intelligence software framework to be used. Tensorflow and PyTorch are the most popular artificial intelligence and deep learning frameworks used worldwide today. The Keras API, which works on these software frameworks and facilitates their use, is widely used in today's deep learning research. In this research, it was decided to work with the TensorFlow software framework using the Python software language, due to a large number of users in the world and the rapid application development. After the software framework has been determined, it has been deemed appropriate to work with the Conda package manager to use different versions of the libraries at the same time, to make experiments, and to provide environmental management easily.

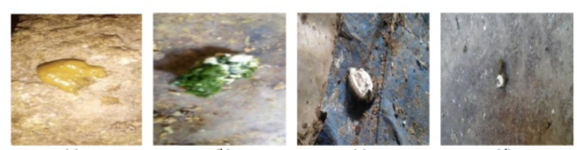
In the first stage, artificial neural networks were run on the CPU to make the experiments, but with the growth of the data set, the use of GPU, which is hardware that can run more than one process in parallel, was needed. For this, the first artificial intelligence models were created with the NVIDIA GTX 1650Ti GPU, and GPU acceleration processes were configured using the NVIDIA CUDA Toolkit. Due to the growth of the network architectures used in artificial intelligence models to reach higher accuracy values and the limited video memory (VRAM) of the GPU used accordingly, the Google Colaboratory, which is offered to researchers free of charge, has been switched to the Colab platform. The Colab notebook, which is accessed through the browser, allows the codes written using the Python programming language to run in the cells it contains. Colab offers access to GPUs in servers located in data centers for free with no extra configuration required for use in machine learning. In this study, it has been actively used and the power of the hardware in the data centers has been used in training artificial intelligence models.

B. Applied Operations on the Dataset

The dataset contains a total of 6812 photographs, of which 2057 are healthy, 2103 are coccidiosis, 376 are Newcastle strains, and 2276 are salmonella disease. Some of these photos were collected by us using the ODK (Open Data Kit) mobile application. ODK is a mobile application that allows quick tagging of photos taken while taking a photo. Data were collected and labeled under the supervision of a veterinarian from a small poultry farm (Fig.1).

Fig. 1: Data Collection and Labeling Using ODK Application

The photos in the dataset are of different resolutions because they were taken by different mobile phone cameras. However, the requirement that all photos fed to the artificial intelligence model must be of the same resolution (for example, 299 pixels x 299 pixels) necessitated the application of intelligent cropping and resizing to each photograph. While doing this, attention was paid to the aspect-width ratio and the value of the data was tried to be preserved as much as possible. Examples of data are shown in Figure (2).



(a) (b) (c) (d)

Fig.2: Examples of Data (a) Coccidiosis (b) Newcastle Strain (c) Healthy (d) Salmonella

The data duplication method, which is another of the preprocessing methods applied to the data set, was used both to increase the number of high-quality data to be fed to the model and to avoid the problem of data imbalance between classes, which is one of the factors affecting the performance of the model.

Table 1: Duplication Operation on Dataset

Classes	Number of Data Before Duplication	Number of Data After Duplication
Healthy	2057	4114
Coccidiosis	2103	4206
Newcastle Strain	376	2256
Salmonella	2276	4552
Total	6812	15128

In the data duplication process, techniques such as random enlargement, vertical or horizontal rotation of the photo, random amount of zoom in/out, and a random amount of clockwise/counterclockwise rotation were applied to each photo, and the number of photos in the dataset increased to 15128. However, more replication was performed in Newcastle Strain disease, which has fewer data than other diseases and causes an imbalance between classes, compared to other classes. Since it would cause poor quality of data in the Newcastle strain class, which reached almost half the number of other classes, no further replication was performed and the imbalance problem between classes, which was the first step towards a solution after preprocessing, was solved during the training phase of the model. The results of this duplication process are shown in Table 1. At the same time, examples of photographs formed after duplication are shown in Figure (3).

(a) (b)

Fig.3: Salmonella Class Data Before (a) and (b) After Replication Process

After duplication, the dataset was divided into 3 parts (80%-10%-10%) for (i) training, (ii) testing, and (iii) validation of the model. The results of this separation process are shown in Table(2).

Table 2: Segmentation of the Dataset into Training-Test-Validation Parts

Classes	Training	Test	Validation
Healthy	3291	411	411
Coccidiosis	3365	421	421
Newcastle Strain	1804	226	226
Salmonella	3642	455	455
Total	10899	1363	1363

C. Training the Deep Learning Models

To feed the data set to the network, which is the first stage of training deep learning models, a software pipeline should be established. The tf.data module in TensorFlow has been preferred to be used for importing the data set due to its high speed and easy application. In other data input generation modules, while the artificial neural networks wait for the data to be processed first and then enter the network, the tf.data data processing module divides the data set into data stacks and queues them in the RAM region, and feeds the incoming data stacks to the network. This module, which is 38 times faster than other data entry creation modules, benefits from the advantages of parallel processing.

After the data set is transferred to the program, before the data set is divided into training and test parts, the problem of imbalance between classes still needs to be resolved in the results obtained by preprocessing. To overcome this problem, it was decided to use the class weights method. The class weights method ensures that certain weights are assigned to each class during the training of the model and that classes with a small number of data in the back-propagation process affect the model more, thus preventing the accuracy rate decreases, which are caused by the unequal distribution of the classes in the data set and especially affecting the F1-score.

Research has been carried out on which network architecture can be used by the artificial intelligence models that will be created when the data set is ready to be fed to artificial neural networks as a training and test set after the preprocessing processes. The performance levels of network architectures achieved in previous studies were examined and studies were started to create models from prominent architectures. While some of the most advanced architectures are readily available within the Keras API, the architectures used to make the first trials were built manually from scratch using object-oriented programming techniques, again over the Keras API. Some of the readily available architectures can be seen in Table 4. The first 1 accuracy rate and top 5 accuracy rate columns are the performance data obtained by testing the model trained using the specified architecture on the ImageNet dataset. Depth refers to how many layers the network has topologically, such as the activation layer, the batch normalization layer, the pooling layer, and similar layers.

Table 3: Data on Different Deep Learning Models

Model	Size (MB)	Top 1 Accuracy Rate	Top 5 Accuracy Rate	Number of Parameters	Depth
Xception	88	0.790	0.945	22,910,480	126
VGG16	528	0.713	0.901	138,357,544	23
VGG19	549	0.713	0.900	143,667,240	26
ResNet152	232	0.766	0.931	60,419,944	-
InceptionV3	92	0.779	0.937	23,851,784	159
MobileNet	16	0.704	0.895	4,253,864	88
MobileNetV2	14	0.713	0.901	3,538,984	88
DenseNet201	80	0.773	0.936	20,242,984	201

Our work in this research started with Mini VGGNet, which uses fewer resources and has lower complexity than advanced architectures. MiniVGGNet;It is an architectural structure inspired by the VGGNet [23]architectural family, with much less complexity than the architectures in the VGGNet architecture family. As the studies progressed, it was decided to increase the complexity of the architecture to increase the accuracy of the model on the data set and to reach a model structure that can generalize real-world scenarios. At the end of the study, considering the mobile application to be developed, Xception[24], which is very popular today, VGG16 from the VGG architecture family, MobileNetV2[25], and Resnet 50[26] optimized for mobile, each model has been started to be trained to compare each model.

The VGGNet architecture, which won the 2014 ImageNet competition, outperformed its predecessors by using a 3x3 Convolution Filter consisting of 16 or 19 layers. Developed by François Chollet, the designer of the Keras deep learning library, Xception is inspired by the Inception architecture. While standard convolutional layers perform spatial computation in one step, depth-wise separable convolution divides the computation into two steps. Developed by Mark Sandler and his colleagues in 2019, MobileNetV2 outperformed many of its predecessors produced for mobile use, taking the state of the art one step further using existing popular datasets. The Resnet architecture, developed by Kaiming He and his colleagues, which won the ImageNet competition in 2015, has been designed to have much less complexity, although it uses 8 times more layers than the VGGNet architecture family.

Transfer learning, another method used with the architectures mentioned above, is a method developed to take the features learned in a problem and use them on a new problem. In this study, previously learned features of different classes were transferred to the models developed by the transfer learning method by using the models created on the ImageNet data set.

Hyperparameters are various parameters that are adjusted according to certain rules and trial-and-error methods when training deep learning models.

Table 4: Hyper Parameters Used in Training the Deep Learning Model

Parameters	Value
Learning Rate	0.0001
Epoch Number	20
Batch size	32
Optimization Algorithm	SGD

The explanations of the parameters mentioned in Table 4 are given below:

(i) Learning Rate: This parameter determines how much the weights of the model will change depending on the margin of error.

(ii) Epoch Number: This parameter determines how many times a data batch (batch) will be learned by the model.

(iii) Batch size: This parameter determines how much data will be learned by the model in each round.

(iv) Optimization Algorithm: This parameter determines which optimization algorithm will be used during the training of the model. Among the most used optimization algorithms, SGD (Stochastic Gradient Descent)[27], Adam[28], and Adagrad [29] can be given.

The sample hyperparameters used for this research took their final form as shown in Table 4 after various attempts were made to train the models. Finally, the training of the models was carried out using the GPU in the Colab notebook.

Table 5: Data on Training Different Deep Learning Models on the Created Dataset

Models	Training Accuracy	Validation Accuracy	F1 Score
Xception	0.93	0.88	0.91
VGG16	0.76	0.72	0.7
MobileNetV2	0.85	0.83	0.82
Resnet 50	0.74	0.66	0.69

The statistical evaluations (Table 5) obtained after the models were trained were compared. Even if the Xception network structure has reached the highest accuracy rate, since the model will work on the mobile device, the MobileNetV2 network structure, which is a more optimized model for working on the mobile device, has been preferred.

D. Mobile Application Development

It has been decided to develop a mobile application so that everyone can benefit from the artificial intelligence models obtained as a result of the studies. Necessary optimizations have been made to enable the artificial intelligence model to work on mobile so that every person with an Android smartphone can analyze whether there is a disease in their chicken.

Flutter is used for the development of the mobile application of this project; It is an open-source UI software development kit created by Google. It uses the Dart programming language created by Google for mobile and web development purposes. Among the reasons for deciding to use the Flutter mobile development kit in this project are Flutter's open-source code, its speed compared to its peers, its ability to easily design impressive interfaces, and its detailed and explanatory documentation. After the decision to use the Flutter mobile development kit, the Flutter development environment was established and the general design of the mobile application was made. Using the TensorFlowLite library, which was developed to use the trained deep learning models in the mobile application, the deep learning model with the best results was optimized and made ready for use in the mobile application.

With the increase in information and data, different methods were needed to store data. One of these methods is databases. Databases work according to the principle of putting the data that wants to be stored in the appropriate row and column under a table. In this study, a database that can only be used for reading (no data transfer from the application to the database), does not need any network connection, and can run on a local device is needed. The necessary literature review was made and it was seen that the SQLite database met the desired features so it was decided to use the SQLite database in the mobile application. Using SQL (Structured Query Language) language, SQLite is an open-source SQL database engine that can be used in many different languages and does not need an external server, that is, can run on a local device. In this study, the SQLite database was used to store information about diagnosed diseases. In this way, diseases added to the database in the future, and their explanations will be able to be used without any changes in the code of the mobile application.

Users who open the mobile application encounter the first page called the "Home Page", where the diagnosis of diseases can be made as "Diagnostics by Photo" or "Diagnostics with Questions" (Figure 4(a)). When the user clicks the "Diagnose with Photograph" button, on the page titled "Diagnose with Photograph" (Figure 4(b)), the user is expected to enter a photo via gallery or camera. The result obtained by processing the input given to the system by the deep learning model is “Click here for information about the disease.” On the page titled “Information Page” (Figure 4(c)), which can be accessed with the help of the button, the name of the disease, the symptoms of the disease, the actions to be taken against the disease, and general information about the disease are examined under 4 headings.

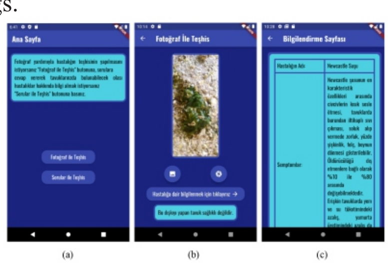
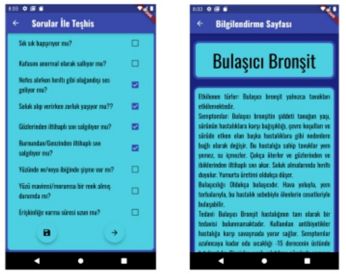


Fig. 4: Screenshots of Mobile Application While Working on Android Virtual Device (a) Home Page, (b) Diagnosis by Photo, (c) Part of Information Page



(a) (b)

Fig. 5: (a) Diagnosis with Questions, (b) Part of the Information Sheet

When the user clicks on the "Diagnostic with Questions" button on the page titled "Home Page", he will be greeted with the questions directed to him on a page titled "Diagnostic with Questions" (Fig. 5a). After giving the necessary answers to the questions, they should record their answers. After clicking on the Save button and clicking on the button to go to the next page, the page titled "Information Page" (Fig. 5b), you will see information about possible diseases/diseases that can be seen in your chickens.

3. Results

After obtaining the necessary data and performing "duplication" and clipping operations on the data, a data set that can be used for training the models was obtained (Table 1). Then, the obtained dataset was divided into 3 parts training-test-verification (Table 2). The models were trained with the parameters specified in Table 3 on the created dataset. Although XceptionNet performed better among the deep learning models that were trained, the MobileNetV2 model, which can work more optimized in the mobile application, was found suitable for the use of the mobile application to be developed (Table 5) and it was made ready to be integrated into the mobile application with the help of the TensorflowLite library. Then, two panels of the mobile application, "Diagnostic by Photo" and "Diagnose with Questions" were developed. After the integration of the database and deep learning model into these panels, the user-friendly interface of the mobile application was improved and the mobile application became ready.

4. Conclusion and Discussion

When the accuracy rates obtained from the trained models were examined, it was seen that the 82% accuracy rate obtained for disease detection from the feces of chickens was suitable for use in the mobile application, and the MobileNetV2 model, which will work in the most optimized way in the mobile application, was integrated into the mobile application after the necessary preparations. Then, the "Diagnostics with Questions" panel of the mobile application was developed, and a connection was established with the database of the mobile application to display information to the user in line with the received data.

5. Suggestions

While doing this study, it was considered that the dataset and database could be expanded with different diseases in the following stages, and the structures created were established to serve this purpose. Therefore, by training different deep learning model structures through the new dataset obtained by expanding the dataset, a higher accuracy rate than the models obtained in this study can be obtained and the newly trained model can be used in the developed mobile application. In addition, the number of questions in the "Diagnosis with Questions" panel of the mobile application can be increased and the database containing data on diseases can be expanded by adding new diseases.

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