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USING DEEP LEARNING MODELS TO DETECT PARASITES EARLY

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ABSTRACT

In today's engineering applications, applications that think and behave like humans are emphasized. The naming used for the human phenomenon to take place in engineering applications is known as machine learning. Machine learning is used in many areas such as increasing speed and quality, security applications, classification, medical diagnosis and diagnostic applications, and predictive approaches for the future.

Convolutional neural networks (CNN) are known as multilayer neural networks. Important studies have been carried out with this neural network system and successful results have been obtained. With convolutional neural networks, significant works have been carried out in many areas such as signal processing, video analysis, image analysis and detection, classification, medical image processing. While using this neural network, some steps are performed. These are defined as pre-processing, feature extraction and classification-detection. At each stage, special approaches are exhibited and studies are carried out to increase accuracy.

Intestinal parasitic infections have been recognized as the most important cause of diseases by the World Health Organization (WHO). Early diagnosis of these diseases is very important after the rapid spread of intestinal parasites. Today, machine learning approaches are used in the early detection of diseases because they provide faster results and less cost.

In this study, VGG16, ResNet50, and Inception-V3 network architectures were selected for the classification of microscopic images of intestinal parasite infections, capillaria philippinensis (roundworm), and enterobius vermiculari (pinworm). Data enlargement, normalization, and resizing of image data, which are pre-processing techniques, were applied to the data set. After data pre-processing, classification was made with VGG16, ResNet50, and Inception-V3 networks, respectively. As a result of the experimental studies, it was seen that the VGG16 network achieved the highest success rate with 98.07% Train Accuracy and Test Accuracy.

Keywords: *Deep learning, Neural networks, Classification*

INTRODUCTION

With deep learning studies, many approaches that will directly affect human health have been put forward. Many findings that are important for human health are used in many processes such as classification, detection, image segmentation, and image production. These processes are mostly done on nervous systems, lungs, eyes, pathological images, cells, chest, heart, abdomen and muscle systems.

With the development of deep learning systems, governments, companies, institutions have shown a great tendency to this issue for R&D; and many large IT companies have made great strides in this regard and have developed new approaches. Google, Microsoft, IBM, Apple, Nvidia, Facebook, Twitter, Amazon and many more IT companies have done important work on deep learning.

Looking at the studies, it is seen that deep learning architectures bring a new approach to artificial intelligence technologies and break new ground. It is seen that deep learning architectures have started to take place in our lives very effectively in order to facilitate human life and to lead a healthy life.

Parasitic infections have been recognized as the most important cause of diseases by the WHO (World Health Organization). Intestinal parasites are one of the leading diseases in developing societies. It is an important problem affecting the whole world, especially in societies where education, living standards, and hygiene are low, and it affects approximately 4 billion people (Babür et al., 2002: 286-291). The only known host of Enterobius Vermiculari (pinworm) parasites, one of the most common species, is humans and approximately 209 million people are infected worldwide (Goldmann et al., 1997:1519).

Approximately 415,000 human deaths are reported each year due to parasite outbreaks (Holmstron et al., 2017: 49).

Early diagnosis and intervention of these diseases after the spread of intestinal parasites is very important. Today, the detection of parasitic diseases is done by examining stool samples in laboratories with limited capacity. However, the examination of parasite eggs with a microscope may take 8-10 minutes by a specialist technician (Holmstron et al., 2017: 49). In the event of a possible epidemic, examining thousands of human feces and classifying them according to the type of parasite will cause a very long time and cost. Therefore, creating an automatic diagnostic system will be an important addition to assist traditional methods. With deep learning, it is aimed to detect and classify these diseases faster.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

When the literature is examined, it has been observed that studies on the detection and classification of human diseases with deep learning methods have increased recently.

Qali and his friends (2020), used the application of thermal image processing for the diagnosis of knee osteoarthritis. The study, it is aimed to diagnose osteoarthritis disorders early using the CNN (Convolutional Neural Networks) method of thermal images taken from different people. The accuracy rate of working with the CNN method was 73%.

Yalçın and his friends (2019) used CNN (Convolutional Neural Networks), which is one of the deep learning approaches, for the early detection of diabetic retinopathy from retinal images. They achieved a success rate of 98.5%.

Farooq and his friends. (2017) performed a classification study for Alzheimer's disease on a dataset with four different classes. Pre-trained GoogleNet, ResNet-18, and ResNet-152 networks were used for classification, in terms of transfer learning, and the best accuracy value was obtained in the GoogleNet network with a value of 98.88%. Considering the other results of the study, 98.01% success was achieved with ResNet-18 and 98.14% with ResNet-152.

No study has been found in the Turkish index on the diagnosis of intestinal parasitic diseases using deep learning methods. On the other hand, foreign sources; Suwannaphong and his friends (2021) classified Ascaris lumbricoides, Hymenolopis diminuta, Taenia spp., and Fasciolopsis buski parasite species with deep learning networks. They achieved 96.93% accuracy with the AlexNet network and 98.25% with the ResNet.

Machaca and his friends (2020) studied an 8-class dataset of 954 images. Data augmentation with preprocessing has been applied to the dataset. Then, classification was made with different deep learning networks. The most successful result was 99.2% with the ResNet50 model.

Oliveria and his friends (2022) examined schistoma mansoni eggs consisting of 66 images using fast R-CNN for egg detection in microscopy images prepared with the Kato-Katz technique and obtained a precision value of 76.5%.

Unlike other studies in the literature, this study examined the classes of capillaria philippinensis and enterobius vermiculari, which are the most important intestinal parasite infections, with VGG16, ResNet50, and InceptionV3 networks, which are deep learning architectures. To obtain better results, data preprocessing was applied to the data set.

This study aims to classify the intestinal parasites Capillaria philippinensis (roundworm) and enterobius vermiculari (pinworm) classes, which are one of the important problems of developing societies, with a dataset consisting of 1500 images and VGG16, ResNet50, and InceptionV3 networks, which are deep learning methods; and to help experts in the detection of intestinal parasites by making their comparative analysis and determining the best method.

RESEARCH METHOD

Material

In the material section, the data set used in the research is mentioned. The dataset "Parasitic egg detection and classification in microscopic images" is taken from ieee-dataport.org. (https://ieee-dataport.org/competitions/parasitic-egg-detection-and-classification-microscopic-images#files). The dataset images used in the study were collected by the University of Chulalongkorn and the University of Bristol. These classes consist of images of 11 different types of parasites seen in the intestines. These images are respectively ascaris lumbricoides, capillaria philippinensis, enterobius vermicularis, fasciolopsis buski, hookworm egg, hymenolepis diminuta, hymenolepis nana, opisthorchis viverrine, paragonimus spp, taenia spp. Egg and Trichuris trichiura species. There are 1000 images of 11 classes in the dataset.

In this study, capillaria philippinensis and enterobius vermiculari classes, which are intestinal parasite species, were used. To get healthier results from the model, data preprocessing was applied to the data set and some images in these classes were removed from the data set. Then, since the number of data belonging to two classes became insufficient, the number of images was adjusted to 750 by applying data enlargement to the data set.

Methods

Data Preprocessing

In data mining, data preprocessing should be done for reliable results and correct output (Oğuzlar, 2003:70). Two classes, capillaria philippinensis, and enterobius vermiculari were selected from the images of 11 classes in the data set. Data enlargement, normalization, and image data resizing techniques were applied to the images in these classes due to the fact that the image data were organized to obtain healthy results and some images were removed from the data set. The size of the image sets must be the same so that the data can be input into the model. For this reason, all of the images in the data set have been resized to a standard size of 128x128.

Data Augmentation

Data augmentation is used when there is insufficient data in the data set. After removing the unwanted images from the capillaria philippinensis and enterobius vermiculari classes in the dataset used in the study, 250 images of both classes remained. However, this number is not enough to get accurate results from the model. For this reason, the number of data belonging to these two classes was increased to 750 by rotating the pictures at 90-degree angles on the horizontal and vertical axis. For the model to work properly, the data has been resized following the normal distribution.

Data Set Normalization

For the data set, which consists of images of different and non-standard sizes, to work more efficiently and quickly during the model training phase, the data was reduced to 128x128x3 size, and the normalization process was applied by reducing the pixel values between 0 and 255 on the pixels. In this way, the VGG16, ResNet50, and InceptionV3 models created can process image data much faster. The new values obtained after dividing all pixel values by 255 as a result of the normalization process represent the new pixel values of the image.

Convolutional Neural Network

Convolutional Neural Network (CNN), which is a multi-layered feed forward artificial neural network, is especially used for image analysis. It was put forward with an approach based on the animal vision system (Hubel & Wiesel, 1968). It is based on filtering. It is one of the most frequently used deep learning methods because it gives successful results in object recognition, tracking, image processing, and classification. Convolutional Neural Network basically consists of Convolution Layer, Pooling Layer, and Fully Connected Layer.

Convolution Layer

In this layer, feature finding operations are performed on the input image through filters. In Convolutional Neural Networks, a new image is obtained by moving small filters such as 2x2, 3x3, and 5x5, which go from the upper left edge to the lower right, and revealing more specific features (İnik et al., 2017:89).

Pooling Layer

Another layer used in Convolutional Neural Network is the pooling layer. This layer also allows to reduce of the image size by keeping the best values in the image for the next layer. This process ensures that the next layer is subject to less computational load and prevents the system from overfitting. (İnik et al., 2017:92).

Fully Connected Layer

After convolution and pooling, the data is converted into a one-dimensional vector and this vector is given as input to the full link layer. Full Link Layer depends on all areas of the layer before it. Each neuron connects with the next neuron (İnik et al., 2017:94).

Transfer Learning

Transfer learning is an approach that examines the use of knowledge learned by machine learning algorithms through training steps in solving different or similar problems. (Koçer, 2012). In this study, VGG16, ResNet50, and InceptionV3 networks, which are transfer learning approaches, were used for the problem of identifying intestinal parasitic diseases.

VGG16 Network

The VGG network proposed by the Oxford Visual Geometry Group (VGG) was introduced in 2014 by Karen and Simonyan in the article "Very Deep Convolutional Networks for Large-Scale Image Recognition" (Simonyan et al., 2014:1409.1556). The VGG16 network is a 41-layer model consisting of 13 convolution layers, 3 fully connected layers, 15 activation (relu) layers, and 5 pooling layers. The number of parameters in the model is about 138 million and it has achieved a success rate of 91.6% in the ImageNet dataset (Güldemir et al., 2021:612). ImageNet is a dataset of more than 14 million images from more than 20,000 classes created for image processing competitions (Russakovsky et al., 2015:211.252).

ResNet50 Network

ResNet50 is a deep learning network consisting of 177 layers presented in 2015 by He and his friends. (He et al., 2016). ResNet50 network uses bottlenecks at some layers to perform faster training. In the ResNet50 network, the input layer is 224x224x3 and approximately 23 million parameters are calculated. Achieved 93.29% accuracy with the ImageNet dataset (Güldemir et al., 2021:612) (Narin et al., 2020:189).

Inception-V3 Network

The Inception-V3 model, defined as a network within a network, was proposed by Szegedy et al. in 2015 (Szegedy vd., 2016). The InceptionV3 network is based on the combination of filtering and pooling stages in the ESA layers (Dandıl et al., 2020:456). The image input on the network is 299x299x3. The Inception-V3 network consists of 315 layers and 24 million parameters. Achieved 93.7% accuracy on the ImageNet dataset (Güldemir vd., 2021:612).

Performance Measures

In this study, performance criteria such as training accuracy, test accuracy, precision, recall, F score, confusion matrix, and roc curve were used. The accuracy value is used to evaluate the performance of the model, but it is not enough on its own. Accuracy value is the ratio of the number of samples classified correctly by the data in the model to the total number of samples (Başer, 2021:115). Precision indicates how many of the positively predicted values are positive (Badem, 2019:633). The Recall value shows how many of the transactions we should classify as positive we have classified as positive. The F score gives the average of the precision and sensitivity values (Başer, 2021:115). Response matrix measures model performance by comparing the prediction of patients with and without.

Findings

In this section, the performance rates of the VGG16, ResNet50, and Inception-V3 classification models are included. Images belonging to the classes capillaria philippinensis and enterobius vermiculari were used to create the required deep learning networks. Epoch is set to 20 and cross validation (Kfold) is set to 10 in VGG16, ResNet50, and Inception-V3 networks used in the model. K-fold is a method used to most accurately evaluate the performance of a machine learning model on data it has not seen before. In the k-fold method, the data set is divided into k groups, the selected group is used as the test set, while the remaining k-1 data set is used for training. The classifier is trained k times by changing the test set each time (Narin et al., 2014:5). With 20 steps and 10 folds of training and test set, the model is repeated and the best result is tried to be obtained. Table 1 shows the success rates of VGG16, ResNet50 and Inception-V3 networks used in model building at the end of 10-fold cross validation.

Table 1. Average Success Rate of VGG16, ResNet50 and Inception-V3 Networks

	Train Accuracy %	Test Accuracy %	*F1 Score %*	Precision %	*Recall %*
VGG16	*98.07*	*92.00*	*92.49*	*94.87*	*90.24*
ResNet50	*69.25*	*67.33*	*72.31*	*58.71*	*94.11*
Inception-V3	*97.85*	*87.33*	*88.88*	*91.42*	*86.48*

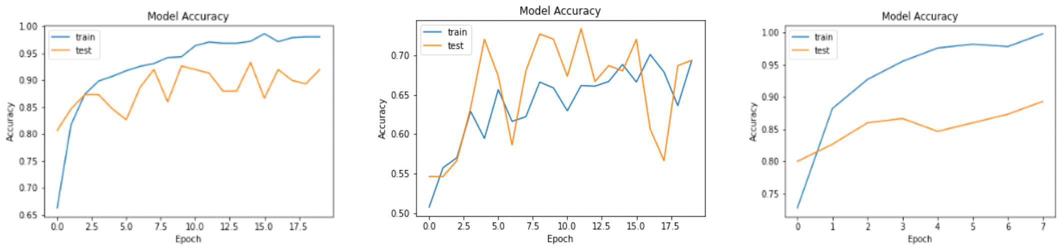
Train accuracy is the accuracy rate of the dataset on which the model is trained. The test accuracy is the accuracy of the dataset used to evaluate the model developed in the training set. It is very important for the success of the model that the train and test accuracies are proportional to each other.

At the end of 20 steps and 10-fold cross validation, for the "Parasitic egg detection and classification in microscopic images" dataset, 98.07% train accuracy, 92.00% test accuracy, 92.87% f1 score, 94.87% precision, and 90.24% recall values are obtained with the Vgg16 network. When all these performance metrics are examined together, it is seen that all values increase proportionally to each other in the model created with the vgg16 network.

In the model created with the ResNet50 network, 69.25% train accuracy, 67.33% test accuracy, 72.31% f1 score, 58.71% precision, and 94.11% recall values were obtained. As seen in the results, the values do not increase proportionally to each other. It is seen that the train and test accuracy values are low, and when the recall value is examined, the values that should be classified as positive are not correctly classified.

Finally, the Inception-V3 network was examined for the "Parasitic egg detection and classification in microscopic images" dataset. With the InceptionV3 network, 97.85% train accuracy, 87.33% test accuracy, 88.88% f1 score, 91.42% precision, and 86.48% recall values were obtained. In the model, it was observed that the performance metrics increased in a balanced way with each other and achieved successful results.

When the results obtained from VGG16, ResNet50 and Inception networks are examined together, it can be said that the most appropriate method used for the "Parasitic egg detection and classification in microscopic images" dataset is the VGG16 network. In the ResNet50 network, on the other hand, it was seen that the train and test accuracy values were much lower than the VGG16 and inception networks. Especially for the ResNet50 network, when all the metrics are examined together, it can be said that the values do not have a balanced increase and it is not a successful model. Inception-V3 network achieved the best results after the VGG16 network. In Figure 6 below, train accuracy and test accuracy result graphs obtained with VGG16, ResNet50 and Inception-V3 networks, respectively, are given.



VGG16 **ResNet50** **Inception-V3**

Figure 1. VGG16, ResnNet50 and Inception-V3 Networks Accuracy Plots

The blue line shown in the graph represents the model train accuracy and the orange line the test accuracy. Train and test accuracy lines approaching one indicate that the training was successful. When the graphics are examined, it can be said that the best success is achieved with the VGG16 network. While VGG16 and ResNet50 networks approached one, the ResNet50 network remained below one.

CONCLUSION AND DISCUSSIONS

The main purpose of this study is to classify parasites in human intestines with less time and cost by using deep convolutional learning methods. When the literature is examined, it has been observed that studies on examining human diseases with deep learning approaches have increased recently. However, no study was found in the Turkish index regarding the detection of human intestinal parasites with deep learning methods.

In the research, VGG16, ResNet50, and Inception-V3 networks, which are deep learning approaches, were used to detect the capillaria philippinensis and enterobius vermiculari classes belonging to intestinal parasites. To get more successful results from the data set used in the study, data preprocessing methods were applied to the data set. These methods are data enlargement, resizing and data set normalization. After removing some erroneous data in both classes in the data set, the number of images was increased to 750 by applying data augmentation to the data set. Again, the images have been brought to a standard size of 128x128 so that the data can be given as input to the model.

In the model, training accuracy, test accuracy, precision, recall, f-score and confusion matrix performance measures were used as performance criteria. As a result of the training steps set as 20 epoch and 10 kfold, it was seen that the VGG16 network achieved the highest success rate with a balanced increase by catching the values of 98.07% train accuracy, 92.00% test accuracy, 92.49% f1 score, 94.87% precision and 90.24% recall. After the VGG16 network, the best success was seen in the Inception-V3 network with 97.85% train accuracy and 87.33% test accuracy, 88.88% f1 score, 91.42% precision and 86.48% recall. On the other hand, ResNet50 network, which has lower results compared to VGG16 and Inception-V3 networks, achieved 69.25% train accuracy and 67.33% test accuracy, 72.31% f1 score, 58.71% precision and 94.11% recall rates. When all these results are examined together, it can be said that the most suitable deep learning architecture for the "Parasitic egg detection and classification in microscopic images" dataset is the VGG16 and Inception-V3 network. ResNet50, on the other hand, was not considered suitable for this dataset due to its poor results and disproportionate increase in performance metrics.

Early detection of intestinal parasitic infections, which pose serious dangers to developing societies, is of great importance for humans. For this reason, it is thought that the use of deep learning architectures in disease diagnosis will increase even more because it provides less time and cost. When the studies in the literature were examined, no study was found in the Turkish index on the examination of intestinal parasite infections with deep learning architectures. For this reason, it is thought that deep learning models used for the classification of these intestinal parasitic infections will be a guide for future disease classification studies.

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