CLASSIFICATION OF LUNG CANCER USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

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The lung is the basic respiratory organ. Lung cancer is a deadly disease that occurs when abnormal cells in the lung grow. The type of lung cancer is basically divided into 3 classes as malignant, benign, normal(non-cancerous). It is the most common type of cancer and has the highest mortality rate. The most common method used to detect lung cancer is to CT images of the patient. Although this traditional method is very helpful for diagnosis, it is very costly and sometimes a waste of time for the patient. In this study, it was aimed to create a simple convolutional neural network (CNN) that classifies lung cancer. CT images are provided as an input to the system. Convolutional neural network structure was created using the Python language in the Visual Studio Code program. Different CNN architectures have been created and the CNN structure that gives the highest accuracy rate among them has been selected.

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Keywords: Convolutional neural network, CT images, lung cancer

Contents

Abbreviations

- CNN: Convolutional Neural Network
- ANN: Artifical Neural Network
- CT: Computer Imaging
- MRI: Magnetic Resonance Imaging
- PET: Positron Emission Tomography
- ReLU: Rectified Linear Unit
- Adam: Adaptive Moment Estimation

INTRODUCTION

The lung is of vital importance for us because it is the most basic organ of the respiratory system and has two important tasks. One of these tasks is to pass oxygen into the blood and ensure that carbon dioxide is removed from the body. Another task is to contribute to the formation of sound. The lung occupies the vast majority of the chest cavity and has a spongy structure. It consists of the bronchi, alveoli, lymph fluid and blood vessels.The lungs are the basic organ of the respiratory system. It is the organ where gas exchange takes place. The lungs are connected to the air ducts thanks to the bronchial tree. Gas exchange takes place thanks to the transport of the alveoli. This condition is of vital importance for us to take in oxygen and give off carbon dioxide. According to statistics, lung cancer is the type of cancer with the most and has the highest mortality rate. Lung cancer is an uncontrolled proliferation of cells located in the lungs. These cells form a massive structure over time. It is a disease with a high mortality rate since it does not show many symptoms in the early stages, its diagnoses are often made late. Currently, there are many ways to detect lung cancer. With the help of imaging methdos such as MRI (Magnetic Resonance Imaging), CT(Computed Tomography), Microscopy, PET (Positron Emission Tomography) lung cancer detection can be made on images. However, these traditional methods can be costly or time-consuming. It is very important to obtain fast and accurate data in terms of the patient's condition. The aim of this study is to use convolutional neural network (CNN) for lung cancer classification and show the potential of computer-assisted decision systems. In recent years, lots of studies have been carried out on artificial intelligence in many areas. Different projects are carried out in many fields such as defense industry, education and medicine. It has been observed that it has given successful results in the field of medicine, especially in image analysis. In this study, it was aimed to get faster and highly accurate results with convolutional neural networks.

There are many studies in the literature that classify lung cancer types using a convolutional neural network. In the studies conducted, people have established different CNN structures. Variables such as the number of layers used, activation functions, period and batch numbers provide different CNN architecture formations and vary as a result of each architecture. Thanks to the different results obtained from the studies, comparisons are made and studies are continuing with the structure that gives the most reliable result.

For example, Pathan and his friends (2024) used the IQ-OTH/NCCD dataset. There are three classes in this data set. There are images belonging to the benign, malignant and normal classes. There are a total of 1097 images, 120 of which are benign, 561 of which are malignant and 416 of which are normal. Using this data set, a 5-layer convolutional neural network architecture was created. ReLU was used as the activation function in the study. Normally, the visual dimension in the data is 512×512, but in this study, the visual dimensions were used as 488×488. As a result of this study, the accuracy is found as 99%, Sensitivity: 92%, Precision: 93%, F1-Score: 92.4%.

In another study, Saleh Abunajm (2024) used the same dataset again. However, in the study, the number of images was increased to 8461 images by data augmentation methods. He scaled the images back and gave them to the training as 214×214. This model is trained in Tensorflow-Keras and Google Colab Pro environment. As a result of these studies, Abunjam has achieved Accuracy: 99.45% Loss: 1.75% values.

In the study of Zafar et al.(2024), the images were again used as 224×224. The batch size and epoch number used in the study are not explicitly stated in the article. The training was conducted in the Google Colab Pro environment. As an activation function, ReLU was used. Two different CNN architecture have been established. The features taken from the two architectures are combined. mRMR (Minimum Redundancy Maximum Relevance) was used as the optimization method. The total accuracy rate of the obtained results is 99.09%.

In the CNN architecture used in the study of Md Apon Riaz Talukder et al. (2024), the ReLU activation function was used, but the input dimensioning of the images was not specified. In this study, the results of CNN architecture and transformer architecture results were compared. The accuracy rate in the CNN architecture is 93.67% but the accuracy rate in the transformer architecture has been observed as 77.33%. This shows that the CNN architecture works more in the classification used in image processing.

In Josie and Al-Suhali's study, three different CNN architectures trained with transfer learning were used and evaluated.The CNN architectures used are; VGG16, ResNet50V2, InceptionV3. The ReLU activation function game was used in all models.The Inception V3 architecture is also run together with Dropout layers, increasing the generalization performance of the model. The results were as follows; ResNet50V2 has the highest accuracy rate in the architecture with an accuracy rate of 99.09%. An accuracy rate of 97.27% was achieved in the VGG16 architecture. An accuracy rate of 93.54% has been achieved in the InceptionV3 architecture.

In this study, it is aimed to create a sample convolutional neural network architecture that classifies lung cancer. It is expected that the CT images provided as input will be classified with a high accuracy rate. The convolutional neural network structure was created using the Python language in the Visual Studio Code program.The images were taken from an open source (kaggle) accessible to everyone, and the IQ-OTH/NCCD Lung Cancer Dataset (Augmented) dataset, which is widely used in lung cancer classification studies, was used. In order to choose the structure that performs the best in classification during the development process, different CNN architectures have been tried and evaluated. In these architectures, many CNN architectures have been created by changing the filter numbers, batch numbers, activation functions. Architectures will be described in more detail in the section 4. The neural network structure with the highest accuracy rate was compared with the neural network structures created during the study. A specific neural network structure has been selected as a result of comparisons to create the highest accuracy.

1 CONCEPTS RELATED TO LUNG CANCER

Cancer is a type of disease that affects the area where it is located in the body. It is an increase in abnormal cells that grow and spread too much compared to normal limits. Its spread to other organs is called metastasis and is one of the primary causes of death. There are many steps in the progression of cancer. Causes of cancer may be caused by genetic factors, exposure to carcinogenic substances. Carcinogens are divided into three types physically, chemically and biologically. Physical carcinogens; UV rays, radiation. Chemical carcinogens; alcohol, tobacco, arsenic. Biological carcinogens are for example infections caused by viruses, bacteria can be given as examples.

1.1 Lung Cancer

If a condition of abnormal growth and uncontrolled spread of cells occurs in the lungs, it is called lung cancer. If these cells have started to spread to other organs and tissues over time, this is called metastasis. The most common type of death is lung cancer. At the same time, the disease rate is high compared to other types of cancer. According to the World Health Organization, as of 2020, 2.2 million new cases of lung cancer have been detected worldwide and 1.8 million people have died due to this disease. Lung cancer is usually a disease that does not manifest itself in the early stages. Its detection is usually carried out at advanced stages. Lung cancer has many symptoms, for example,cough, appetite and weight loss, shortness of breath, chest pain are the most common symptoms. However, these symptoms are similar to the symptoms of many diseases. For this reason, it is difficult to detect the disease early. Lung cancer is divided into two main classes: Small Cell Lung Cancer (SCLC) Non-Small Cell Lung Cancer(NSCLC). SCLC is usually caused by smoking and alcohol use. SCLC is a fast-spreading species. NSCLC follows a slow course, but it accounts for 85% of cases. People who have lung cancer usually have smoking or passive smoking in their histories, as well as people who are exposed to chemical carcinogens get this disease. When diagnosing the disease, a physical examination is performed first, and then if there are suspicious signs, a decision is made with an image. These images are obtained by imaging techniques such as MR, CT, PET. After the diagnosis of the disease, its stage is examined and the treatment process is initiated according to its stage. If it is in the early stages, treatment can be performed with surgical intervention. However, in the advanced stages, treatments such as chemotherapy and radiotherapy are performed in the patient, taking into account his condition.

1.2 Classification And Definitions Of Lung Cancer

The classification of the cell type in the diagnosis of lung cancer is divided into benign, malignant and normal into three. Benign cancer cells do not spread to other parts of the body and grow slowly. It is unlikely that they will damage the surrounding tissues. Such tumors can be removed by surgical intervention. Tumors that grow very quickly and metastasize, that is, types that can spread to other parts of the body, are also called malignant tumors. It also damages other tissues around the malignant tumor. Here, the treatment method is selected according to the patient's condition, a combination of radiotherapy and chemotherapy can be used for radical purposes. Healthy and non-problematic lung cells are classified as normal. In a normal-celled lung, the cells divide properly and can perform their functions well. they are classified under.

There are 4 basic stages of lung cancer, these four basic stages have a total of 10 sub-stages in themselves. In short, if we start from these four basic stages; 1.at this stage, the cancer cell is located only in the lung tissue. 2. stage is a condition in which the cancer has spread to the lymph nodes. 3. at this stage, the cancer spreads to tissues and lymph nodes. 4. the stage is the condition of metastasis to organs.

1.3 Imaging Techniques

MRI (Magnetic Resonance Imaging), CT(Computed Tomography), Microscopy, PET (Positron Emission Tomography), X-ray are some of the most preferred imaging techniques. Cancer can be diagnosed with these imaging techniques. At the same time, there are also methods such as bronoscopy and biopsy to make a diagnosis. CT plays a very important role in imaging lung cancer. It helps us not only with the presence of a cancer cell, but also with its location and size. The images in this study are CT images. CT scans give us 3-dimensional data. For this reason, it provides a more convenient examination of tissue, bone and organ structures. Computed tomography devices are shaped like hollow cylinders, and inside this device there is an x-ray tube and a detector. When the patient is placed inside the device, the X-ray tube rotates around the patient to take various images. As a result, these images are processed by a computer and detailed images with cuts are extracted.These devices emit radiation, so once taken, images are not always taken from the patient unless necessary. It emits a certain amount of radiation, especially in high-resolution images. For this purpose, an image is not always taken, and low-dose computed tomography is used in people at high risk.

2 Convolutional Neural Networks

2.1 Artifical Neural Networks

The principle of operation of artificial neural networks has been likened to the operation of nerve cells in humans.Our nervous system consists of neurons, nuclei, cell bodies, axons and dendrites. Neurons are divided into three types: sensory neurons, motor neurons, and intermediate neurons decoupled. Sensory neurons transmit the information they receive from 5 sensory organs to the brain. Motor neurons control the muscles and enable movement. Nuclei is responsible for cell function and regulation. The task of the axon is to transmit the received information to other nerve cells and muscles. The task of the dendrite is to transmit the information received from the other neuron from the neuron to the cell body. The part where the information is transferred from axons to dendrites is called the synapse gap. Here, electricity transmission takes place thanks to neurotransmitter substances .When a stimulus comes to us from the outside, there is a rapid change in the electrical charge, this change can be an increasing or decreasing electrical charge. This sudden change is called the action potential. During this sudden change, millions of nerve cells are stimulated. The stimulus information we receive from the outside is transmitted to the brain. Then the brain decides on the reaction it will give. Synaptic connections increase in the human brain during the learning process. Artificial neural networks have also been created inspired by these processes. The first artificial neural network model was created in 1943 thanks to Warren McCulloch and Walter Pitts. An artificial neural network(ANN) consists of layers; there is an input layer, hidden layers, and an output layer.

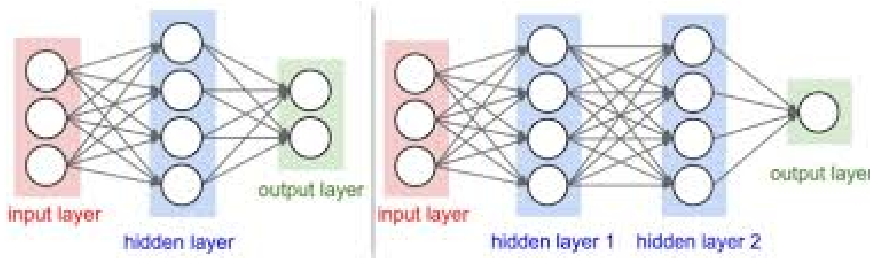

Figure 1: Artifical Neural Networks Layers

The structure of artificial neural networks is simple and it can work with all kinds of data, but it cannot work well with image data in some situations. Artificial neural networks are very useful for working with numerical data. Convolutional neural networks, which are very similar in principle of operation in working with images, are healthy. In this study, convolutional artificial neural network architecture was created and used. Now we will discuss the convolutional neural network structure and its layers.

The strength of each synaptic bond in a human nerve cell is not the same, while artificial neural networks are compared to a human nerve cell, the weight coefficient was considered instead of synaptic bonds. we have n entries $(x_1, x_2, x_3, ..., x_n)$ and our n grain weight coefficient$(w_1, w_2, w_3, ..., w_n)$, each input is multiplied by the weight coefficients to enter the total function and the error value is added. The margin of error is shown as an input and indicated as x_0. All this is obtained after the activation has been passed through the function and the output is obtained. The working principle is the same in a convolutional neural network.

$$f\left(\sum_i w_i x_i + b\right) \tag{2.1}$$

- Y : output
- f : activation function
- w_i :initial weight
- x_i : initial input

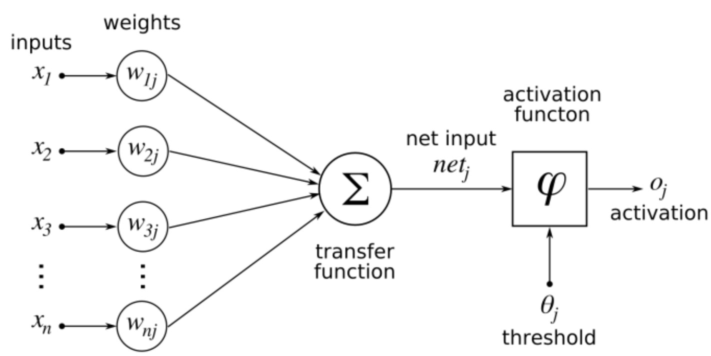

Figure 2: CNN STRUCTRE

The error calculation is made by the sum of the differences between the output and the actual outputs of the given inputs.

$$\text{Error}_{\text{sum}} = \sum \frac{1}{2} \left(\text{real value} - \text{output}\right)^2 \tag{2.2}$$

If the error value approaches 0, it indicates that the learning of the convolutional neural network is in a good degree. It happens by updating the weights during the learning process in an artificial neural network. There are different optimization techniques to be able to approach zero. Usually, the backpropagation algorithm and gradient descent technique are used.In 2.1 we found the output from the formula and in 2.2 we found the error. The error we calculated spreads backward from the last layer of the network, and each weight has its contribution to the error. Attention is paid to the effect of all weights on this error and the derivative is taken. The weights are updated again with this derivative.

$$w = w - \eta \cdot \frac{\partial L}{\partial w} \tag{2.3}$$

- w : Weight
- η : Learning rate
- $\frac{\partial L}{\partial w}$: Derivative of the loss function with respect to the weight

The more the number of iterations, the more attempts are made to reduce the error value. In other words, the fact that the epoch number is too high during training means that the weights become better. Convolutional neural networks are composed of layers. There are sequential layers decoupled between the input and output layers. There are convolution layers, pooling layers and fully connected layers in convolutional neural networks. Each layer has a different function.

2.2 Input Layer

The data structure that the model will receive is created at the input layer. The input layer in a convolutional neural network defines a specific size and number of channels for given images. The purpose of this layer is to convert the visually given data into a numerical structure. The model understands this data with a numerical structure and transfers it to other layers. The learning process does not take place at this layer. The images used in the studies can be color or grayscale images. The image sizes and image colors in each data set may not be the same. In this study, CT images of IQ-OTH/NCCD (Augmented) dataset are given in 3 layers with a size of 224×224.

2.3 Convolution Layer

The convolution layer extracts the attribute of the images provided as input. There are filters, and each filter produces a different attribute map. The attribute map allows you to recognize the model and it is important to learn. In each iteration, the filters are updated according to the error in the output and perform the learning process in the network. In the Figure 3 filtering process, a 3×3 dimensional filtering was used to a matrix of dimension 5×5. The output size was $5 - 3 + 1 = 3$. To generalize, the size of the input matrix is $n \times n$, the size of the filter is $f \times f$, and the size of the output matrix is $n - f + 1$. As we can see in Figure 3, the size of the output matrix is decreasing. We can add extra pixels to the input matrix so that the size does not shrink. Usually these pixels are 0. $p = \frac{f-1}{2}$ the number of input matrices is filled with zeros. This process is called padding.

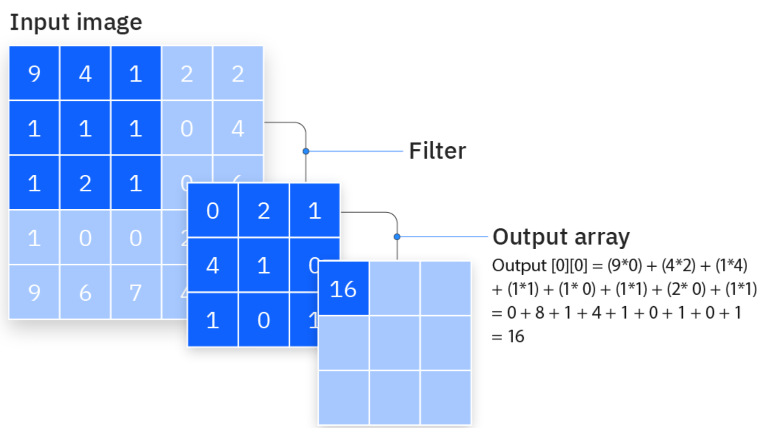

Figure 3: FILTERING PROCESS

2.4 Activation Functions

Nonlinear networks allow artificial neural networks to learn complex relationships. In order to avoid linearity here, attribute maps are processed with activation functions. Activation functions are processes that determine how neurons respond to inputs. There are many types of activation functions.

2.4.1 Sigmoid Activation Function

It is used for probability calculations and gives results in between 0 and 1. For example, if the result of the procedure turned out to be 0.95, because it is close to 1, the cancerous cell is a cancer cell

$$f(x) = \begin{cases} -1, & \text{if } x < 0 \\ 0, & \text{if } x = 0 \\ 1, & \text{if } x > 0 \end{cases}$$

the formula is as above.

2.4.2 Threshold function

This function is a very basic function, but it is also an important function. There is a threshold for the output to occur, if the value exceeds the threshold, it gives 1, if it does not exceed, the result is 0.Mathematically, it is shown as follows:

$$f(x) = \begin{cases} 0, & \text{if } x < 0 \\ 1, & \text{if } x \geq 0 \end{cases}$$

The derivative of the threshold function is not defined, which makes it difficult to implement learning with the replication algorithm. For this reason, it has been replaced by distinct activation functions in modern deep learning models, for example, structures such as ReLU, Sigmoid or Tanh.

2.4.3 ReLU (Rectified Linear Unit)

The main purpose of the ReLU activation function is to model nonlinear relationships in the network. The ReLU activation function takes the negative input values to zero and the positive input values to itself. This means that there is no loss of information in positive values. The ReLU activation function provides faster convergence than other activation functions. It is also very simple to calculate. For these reasons, the training period lasts shorter compared to other functions and increases performance. This function, which is very widely used, takes negative inputs to zero and positive ones to itself.

$$f(x) = \max(0, x) = \begin{cases} 0, & \text{eğer } x < 0 \\ x, & \text{eğer } x \geq 0 \end{cases}$$

2.5 Leakly ReLU

In this study, an experiment was conducted with the Leakly ReLU function. Leakly relu is an improved version of the relu function. Since negative values of Relu function are taken to zero, it may cause some neurons to stop learning. For this reason, leakly relu has been developed. Here, a small slope is given to the input negative values. Thus, information is obtained from negative input values in a limited way.

$$f(x) = \max(0, x) = \begin{cases} \alpha \times \text{x}, & \text{eğer } x < 0 \\ x, & \text{eğer } x \geq 0 \end{cases}$$

The value of α determines how much leakage will be made to negative values. It is taken as a fixed number.

2.5.1 Softmax

The Softmax function is a common activation function used in multiple classifications. It is used in the output layer of the model and makes probability calculations for each class. Normalizes the values belonging to each class and compresses them between 0 and 1. Decrypts the values of each class. The sum of all output values must be 1. The mathematical representation of the Softmax activation function is as follows:

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

- z_i : i. Model's output,
- K : The total number of classes,
- e : Euler's constant

2.6 Pooling Layer

As in the convolution layer, the matrices are filtered in this layer, the purpose of which is to reduce the size of images that are large in size. When we reduce the size, the complex calculation will be reduced. However, there is no weight of the filters in the filtering performed here. There are two types of maximum pooling and average pooling. At the maximum pooling, the largest element of the cell corresponding to the image matrix is selected. In the average pooling, the average of the cell corresponding to the image matrix is taken. Thanks to the pooling layer, the image size decreases as important attributes are preserved and the computational cost of the model decreases. In addition, reducing the size also reduces the risk of over Octane learning. It also allows the model to show more resistance to small changes or distortions of the image.

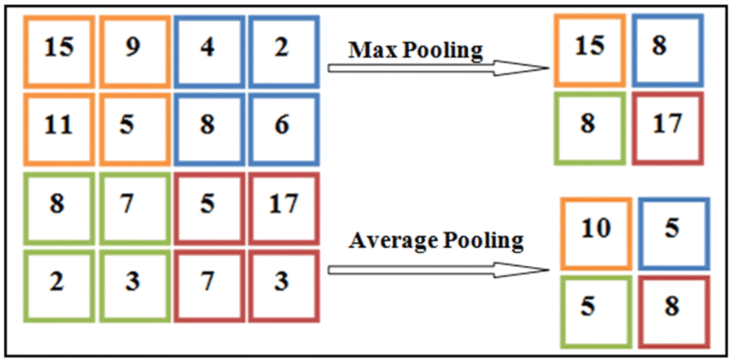

Figure 4: Maximum pooling and average pooling operation

2.7 Fully Connected Layer

This layer works similar to the principle of neural networks in humans, because in the fully connected layer, the input neurons are connected to the output neurons. Training takes place at this level and classification is made.

Figure 7 shows the fully connected layer in the study. Here, the matrices are converted to vectors, that is, they are switched from multi-dimension to one-dimension. The attributes are preserved and then the classification is done. In this study, the softmax activation function was used for classification and the images were divided into three classes as benign, malignant and normal.

2.8 Performance Criteria

Performance criteria give us other aspects of the accuracy of the study. There are various performance criteria.

2.8.1 Confusion Matrix

It gives us an accuracy result by comparing between the prediction of the model and the actual labels in the confusion matrix. Thanks to this criterion, we can observe how accurately the model predicts or where there are errors. the complexity matrix is a table that shows that the classification made in the test data makes a correct or incorrect classification. There are 4 methods;

- **True Positive**: It is positive in the given images and positive classification when classifying in the model. For example, according to this study, the classification of an image belonging to a benign cancer cell as a benign cancer cell in its model.
- **False Positive**: A negative is the classification of an image as positive. For example, the model predicts a benign cell as malignant
- **True Negative**: What is negative is the classification of the sample as negative. For example, classifying an image with a normal result as normal.
- **False Negative**: The positive one is that the model predicts the appearance negatively. Here it is a case of guessing the malignant as the model is normal.

2.8.2 Accuracy

It is the ratio of the images that the model classifies correctly to all the classified images. In other words, it is the ratio of the sum of the true positive and the true negative to all of them. It is mathematically shown as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

This process gives us a percentage accuracy result.

2.8.3 Precision

The precision value is the ratio of true positives to all positive classifications.

$$\text{Precision} = \frac{TP}{TP + FP}$$

2.8.4 Recall

The goal here is to find out how many of the true positives are classified correctly. Its formula is as follows;

$$\text{Recall} = \frac{TP}{TP + FN}$$

2.8.5 F1 Score

This method is used if there is an imbalance in the number of data. The precision and recall results of the model should be known for the calculation of the F1 score because it is calculated by the harmonic average of the two. Its formula is as follows;

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

2.8.6 Cross-Validation

In the training phase not all of the data is given, to the network some of it is used for teaching, some of it is used for testing. This method is important because if the model adapts too much to the training set, sometimes the model memorizes instead of learning. This situation leads us to erroneous conclusions. In the most common k-fold cross-validation, the data set is divided into k equal parts and then the model is trained up to k-1 part in each sphere. There remains an extra in or 1 part, and this part is for verification.

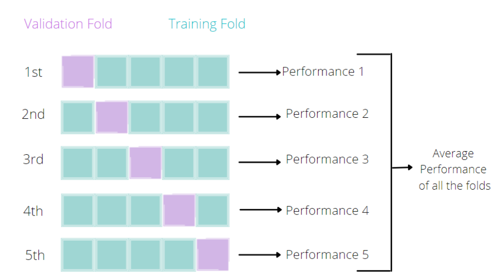

Figure 5: k-th order Cross- Validation

3 MATERIAL AND METHOD

3.1 Material

In this thesis study, a publicly available lung cancer CT image dataset downloaded from kaggle webpage (https://www.kaggle.com/datasets) was used. The IQ-OTH/NCCD Lung cancer dataset used in this study was obtained from an archived source. The images are in JPEG format, and the number of images has been increased by using image augmented methods. The cross sections to be used in this study are set to 224×224 pixels. There are a total of 3610 images in this data set. The images are divided into three classes:

- Benign: 1200 images
- Malignant: 1201 images
- Normal(healthy): 1208 images

Figure 6: Randomly selected images from the generated data set

The data set used has been cited a lot in the literature, as mentioned in the Introduction section, and it has been used together with different CNN architectures. In many studies, high accuracy rates have been achieved.

3.2 Method

The aim of this study is to obtain a high accuracy value. Therefore, the convolutional neural network architecture created plays an important role. In order to achieve high accuracy, a convolutional neural network architecture has been created that is optimal for the process. First of all, different CNN models were made one by one using the trial and error method and compared among themselves decently. In the CNN model with the highest accuracy result, the ReLU activation function was used, the epoch number is 50, the batch number is 8. Two Convolution layers were used in the model. The CNN architecture of the model is also included in Figure 7.

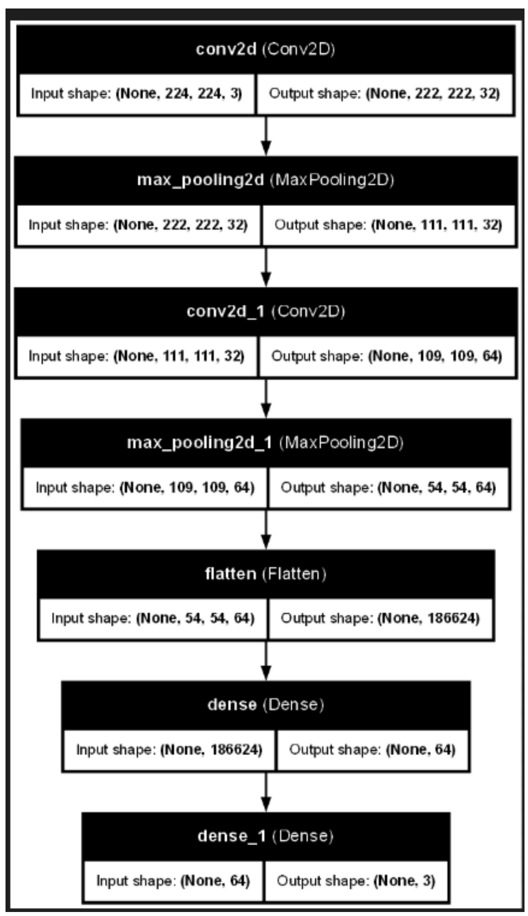

Figure 7: The CNN architecture with the highest accuracy rate

The selected parameters in this table are the ones that give the best results. Previously, different parameters were selected and the results were compared. A comparison of the other parameters and results of the trial is given below.

ACTIVATION FUNCTION	EPOCH	BATCH	NUMBER OF CONVOLUTION LAYER	TRAINING TIME	ACCURACY
Leakly ReLU - Softmax	50	8	2	38 min	0.9821
Elu - Softmax	50	8	2	31min 45 sec	0.3347
Swish - Softmax	50	8	2	30 min	0.8565
Swish - Softmax	50	8	4	51 min	0.9931
Tanh	50	8	2	33 min 34 sec	0.3327
ReLU - Softmax	50	8	2	31min 6 sec	0.9937
ReLU - Softmax	50	8	4	45 min 3 sec	0.9701
ReLU - Softmax	80	8	2	51min	0.9701
ReLU - Softmax	50	16	2	32 min	0.9734

Figure 8: Comparison Table

After these data were saved manually, a different study was conducted using the adam optimization technique and genetic algorithm by combining two activation functions, 3 different filter sizes and 4 different batch sizes to create the automatically saved data. A total of 24 combinations were formed. Table 1 shows the result of all combinations. The CNN architecture activation function that gives the best result as a result of intermixtures is Leakly ReLU, batch size 24, (5,5)-(5,5) kernel-sized. The structure of the selected architecture will be described in detail in the Model Structure Section. In the second study, it is seen that the results are more realistic and more stable when the optimization technique is used.

Table 1: Optimized and genetic algorithm used study results

Activation	**Batch**	**Kernel1**	**Kernel2**	**Val Accuracy**	**Precision**	**Recall**	**F1 Score**
relu	8	(3,3)	(3,3)	0.9389	0.9391	0.9393	0.9392
relu	8	(5,5)	(5,5)	0.4619	0.7255	0.4410	0.3826
relu	8	(7,7)	(5,5)	0.4619	0.7228	0.4410	0.3825
relu	16	(3,3)	(3,3)	0.9556	0.9560	0.9560	0.9560
relu	16	(5,5)	(5,5)	0.9348	0.9361	0.9347	0.9352
relu	16	(7,7)	(5,5)	0.9487	0.9498	0.9483	0.9484
relu	24	(3,3)	(3,3)	0.9223	0.9221	0.9230	0.9224
relu	24	(5,5)	(5,5)	0.9639	0.9642	0.9643	0.9642
relu	24	(7,7)	(5,5)	0.4591	0.7436	0.4376	0.3736
relu	32	(3,3)	(3,3)	0.9473	0.9477	0.9478	0.9476
relu	32	(5,5)	(5,5)	0.9570	0.9572	0.9569	0.9570
relu	32	(7,7)	(5,5)	0.9112	0.9117	0.9121	0.9115
leaky_relu	8	(3,3)	(3,3)	0.9639	0.9638	0.9648	0.9642
leaky_relu	8	(5,5)	(5,5)	0.9570	0.9582	0.9569	0.9573
leaky_relu	8	(7,7)	(5,5)	0.9515	0.9524	0.9534	0.9519
leaky_relu	16	(3,3)	(3,3)	0.9431	0.9439	0.9450	0.9437
leaky_relu	16	(5,5)	(5,5)	0.9209	0.9267	0.9232	0.9221
leaky_relu	16	(7,7)	(5,5)	0.9556	0.9572	0.9555	0.9561
leaky_relu	24	(3,3)	(3,3)	0.9667	0.9671	0.9670	0.9670
leaky_relu	24	(5,5)	(5,5)	0.9723	0.9722	0.9727	0.9724
leaky_relu	24	(7,7)	(5,5)	0.9348	0.9387	0.9346	0.9358
leaky_relu	32	(3,3)	(3,3)	0.9709	0.9709	0.9716	0.9712
leaky_relu	32	(5,5)	(5,5)	0.9626	0.9629	0.9630	0.9629
leaky_relu	32	(7,7)	(5,5)	0.9695	0.9694	0.9701	0.9696

4 MODEL STRUCTURE

This work was developed in Visual Studio Code version 1.89.1, which runs on the Windows 11 Pro operating system. It was implemented using Python 3.10.12 language and TensorFlow 2.13.0 library.

PARAMETER	THE SELECTED VALUE
The visual size of the entry	224 × 224 × 3
Number of first layer filters	32
Size of first layer filters	5x5
Number of second layer filters	64
Size of second layer filters	5x5
Epoch	50
Loss Function	Categorical Crossentropy
Model Saving Format	.h5
Optimization technique	Adam
Activation Function	Leakly ReLU

Figure 9: Parameter Selections

As a result of different experiments, the parameters of the CNN model that gives the best result is given in Figure 9. As a result of this study, the loss and accuracy graphs are as shown in Figure 10 and Figure 11.

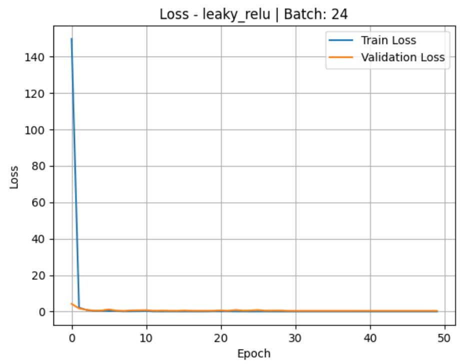

Figure 10: Graph of the loss function

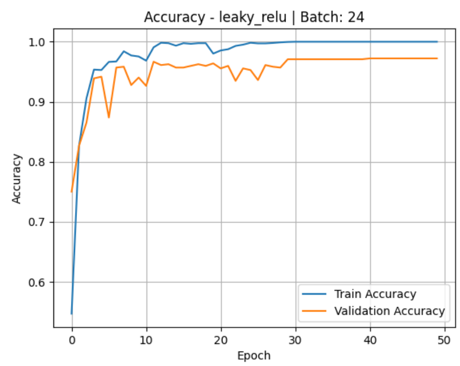

Figure 11: Accuracy value graph

The accuracy value of this neural network was obtained as 97.23%. Random images were selected from the data set and predictions were asked to be made. According to these estimates, the confusion matrix is given below.

	Benign	Malignant	Normal
1	228 97.85%	2 0.86%	3 1.29%
2	3 1.31%	224 97.82%	2 0.87%
3	7 2.70%	3 1.16%	249 96.14%

Figure 12: The confusion matrix of the model

According to the confusion matrix in Figure 12, the model took 233 images from the benign class and correctly predicted 228 of them and predicted 2 of them as malignant and 3 as normal. Model received 229 images from the malignant classification. 3 of them were estimated as good, 2 of them as normal. It took 259 images from its normal class and estimated 7 of them as benign and 3 as malignant. Based on this, it is observed that the overall accuracy rate is 97.63%. The accuracy rate of the confusion matrix gives us a high accuracy rate, but nevertheless, examining the accuracy, sensitivity and F1 score values helps us to make healthier comments.

Table 2: Classification Performance Report

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Benign	0.96	0.98	0.97	233
Malignant	0.98	0.98	0.98	229
Normal	0.98	0.96	0.97	259
Accuracy		**0.97**		**721**
Macro Average	0.97	0.97	0.97	721
Weighted Average	0.97	0.97	0.97	721

As we can see from Table 2, the values of each class were calculated separately. The overall accuracy rate was achieved as 97%. This rate is high enough and satisfactory.

5 CONCLUSION AND DISCUSSION

In recent years, with the progress of technology, studies in the field of artificial intelligence have increased. Artificial intelligence applications are now used in many parts of our lives. The opportunities provided by artificial intelligence are included in many fields such as education, health, transportation, finance, industry. In this study, it is shown that artificial intelligence can help in the field of health. Early diagnosis of a patient with cancer is of vital importance for the patient. Getting fast and accurate results in the health sector, as well as reducing the cost in the diagnosis and treatment process will be very beneficial for humanity.

In this thesis study, a suitable convolutional neural network was created and the classification of lung cancer cells as for benign, malign or normal was made in a specific data set. The reason why more than one neural network was created in this study and the results of all of them were evaluated is to try to achieve the highest accuracy rate. In this case, the dimensions, numbers, layers, activation functions, epoch, batch numbers of the filters to be used in the creation of convolutional neural network architecture play an important role.

Experiencing problems such as excessive learning in artificial neural networks changes the accuracy values. Optimization techniques have been developed and started to be used in order to avoid this problem. The optimization method called Adam (Adaptive Moment Estimation) is also an optimization algorithm that performs gradient descent during backpropagation in python code for different neural network variations. As a result, it provides fast and stable learning.

In this study, it was observed how much adam optimization helps in the development of convolutional neural networks. The fact that the study has a high accuracy rate is of great importance for ensuring the diagnosis of a patient in the future.

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