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Araştırma Makalesi / Research Article

Akciğer Görüntülerinden Tümörlü Verilerin Derin Sinir Ağları ve Evrişimsel Sinir Ağları ile Tahmini

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Anahtar Kelimeler
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Öz

Akciğer tümörleri günümüzde sıklıkla görülür ve yaygın bir şekilde insanlarda ölümlere neden olan tehlikeli bir hastalıktır. Ancak çoğu zaman uzmanlar tarafından yapılan manuel tetkikler yanlış teşhise sebep verebilir. Bunun yerine bilgisayar destekli otomatik, doğru ve ayrıntılı yapılan erken kanser teşhisine ihtiyaç bulunmaktadır. Bu sebeple bu çalışmada akciğer hastalıkları ile yapılan çalışmalar ayrıntılı bir şekilde incelenmiştir. Çalışmanın ilk aşamasında 1190 akciğer tomografi görüntüsü önerilen derin öğrenme modelleri için hazırlanmıştır. İkinci aşamasında ise derin öğrenme modellerinden Evrişimsel Sinir Ağı (Convolutional Neural Network – CNN) ve Derin Sinir Ağları (Deep Neural Network – DNN) kullanılarak akciğer tümörleri ile normal akciğer görüntülerinin tespiti gerçekleştirilmiştir. Kullanılan her modelin doğruluğu duyarlılık, kesinlik ve F1-Skor gibi farklı değerlendirme metrikleri ile hesaplanmış ve sonuçlar karşılaştırılmıştır. Ayrıca her model için performans analizleri yapılmış ve eğitim, test ve valid görüntüleri için karmaşıklık matrisleri ile ROC analizleri sunulmuştur.

Prediction of Tumor Data from Lung Images with Deep Neural Networks and Convolutional Neural Networks

Keywords
lung cancer, deep neural network, deep learning, CT, diagnosis

Abstract

Lung tumors are common today and are a dangerous disease that commonly causes death in people. However, manual examinations performed by experts can often lead to incorrect diagnosis. Instead, computer-assisted, automatic, accurate and detailed early cancer diagnosis is needed. For this reason, studies on lung diseases were examined in detail in this study. In the first stage of the study, 1190 lung tomography images were prepared for the proposed deep learning models. In the second stage, lung tumors and normal lung images were detected by using Convolutional Neural Network (CNN) and Deep Neural Network (DNN), which are deep learning models. The accuracy of each model used was calculated with different evaluation metrics such as sensitivity, precision and F1-Score, and the results were compared. In addition, performance analyzes were performed for each model, and complexity matrices and ROC analyzes were presented for training, testing and valid images.

1. Introduction

The lungs are vital organs responsible for oxygen intake and carbon dioxide removal through gas exchange during essential bodily functions. Rapid proliferation of cells and tissues in the lungs causes lung cancer. These cells, which proliferate uncontrollably, can cause serious damage by surrounding tissues or by spreading to another organ. According to the report published by the World Health Organization, lung cancer is the most lethal cancer type worldwide and causes the death of approximately 1.6 million people every year (Ayayna, 2023).

Lung diseases can be detected by experts using computer-aided analysis (Chaudhary and Singh, 2012). Environmental factors such as cigarette, pipe and cigar use, long-term exposure to harmful gases, asbestos and air pollution, as well as other lung diseases, also increase the risk of cancer. For example, someone who has had tuberculosis is more likely to develop lung cancer.

Malignant tumors in the lung are formed by the rapid and unbalanced proliferation of cells. Malignant tumors, which multiply over time and spread to all tissues and organs, cause serious and fatal diseases such as cancer (Thakur et al. 2020). For this reason, diagnosing lung cancer in its early stages is very important for the person's survival. Lung cancer is detected as a result of pathological examinations such as CT, PET and MRI. However, most of the time, lung cancer in its early stages may not be diagnosed during radiological examination, or the diagnosis made manually by experts may be incorrect (De Margerie-Mellon and Chassagnon, 2023). Approximately 20% of these diagnoses may be misdiagnosed. Therefore, there is a need for computer-aided applications that can automatically detect lung cancer and make early diagnosis.

Early detection and diagnosis of lung cancer are made as a result of evaluations such as chest radiography, MRI, PET, CT, biopsy, endoscopic examination of the bronchi, mediastinoscopy and thoracoscopic surgery of the lymph nodes (Bayram, 2019). In addition, these tests and examinations allow the detection of other diseases related to lung diseases. However, most of the time, these tests and examinations are misinterpreted by experts, making it difficult to detect the disease in its early stages. For this reason, in recent years, artificial intelligence methods have begun to be used for the early detection and diagnosis of lung diseases. Additionally, decision support mechanisms have been created using these methods. Literature studies conducted in recent years are summarized below:

In one study, different diseases were diagnosed from CT and chest X-ray images using deep learning methods (Ibrahim et al. 2021). Normal and abnormal features appearing in CT images were detected on the increased dataset using data augmentation methods. Additionally, the accuracy and performance of both datasets were calculated with ResNet152V2, VGG19-CNN, ResNet152V2 + Bidirectional GRU (Bi-GRU) and ResNet152V2 + Gated Recursive Unit (GRU) methods. When the results are compared, among these methods, VGG19+CNN is more successful than the other three methods. The VGG19+CNN method provided 99.5% specificity (SPC), 98.24% F1 score, 98.05 accuracy, and 98.43% sensitivity. To increase the performance of this study, more images can be obtained with methods such as classification and data augmentation GAN.

In the cited study, data from the Victorian Lung Cancer Registry (VLCR) between 2011 and 2022 were used (Earnest et al. 2023). In this study aim is to classify and estimate the quality of life of patients with lung cancer and the timeliness of patients' care. Additionally, Area Under the Receiver Operating Characteristic Curve (AUC-ROC) analysis were evaluated with all machine learning techniques. Results were analyzed with 10 K-fold cross validation. Study includes 11602 patient data. The SVM method gave better results than other machine learning methods, with an AUC of 0.89. With this study, possible delays in the treatment of patients and case management are carried out by monitoring the patients. However, more successful results can be obtained by optimizing the parameters used in the proposed machine learning methods. Extra costs in the field of healthcare can be reduced by practical application in clinics.

A computer-aided lung cancer evaluation support system was created using Medical Body Area Network (MBAN) information and deep learning (DL) models (Masood et al. 2018). The method called DFCNet detected four stages of lung cancer using a fully convolutional neural network. The DFCNet method shows that it is effective in recognizing and identifying the signs of lung cancer. Approximately 84.58% accuracy was achieved with this method. Although this method performs better in detecting the lung model (benign, malignant), it does not give the same results at different screening parameter values in false positive cases in detecting the malignant nodule.

The Mask-RCNN method was used for the diagnosis and characterization of pneumonia in lung x-ray images (CXR) (Jaiswal et al. 2019). They developed the Mask-RCNN model in their study to identify people with pneumonia. This model has a deep learning network and is often used in object tracking. This study was tested on RSNA data and this dataset consists of 30,000 images in total. The model they proposed achieved approximately 97% success. However, more hyperparameters may be required to detect pneumonia in images with different lung sizes.

By combining lung lobe segmentation and M-2 UNet classification on 3D CT data images, a collaborative method is proposed to automatically identify COVID-19 (He et al. 2021). The goal of multitasking is to rank this epidemic and segment the lung. In this study, 98.50% accuracy was achieved. The method used in this study can be analyzed for automatic classification and segmentation of different diseases.

COVID-19 patients were identified with the community model (Zhou et al. 2021). In the study, 2933 COVID - 19 CT images obtained from historical reports and online databases were used. Three transfer learning methods, AlexNet, ResNet and GoogleNet, were used to pre-train the input variables and the CNN model. These models were used to extract features on all images. The accuracy rate obtained in this study is 99.44% with ResNet. The success of the proposed model can be measured on larger datasets in the future.

A new approach called GSA DenseNet121 has been developed to detect various lung diseases (Ezzat and Ella, 2020). This method uses a CNN model called DenseNet121 and includes a generalized search engine (GSA). In the results obtained, the accuracy rate of the test data set of the proposed method is 98.38%.

CNN, Res-Net-50 and VGG 16 models were used to diagnose COVID-19 on medical data (Das et al. 2021). They divided the chest x-ray images into three classes: infected, uninfected patients and positive patients. The VGG-16 model gave more successful results than the other models used in the study, with 97.67%.

A study on the application of ML methods for automatic localization of pneumonia in chest X-ray images is proposed (Sirazitdinov et al. 2019). An ensemble method from the CNN network was used along with the RetinaNet and Mask R-CNN methods. A dataset of 26,684 images was used and a reliable solution for automatic pneumonia diagnosis was developed with a recall of 0.793. This study has yielded very successful results on a large labeled data set, and it is aimed to expand the study as a result of the feedback received from medical experts.

In other study, COVID-19 cases were classified using the CoroDet method on CT images (Hussain et al. 2021). This model aims to diagnose two, three or four-class COVID-19 cases. The results obtained with this study achieved 95.1%, 94.2% and 91.2% accuracy for two, three and four classes, respectively. However, in larger data sets, the proposed method may need to be compared with different methods in terms of accuracy, cost and speed. Additionally, the images used in training can be increased to improve the model.

When we look at the studies, many studies have been conducted in the literature on the diagnosis and diagnosis of lung cancer. Artificial intelligence-based methods have been proposed in these studies, and these studies in the field of medicine have been increasing daily in recent years. However, despite the developments in the use of artificial intelligence methods in the field of health in recent years, the need for computer-aided analysis and applications is increasing daily due to the increase and rapid spread of disease types. The unique value of our study, unlike other studies, is that the proposed methods use unique network structures to increase performance and success by making multiple classifications in the early detection and diagnosis of lung cancer. In order to increase the quality of life of patients by reducing the serious mortality rate caused by lung cancer, deep learning-based models have been developed and multiple classifications have been made. Our study also provided accurate, rapid and low-cost solutions for the detection of lung cancer.

Our study proposed computer-aided approaches using deep learning models to help experts diagnose lung cancer through CT images. Because experts may misinterpret chest radiographs and make the wrong diagnosis. In addition, manual evaluations make early and accurate diagnosis difficult in terms of cost and time. Considering these problems, our study aims to reduce the risk of misdiagnosis by detecting tumor data (benign, malignant and normal) from lung images at the early stage of the disease with Deep Neural Networks (DNN) and Convolutional Neural Networks (CNN). Models with different network structures have been created for multi-class disease detection and prediction, and the most appropriate hyper-parameters for the methods used are discussed in detail in our study with optimization methods. By comparing the results of the proposed methods with different evaluation criteria, the groundwork was laid for the creation of decision support systems that provide computer-aided disease detection for other lung diseases in the future. Because lung cancer, like other types of cancer, increases the chances of survival of patients with early diagnosis and increases the quality of life of people diagnosed with cancer.

The scientific contribution of our study is to create deep learning models with different network structures and to ensure that these models help experts, especially in medical fields. By extracting important features in the proposed deep learning models, success and performance have been increased, and it is aimed to make significant contributions to the diagnosis and treatment of different types of cancer in the future. The problems we addressed in our study are presented below:

• Can automatic, accurate, fast and cost-effective detection of lung cancer be achieved with computer-aided applications (Hussain et al., 2021)?

• Can the parameters of the deep learning methods be adjusted to provide the most successful performance and accuracy (Sabzalian et.al., 2023)?

• Have the proposed methods been encountered in the literature with studies using the same dataset (Sabzalian et.al., 2023)?

• Do the proposed deep learning models for big data provide the same success in other types of cancer and diseases (Solyman and Schwenker, 2022)?

The solutions we developed for the problems we addressed in our study are presented below:

• Deep learning models (DNN and CNN) have been created to automatically detect lung cancer quickly, accurately and cost-effectively.

• Hyperparameters are automatically adjusted to increase success with optimization algorithms.

• It is discussed in the conclusion section that it gives more successful results than the methods using the same dataset in the literature.

• It is aimed to lay the groundwork for future methods to be developed for large data sets.

The models we propose aim for radiologists to work on the early diagnosis of lung cancer and different lung diseases. In this way, misdiagnoses that may occur in manual evaluations made by experts will be reduced.

2. Materials ve Methods

The dataset we used was obtained through Kaggle. The data set called IQ-OTH/NCCD, obtained from a hospital in Iraq, was used in our study (https://www.kaggle.com/datasets/adityamahimkar/iqothnccd-lung-cancer-dataset). The dataset was collected over three months at select specialist hospitals in autumn 2019. This special data set includes computed tomography (CT) scans of patients diagnosed with lung cancer at different stages and healthy individuals. In total, there are 1190 images representing 110 situations.

In this study, a data set containing 1190 images was used to detect and classify lung cancer. Some images are shown in Figure 1 from this dataset. There are three classes in the dataset used for early diagnosis of lung cancer: Benign, Normal and Malignant. The number of samples and their distributions of these classes are shown in Figure 2.

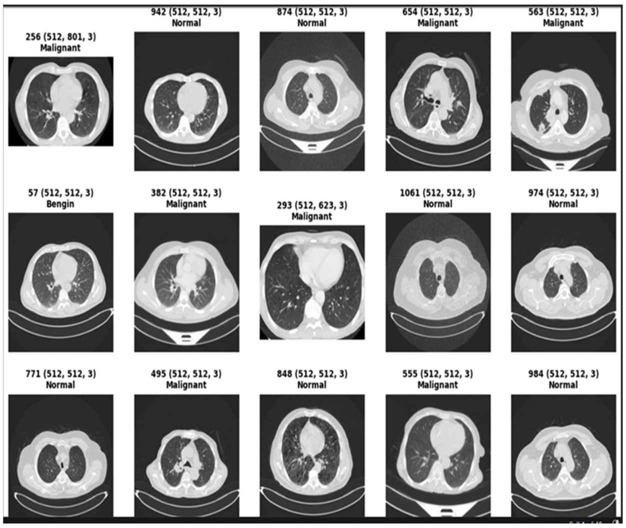

Figure 1. Images from data used for lung cancer

The flow block for the proposed deep learning models is given in Figure 3. Additionally, numerical values of training, valid and test images and their distribution within classes are shown in Figure 2. The 1190 lung images used in the study were pre-processed by going through pre-processing steps such as filtering, normalizing and bringing the image to a common size. 70% of the image dataset was used as training, 15% as validation and the remaining 15% as testing. Proposed deep learning models (DNN and CNN) with different and deep network structures were analyzed with different evaluation criteria. Additionally, the results obtained for both models are presented comparatively.

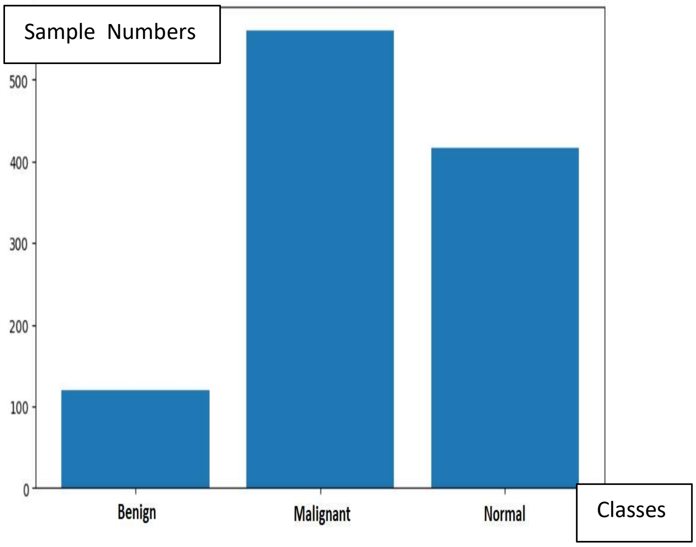

Figure 2. Distribution of lung images within classes

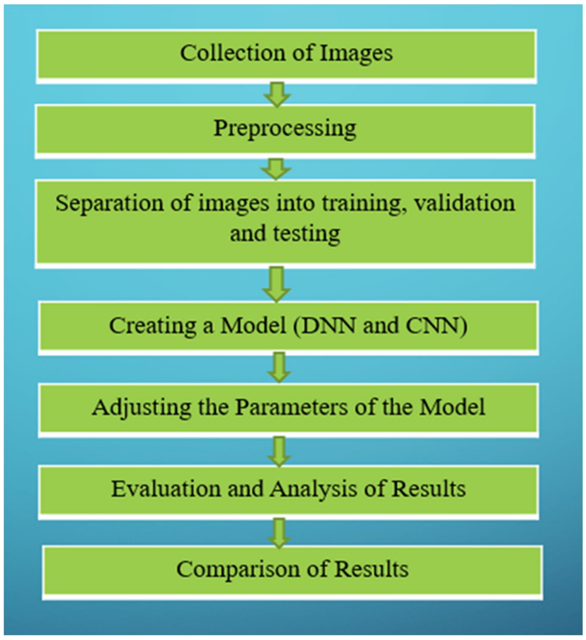

Figure 3. Workflow block of recommended models

2.1 Deep Neural Network (DNN)

Deep Neural Networks (DNNs), a prominent type of Artificial Neural Networks, are used especially within the concept of deep learning (Mothkur and Veerappa, 2023). Deep learning focuses on improving learning capabilities using a multi-layered and complex neural network architecture.

DNNs generally have a structure containing more than one hidden layer and connections are established between these layers (Prasad et al. 2023). Each hidden layer takes the output from the previous layer and uses this information to learn more sophisticated features. Typically, an arrangement consists of an input layer, one or more hidden layers, and an output layer.

The DNN network model proposed in our study and the hyperparameters used are given in Figure 4. In the study, all lung CT images of different sizes were converted to 150x150 images and the most appropriate hyperparameters were determined in each iteration for 100 epochs. In this study, the epoch value was selected as 100 and 10 iterations were determined for every 100 epochs. The batch size value is 50 to stop the model at the appropriate place. 50 batch size was used for 100 epoch cycles, and relu and softmax were used as activation functions. Additionally, all parameters obtained after the layers used in the study are shown in Table 1.

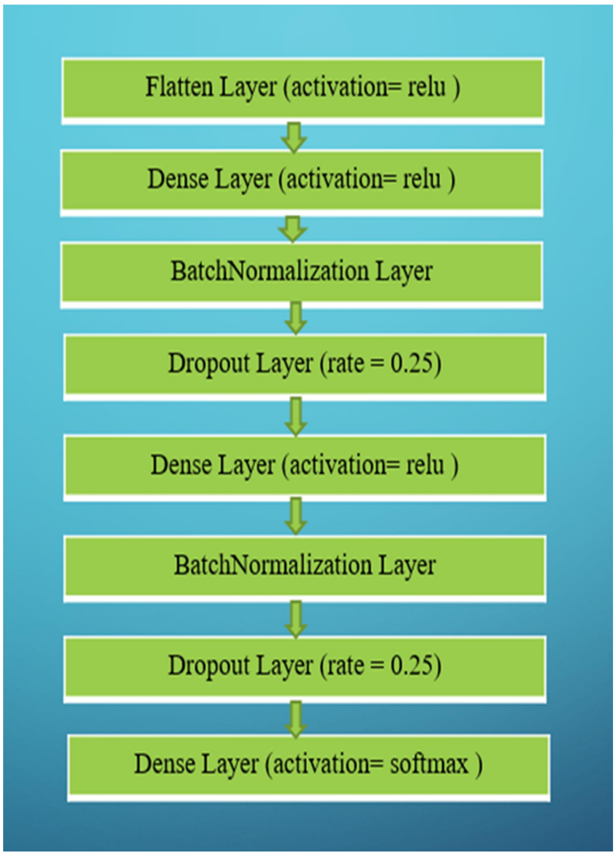

Figure 4. Proposed DNN model

Table 1. Proposed DNN model parameters

Layer	Output Shape	Param #
Flatten1 (Flatten)	(None, 67500)	0
Dense1 (Dense)	(None, 128)	8640128
Norm1 (BatchNormalization)	(None, 128)	512
Dropout1 (Dropout)	(None, 128)	0
Dense2 (Dense)	(None, 32)	4128
Norm2 (BatchNormalization)	(None, 32)	128
Dropout2 (Dropout)	(None, 32)	0
Dense3 (Dense)	(None, 3)	99
Total params: 8644995 (32.98 MB)		
Trainable params: 8644675 (32.98 MB)		
Non-trainabl params: 320 (1.25 KB)		

2.2 Convolutional Neural Network (CNN)

CNN is a deep learning model that is very effective in applications such as visual data analysis and recognition (Provath et al. 2023). It is widely used to achieve successful results, especially in areas such as image recognition, object detection and face recognition. It is an algorithm used in the field of deep learning and usually works with images. This algorithm performs the classification task using the features of images. Compared to other classification algorithms, the data pre-processing required for CNN is less. This is because CNN can learn filters, which distinguishes it from other classification algorithms.

An example of CNN architecture basically consists of three main layers, as shown in Figure 5: Convolutional Layer, Pooling Layer and Fully Connected Layer. As the image passes through these layers, it undergoes various processes and becomes suitable for the deep learning model.

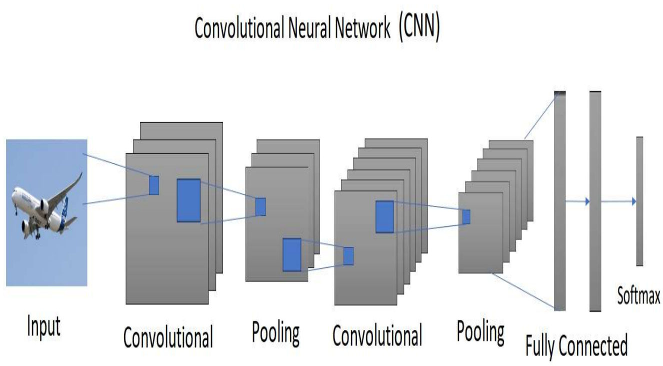

Figure 5. CNN structure

The CNN network model proposed in our study and the hyperparameters used are given in Figure 6. In the study, all lung CT images of different sizes were converted to 150x150 images and the most appropriate hyperparameters were determined in each iteration for 100 epochs. Softmax and relu layers were added to the layers determined in the convolution and pooling layer, and the number of filters was increased to ensure accurate classification and disease detection in the training and test images. Additionally, 3 x 3 convolution and 2 x 2 pooling layers were used. All parameters obtained after the layers used in the study are shown in Table 2.

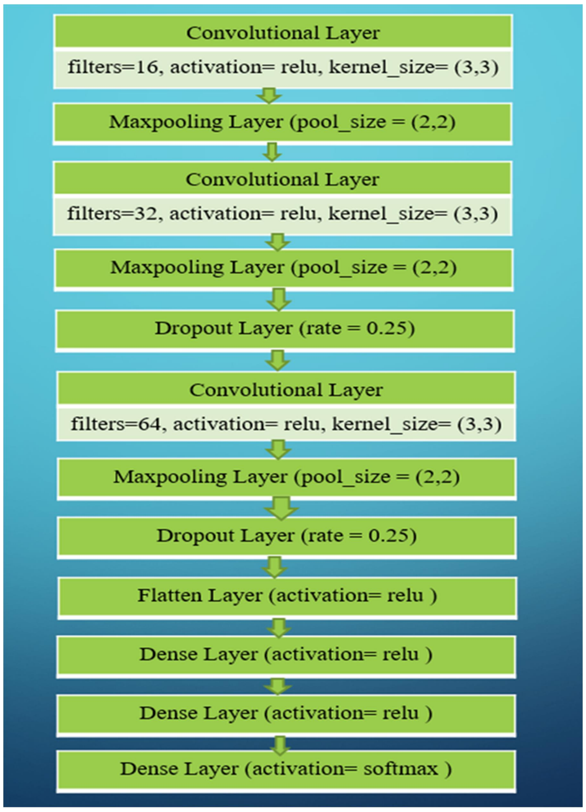

Figure 6. Proposed CNN model

Table 2. Recommended CNN model parameters

Layer	Output Shape	Param #
Conv1 (Conv2D)	(None, 150, 150, 16)	448
MaxPool1 (MaxPooling2D)	(None, 75, 75, 16)	0
Conv2 (Conv2D)	(None, 75, 75, 32)	4640
MaxPool2 (MaxPooling2D)	(None, 37, 37, 32)	0
Dropout1 (Dropout)	(None, 37, 37, 32)	0
Conv3 (Conv2D)	(None, 37, 37, 64)	18496
MaxPool3 (MaxPooling2D)	(None, 18, 18, 64)	0
Dropout2 (Dropout)	(None, 18, 18, 64)	0
Flatten1 (Flatten)	(None, 20736)	0
Dense1 (Dense)	(None, 128)	2654336
Dense2 (Dense)	(None, 32)	4128
Total params: 2682147 (10.23 MB)		
Trainable params: 2682147 (10.23 MB)		
Non-trainabl params: 0 (0.00 Byte)		

3. Results

The performance results of the DNN and CNN models proposed in our study were taken separately for training and testing. Complexity matrices and ROC analyzes were analyzed in detail. The accuracy rates of DNN and CNN models calculated according to the hyperparameters that give the most optimum results for training, valid and test data are shown in Figure 7. As a results, both recommended methods gave successful results in the diagnosis and diagnosis of lung cancer.

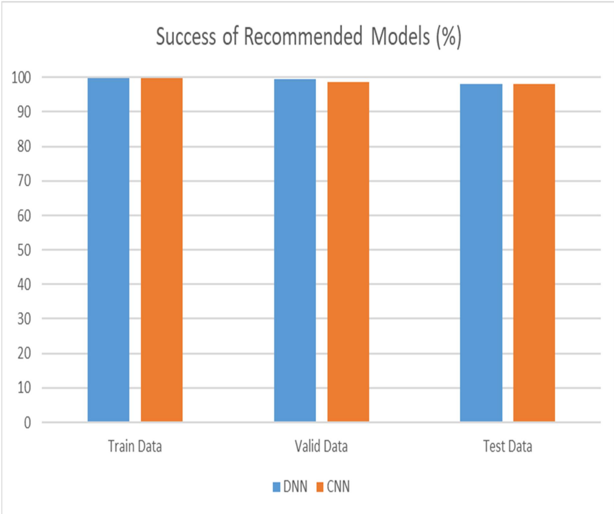

Figure 7. Success of Recommended Models (%)

3.1 DNN Results

The change in cross entropy error values for the data set we used is shown according to epoch values in Figure 8.

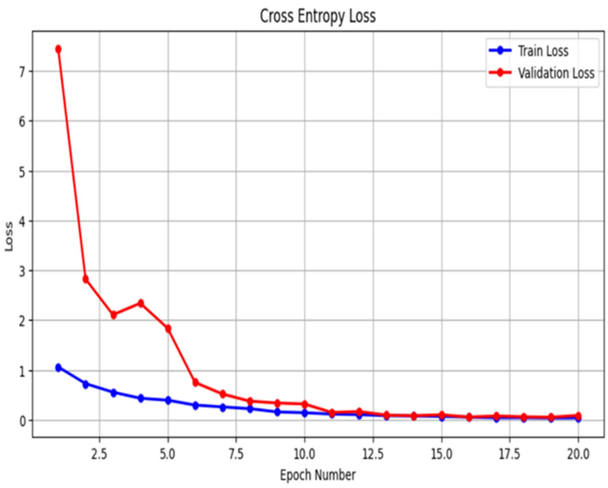

Figure 8. Cross Entropy Loss for the proposed DNN

As can be seen from the graph, the error is lowest at some epoch values. In our study, the learning coefficient was determined as 0.001, the batch size was 50, the "man" optimizer algorithm was determined for optimization, and the accuracy criterion was determined as the evaluation metric. The best learning is achieved by updating the weights in the classification accuracy graph given in Figure 9. When the classification accuracy for training and validation was analyzed, the epoch values of the best learning in training and validation accuracy were given.

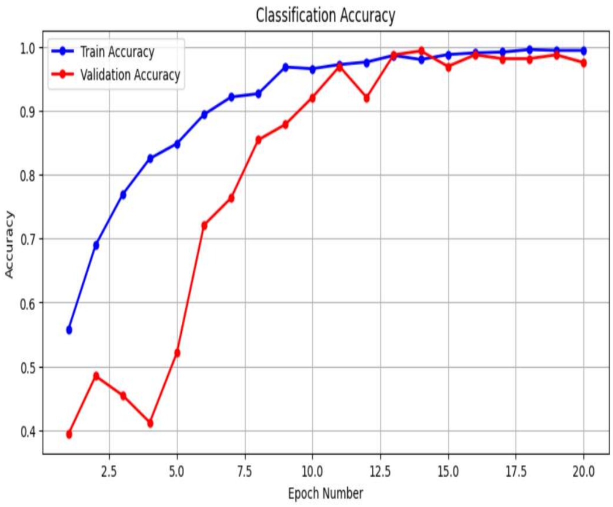

Figure 9. Classification Accuracy for the Proposed DNN

In Figure 10, the complexity matrix is given according to the most optimal hyperparameter selection for all data in the proposed DNN model.

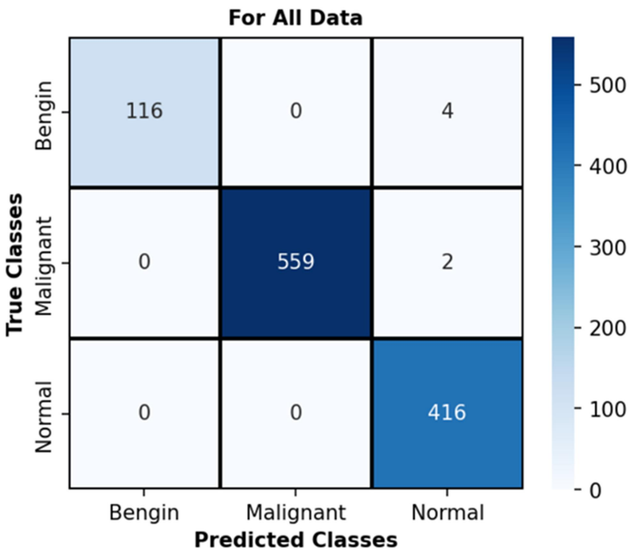

Figure 10. Complexity matrix for all data

In Figure 11, the complexity matrix is given according to the most optimal hyperparameter selection for the training data in the proposed DNN model.

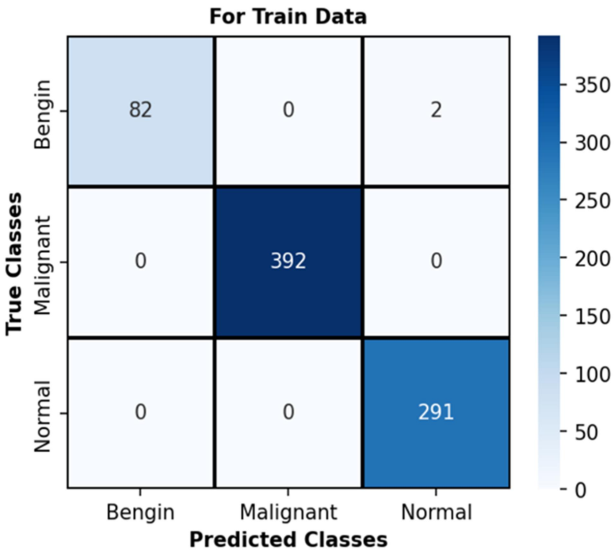

Figure 11. Complexity matrix for training data

In Figure 12, the complexity matrix is given according to the optimal hyperparameter selection for validation in the proposed DNN model.

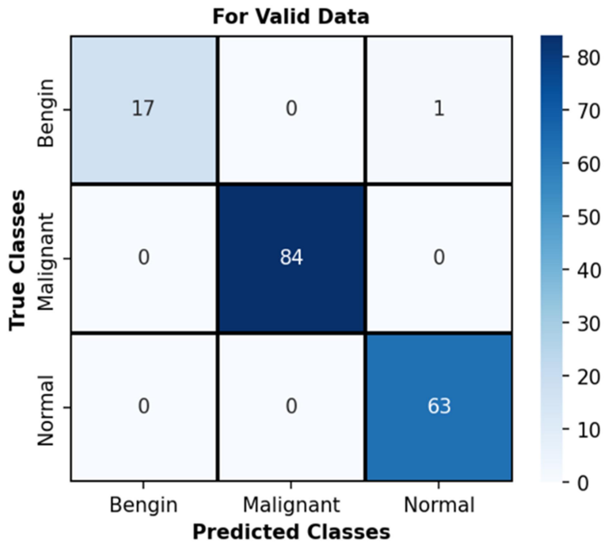

Figure 12. Complexity matrix for valid

Figure 13 shows the complexity matrix according to the most optimal hyperparameter selection for the test data in the proposed DNN model.

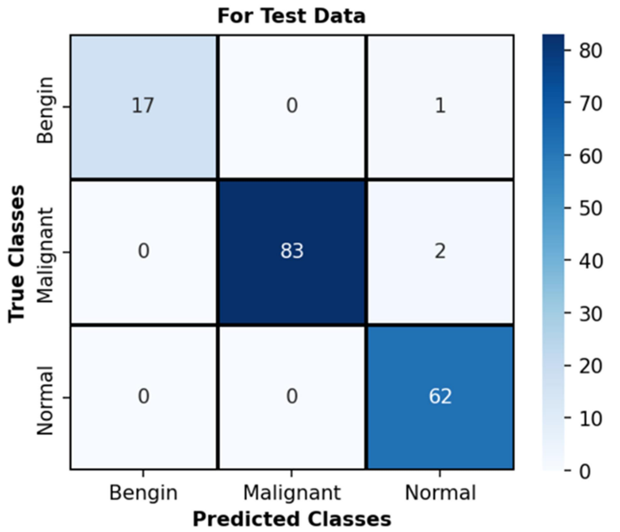

Figure 13. Complexity matrix for test data

Table 3 shows the diagnosis and classification results of lung cancer (benign, normal, malignant) according to some evaluation metrics for all training and valid data of the proposed DNN model.

Table 3. Classification report for training and valid

For All Data	Precision	Recall	F1-Score	Support
Benign	1.0000	0.9667	0.9831	120
Malignant	1.0000	0.9964	0.9982	561
Normal	0.9858	1.0000	0.9928	416
Accuracy			0.9945	1097
Macro Avg	0.9983	0.9877	0.9914	1097
Weighted Avg	0.9946	0.9945	0.9945	1097
For Train Data	**Precision**	**Recall**	**F1-Score**	**Support**
Benign	1.0000	0.9762	0.9880	84
Malignant	1.0000	1.0000	1.0000	392
Normal	0.9932	1.0000	0.9966	291
Accuracy			0.9974	767
Macro Avg	0.9977	0.9921	0.9948	767
Weighted Avg	0.9974	0.9974	0.9974	767
For Valid Data	**Precision**	**Recall**	**F1-Score**	**Support**
Accuracy			0.9818	165
Macro Avg	0.9846	0.9736	0.9786	165
Weighted Avg	0.9827	0.9818	0.9819	165

Figure 14 shows the ROC graph of the proposed DNN model for all data. When the ROC curve was analyzed, it was observed that it was quite successful in detecting lung cancer.

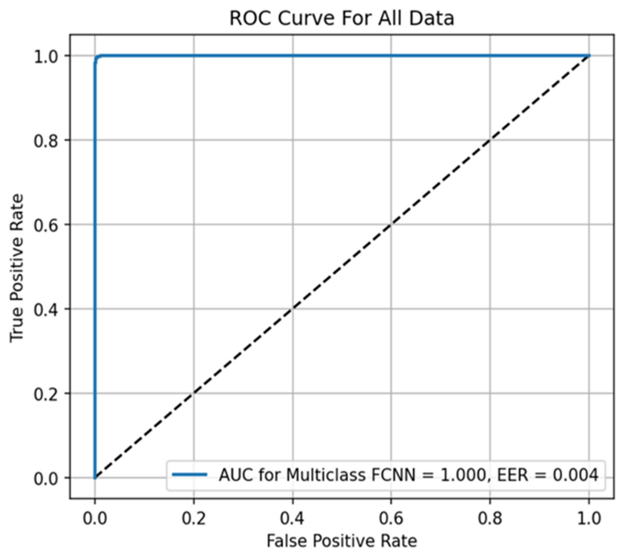

Figure 14. ROC analysis for all data

Figure 15 shows the ROC graph for the training data of the proposed DNN model. When the ROC curve was analyzed, it was observed that it was quite successful in detecting lung cancer.

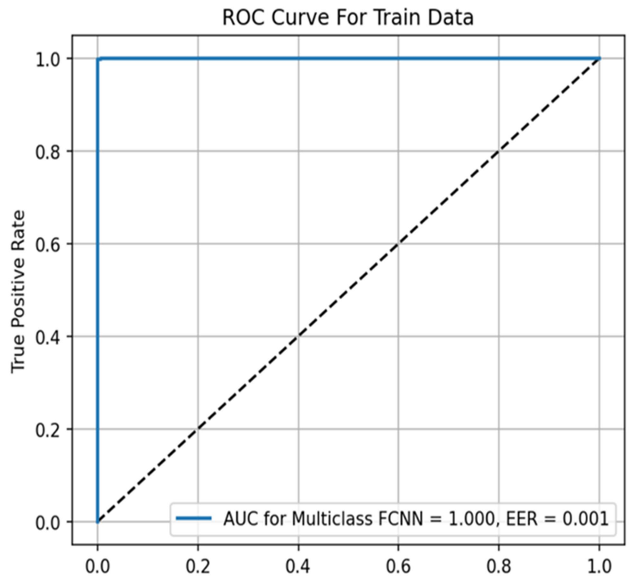

Figure 15. ROC analysis for training data

Figure 16 shows the ROC graph for the validity of the proposed DNN model. When the ROC curve was analyzed, it was observed that it was quite successful in detecting lung cancer.

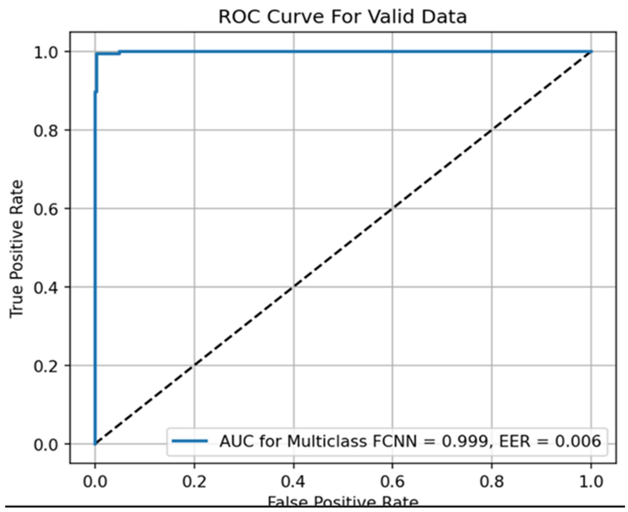

Figure 16. ROC analysis for valid

Figure 17 shows the ROC graph for the test data of the proposed DNN model. When the ROC curve was analyzed, it was observed that it was quite successful in detecting lung cancer.

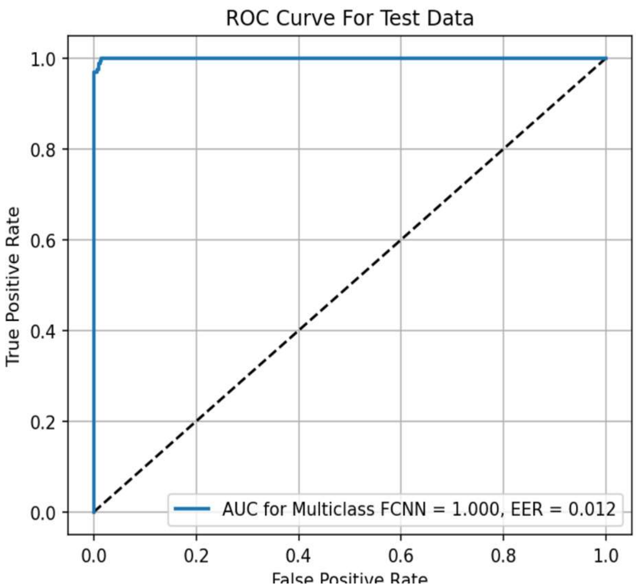

Figure 17. ROC analysis for test

3.2 CNN Results

The change in cross entropy error values for the data set we used is shown according to epoch values in Figure 18. As can be seen from the graph, the error is lowest at some epoch values. In our study, the learning coefficient was determined as 0.001, the "man" optimizer algorithm was determined for optimization, and the accuracy criterion was determined as the evaluation metric.

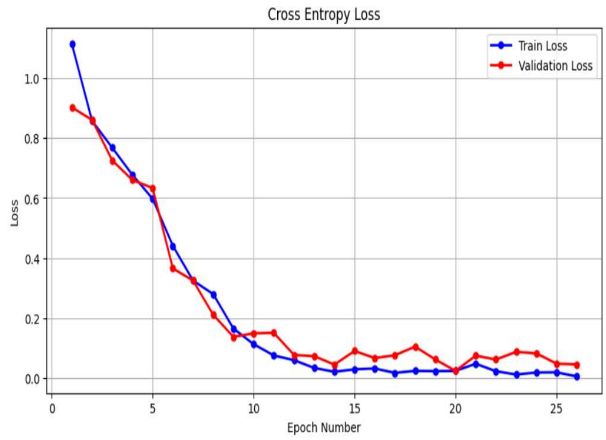

Figure 18. Cross Entropy Loss for the proposed CNN

The best learning was achieved by updating the weights in the classification accuracy graph given for the proposed CNN model in Figure 19.

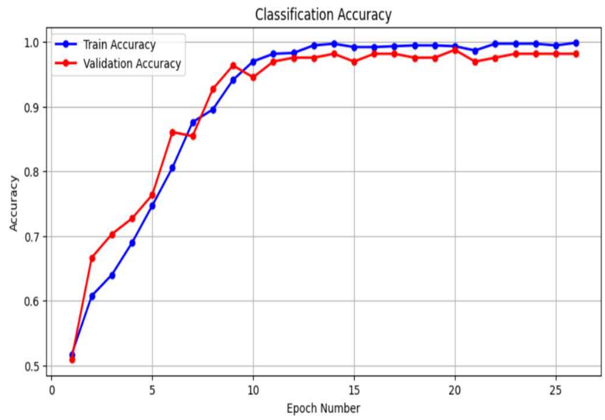

Figure 19. Classification Accuracy for the proposed CNN

In Figure 20, the complexity matrix is given according to the most optimal hyperparameter selection for the entire data in the proposed CNN model.

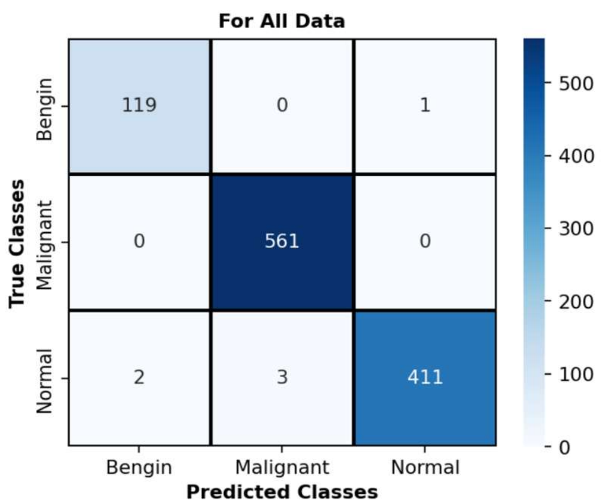

Figure 20. Complexity matrix for all data

In Figure 21, the complexity matrix is given according to the most optimal hyperparameter selection for the training data in the proposed CNN model.

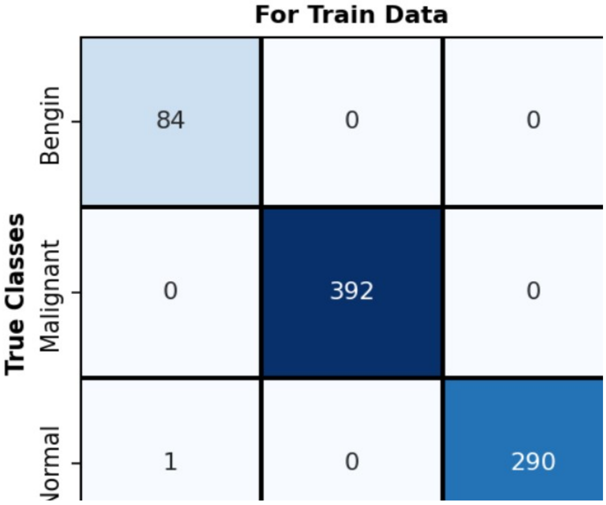

Figure 21. Complexity matrix for training data

Figure 22 shows the complexity matrix according to the optimal hyperparameter selection for valid in the proposed CNN model.

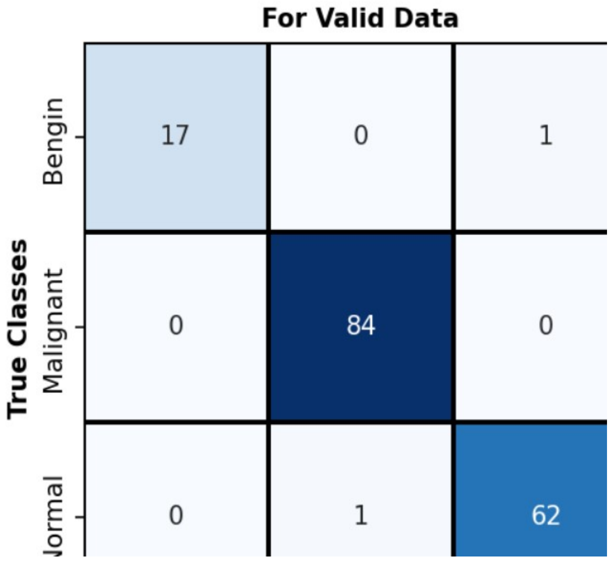

Figure 22. Complexity matrix for Valid

Figure 23 shows the complexity matrix according to the most optimal hyperparameter selection for the test data in the proposed CNN model.

Figure 23. Complexity matrix for test data

Table 4 shows the diagnosis and classification results of lung cancer (benign, normal, malignant) according to some evaluation metrics for all training and validation data of the proposed CNN model.

Table 4. Classification report for training and valid

For All Data	**Precision**	**Recall**	**F1-Score**	**Support**
Benign	0.9835	0.9917	0.9876	120
Malignant	0.9947	1.0000	0.9973	561
Normal	0.9976	0.9880	0.9928	416
Accuracy			0.9945	1097
Macro Avg	0.9919	0.9932	0.9925	1097
Weighted Avg	0.9946	0.9945	0.9945	1097
For Train Data	**Precision**	**Recall**	**F1-Score**	**Support**
Benign	0.9882	1.0000	0.9941	84
Malignant	1.0000	1.0000	1.0000	392
Normal	1.0000	0.9966	0.9983	291
Accuracy			0.9987	767
Macro Avg	0.9961	0.9989	0.9975	767
Weighted Avg	0.9987	0.9987	0.9987	767
For Valid Data	**Precision**	**Recall**	**F1-Score**	**Support**
Accuracy			0.9818	165
Macro Avg	0.9748	0.9839	0.9789	165
Weighted Avg	0.9824	0.9818	0.9817	165

Figure 24 shows the ROC graph of the proposed CNN model for all data. When the ROC curve was analyzed, it was observed that it was quite successful in detecting lung cancer.

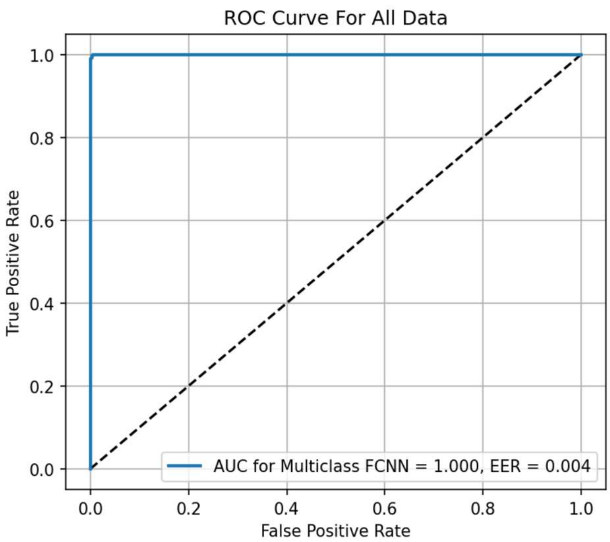

Figure 24. ROC analysis for all data

Figure 25 shows the ROC graph for the training data of the proposed CNN model. When the ROC curve was analyzed, it was observed that it was quite successful in detecting lung cancer.

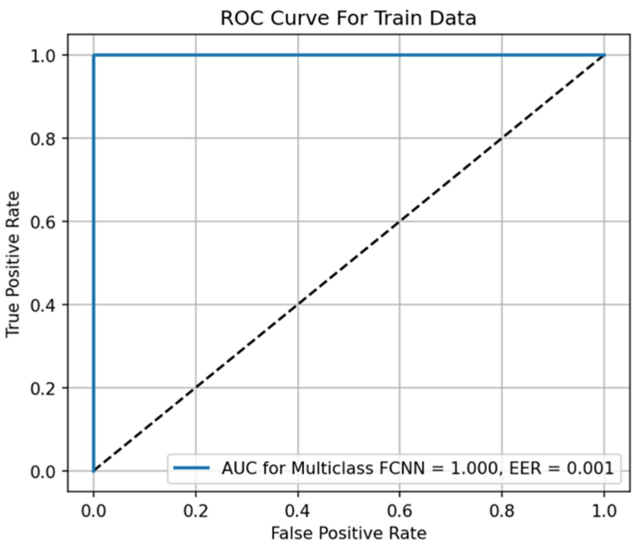

Figure 25. ROC analysis for training data

Figure 26 shows the ROC graph for the validity of the proposed CNN model. When the ROC curve was analyzed, it was observed that it was quite successful in detecting lung cancer.

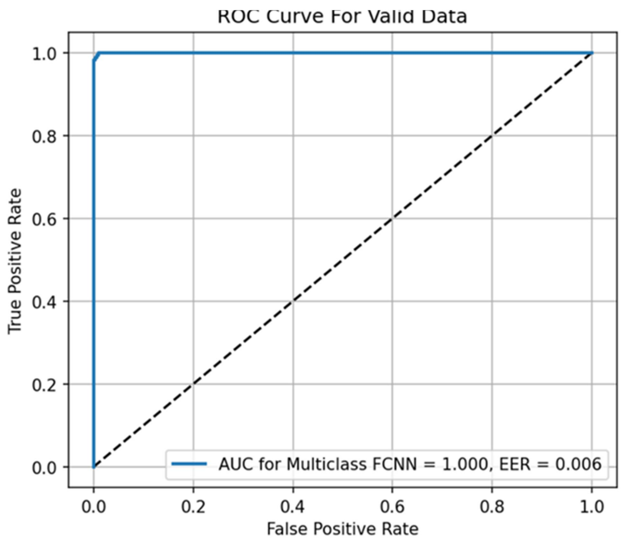

Figure 26. ROC analysis for valid

Figure 27 shows the ROC graph for the test data of the proposed CNN model. When the ROC curve was analyzed, it was observed that it was quite successful in detecting lung cancer.

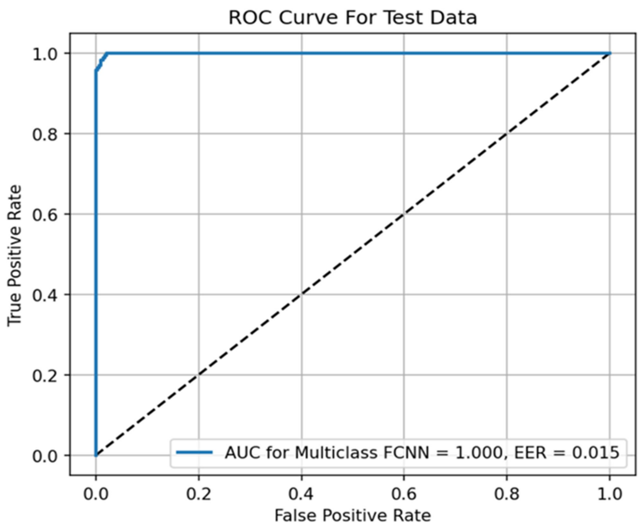

Figure 27. ROC analysis for test data

4. Discussion and Conclusion

Table 5 shows the results of some studies conducted in the literature with the model we proposed on the same dataset (IQ-OTH/NCCD lung CT images). Our study has been shown to give very successful results on this dataset.

In this study, it was aimed to diagnose lung cancer, which has the highest mortality rate, by using deep learning models. In addition, deep learning-based models have been proposed to overcome the workload of healthcare professionals and the difficulties of manual diagnosis. In this way, decision support mechanisms that make accurate and fast decisions in the medical field have been created, thus reducing the workload of healthcare professionals in terms of diagnosis. Benign, normal and malignant tumors were detected with DNN and CNN models in our study. In the study, an accuracy of 99.39 was found with the DNN method applied on the data set used, and an accuracy of 98.78 with the CNN method on the valid data.

Table 6 shows the results of some studies conducted in the literature with the model we proposed on the same dataset (IQ-OTH/NCCD lung CT images). Our study has been shown to give very successful results on this dataset.

Table 5. Studies in the literature

Studies Conducted in the Literature	**Used Method**	**Success Rate (%)**
Al-Huseiny et.al	Transfer learning with GoogLeNet	94.38%
Sabzalian et.al	Bidirectional Recurrent neural network	97.06%
Solyman and Schwenker	Ensemble learning techniques	92.80%
Kareem et.al	SVM	89.88%
Raza et.al	EfficientNet	99.10%
Proposed Method	**DNN**	**99.39%**

In future studies, it is aimed to develop a model that can automatically detect various diseases that can trigger cancer formation, such as pneumonia, tuberculosis, COPD, and COVID-19, from lung radiographs, thanks to the proposed method.

5. References

Al-Huseiny, M. S., & Sajit, A. S. (2021). Transfer learning with GoogLeNet for detection of lung cancer. Indonesian Journal of Electrical Engineering and Computer Science, 22(2), 1078-1086.

Ayayna, F. (2023). Akciğer kanserinin derin öğrenme yaklaşımları kullanılarak tespit edilmesi (Master's thesis, Batman Üniversitesi Lisansüstü Eğitim Enstitüsü).

Al-Huseiny, M. S., & Sajit, A. S. (2021). Transfer learning with GoogLeNet for detection of lung cancer. Indonesian Journal of Electrical Engineering and Computer Science, 22(2), 1078-1086.

Al Mamlook, R. E., Chen, S., & Bzizi, H. F. (2020, July). Investigation of the performance of machine learning classifiers for pneumonia detection in chest X-ray images. In 2020 IEEE International Conference on Electro Information Technology (EIT) (pp. 098-104). IEEE.

Ayayna, F. (2023). Akciğer kanserinin derin öğrenme yaklaşımları kullanılarak tespit edilmesi (Master's thesis, Batman Üniversitesi Lisansüstü Eğitim Enstitüsü).

Ibrahim, D. M., Elshennawy, N. M., & Sarhan, A. M. (2021). Deep-chest: Multi-classification deep learning model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases. Computers in biology and medicine, 132, 104348.

Jaiswal, A. K., Tiwari, P., Kumar, S., Gupta, D., Khanna, A., & Rodrigues, J. J. (2019). Identifying pneumonia in chest X-rays: A deep learning approach. Measurement, 145, 511-518.

Kareem, H. F., AL-Husieny, M. S., Mohsen, F. Y., Khalil, E. A., & Hassan, Z. S. (2021). Evaluation of SVM performance in the detection of lung cancer in marked CT scan dataset. Indonesian Journal of Electrical Engineering and Computer Science, 21(3), 1731.

Masood, A., Sheng, B., Li, P., Hou, X., Wei, X., Qin, J., & Feng, D. (2018). Computer-Assisted Decision Support System in Pulmonary Cancer detection and stage classification on CT images. Journal of Biomedical Informatics, 79(June 2017), 117–128.

Mothkur, R., & Veerappa, B. N. (2023). Classification Of Lung Cancer Using Lightweight Deep Neural Networks. Procedia Computer Science, 218, 1869-1877.

Prasad, U., Chakravarty, S., & Mahto, G. (2023). Lung cancer detection and classification using deep neural network based on hybrid metaheuristic algorithm. Soft Computing, 1-24.

Provath, M. A. M., Deb, K., Dhar, P. K., & Shimamura, T. (2023). Classification of Lung and Colon Cancer Histopathological Images Using Global Context Attention Based Convolutional Neural Network. IEEE Access.

Raza, R., Zulfiqar, F., Khan, M. O., Arif, M., Alvi, A., Iftikhar, M. A., & Alam, T. (2023). Lung-EffNet: Lung cancer classification using EfficientNet from CT-scan images. Engineering Applications of Artificial Intelligence, 126, 106902.

Sabzalian, M. H., Kharajinezhadian, F., Tajally, A., Reihanisaransari, R., Alkhazaleh, H. A., & Bokov, D. (2023). New bidirectional recurrent neural network optimized by improved Ebola search optimization algorithm for lung cancer diagnosis. Biomedical Signal Processing and Control, 84, 104965.

Sirazitdinov, I., Kholiavchenko, M., Mustafaev, T., Yixuan, Y., Kuleev, R., & Ibragimov, B. (2019). Deep neural network ensemble for pneumonia localization from a large-scale chest x-ray database. Computers & electrical engineering, 78, 388-399.

Solyman, S., & Schwenker, F. (2022, October). Lung Tumor Detection and Recognition Using Deep Convolutional Neural Networks. In Pan African Conference on Artificial Intelligence (pp. 79-91). Cham: Springer Nature Switzerland.

Thakur, S. K., Singh, D. P., & Choudhary, J. (2020). Lung cancer identification: a review on detection and classification. Cancer and Metastasis Reviews, 39, 989-998.

www.kaggle.com/datasets/adityamahimkar/iqothnccd-lung-cancer-dataset

Zhou, T., Lu, H., Yang, Z., Qiu, S., Huo, B., & Dong, Y. (2021). The ensemble deep learning model for novel COVID-19 on CT images. Applied soft computing, 98, 106885.