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Classification of Lung and Colon Cancer Histopathological Images using a Novel Artificial Intelligence Method

İsmail Akgül[a], **Volkan Kaya**[*b], **Tuğba Bal Taştan**[c]

ABSTRACT

Cancer is a disease in which cells acquire autonomous growth, genetic instability, and significant metastatic strength, and is considered one of the most common causes of death worldwide. The most important types of cancer-causing these deaths are lung and colon cancers. Although they are rarely seen at the same time, the rate of metastasis of cancerous cells between these two organs is quite high if not diagnosed early. Histopathological diagnosis and appropriate treatment are the only ways to distinguish cancer types and reduce cancer death rates. The use of artificial intelligence in histopathological diagnosis can also provide experts with significant assistance with less effort, time, and cost. In this study a dataset, containing 25000 histopathological images belonging to 5 classes to classify colon and lung cancer types, was used. In order to obtain successful classification results from this dataset, the versions of the DenseNet algorithm, one of the deep learning algorithms, (DenseNet121, DenseNet169, and DenseNet201) were used firstly. Then, 3 novel models (DenseNet121_Improved, DenseNet169_Improved, and DenseNet201_Improved) were proposed by adding a cut-point layer, an auxiliary layer, and making frozen status improvements to the versions of the DenseNet algorithm. Versions of the DenseNet algorithm and proposed models were trained with stratified k-fold cross-validation technique first on colon cancer containing 2-class histopathological images, then lung cancer containing 3-class histopathological images, and lastly on 5-class histopathological images containing both colon and lung cancer. Finally, classification success rates were obtained. According to the experimental results performed on 3 different datasets, 97.60%, and 98.48% classification success rates in the lung cancer dataset and in both colon and lung cancer datasets were obtained respectively. The best classification success rate was achieved with DenseNet201_Improved, which was recommended with 99.80% in the colon cancer dataset.

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Keywords: Artificial intelligence, deep learning, transfer learning, auxiliary layer, stratified k-fold cross-validation, lung and colon cancer

Yeni Bir Yapay Zekâ Yöntemi Kullanılarak Akciğer ve Kolon Kanseri Histopatolojik Görüntülerinin Sınıflandırılması

ÖZ

Kanser, hücrelerin otonom büyüme, genetik instabilite ve önemli metastatik güç kazandığı bir hastalıktır ve dünya çapında en yaygın ölüm nedenlerinden biri olarak kabul edilir. Bu ölümlere neden olan en önemli kanser türleri akciğer ve kolon kanserleridir. Nadiren aynı anda görülmelerine rağmen, erken teşhis edilmezse bu iki organ arasındaki kanserli hücrelerin metastaz oranı oldukça yüksektir. Histopatolojik tanı ve uygun tedavi, kanser türlerini ayırt etmenin ve kanser ölüm oranlarını azaltmanın tek yoludur. Histopatolojik tanıda yapay zekanın kullanılması, uzmanlara daha az çaba, zaman ve maliyetle önemli bir yardım da sağlayabilir. Bu çalışmada, kolon ve akciğer kanseri türlerini sınıflandırmak için 5 sınıfa ait 25000 histopatolojik görüntü içeren bir veri seti kullanıldı. Bu veri setinden başarılı sınıflandırma sonuçları elde edebilmek için öncelikle derin öğrenme algoritmalarından DenseNet algoritmasının versiyonları (DenseNet121, DenseNet169 ve DenseNet201) kullanıldı. Daha sonra, DenseNet algoritmasının versiyonlarına blok kesme, katmanı, yardımcı katman ekleme ve dondurma durumu iyileştirmeleri yapılarak 3 yeni model (DenseNet121_Improved, DenseNet169_Improved ve DenseNet201_Improved) önerildi. DenseNet algoritmasının versiyonları ve önerilen modeller, ilk önce 2 sınıflı histopatolojik görüntüler içeren kolon kanseri, ardından 3 sınıflı histopatolojik görüntüler içeren akciğer kanseri ve son olarak hem kolon hem de akciğer kanseri içeren 5 sınıflı histopatolojik görüntüler üzerinde katmanlı k katlı çapraz doğrulama tekniği ile eğitildi. Son olarak, sınıflandırma başarı oranları elde edildi. 3 farklı veri kümesinde gerçekleştirilen deneysel sonuçlara göre, akciğer kanseri veri kümesinde %97,60 ve hem kolon hem de akciğer kanseri veri kümelerinde sırasıyla %98,48 sınıflandırma başarı oranları elde edildi. Kolon kanseri veri setinde %99,80 ile önerilen DenseNet201_Improved ile en iyi sınıflandırma başarı oranı elde edildi.

Anahtar Kelimeler: Yapay zekâ, derin öğrenme, transfer öğrenmesi, yardımcı katman, katmanlı k katlı çapraz doğrulama, akciğer ve kolon kanseri

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1. Introduction

Cancer, caused by factors such as genetic, environmental, poor diet, smoking and alcohol, is a terrible disease that greatly affects an individual's lifestyle. Cancer can spread rapidly to all other organs via metastasis. Cancer is the second most effective disease in our country after cardiovascular diseases [1,2]. It most commonly affects the lungs, chest, colon, brain, rectum, stomach, and liver. Among these, lung and colon cancers are the cancer types that result in the most deaths in all individuals. In 2018, they are responsible for more than 2.5 million deaths and 2.9 million new cancer cases in the USA alone [3].

Lung cancer is the second most common type of cancer, accounting for 11.4% of new cases. As a result of the researches, among cancer-related deaths, the death rate in lung cancer ranks first in the world and constitutes 18.0% of the total mortality rate [4]. On the other hand, in Turkey and according to the 2022 data published by the American Cancer Society, colon cancer has been reported to be the 3rd most common type of cancer in both men and women [5].

Lung cancer is the most common type of cancer in the world and is caused not only by smoking but also by exposure to toxic chemicals such as arsenic, radon, and asbestos. In recent advances in lung cancer genome analysis, EGFR has been molecular differences in the KRAS, MET, LKB1, BRAF, PIK3CA, ALK, RET, and ROS1 genes have also been reported to be responsible for the formation of lung cancer [6]. Since 70% of patients with lung cancer are in the advanced stage at the time of diagnosis, only 15% are still alive 5 years later. The most common subtypes of lung cancer that require visual inspection and differentiation by an experienced pathologist are Adenocarcinoma (LUAD) and squamous cell carcinoma (LUSC) [7,8].

Colon cancer is also a type of cancer that is usually caused by genomic and mitochondrial mutations [9,10] and has 50% liver metastasis [11]. Colon cancer, most common in the gastrointestinal tract, begins in the large intestine and extends to the lower parts of the digestive system. Cancer is formed in the cells lining the colon's inner surface, and swellings called polyps occur over time. These polyps cause tumors and cancer, and for their examination, traditional methods are used such as colonoscopy and MRI (magnetic resonance). Colonoscopy is a painful procedure that patients do not look forward to because of their feelings of shame, shyness, and fear. Unfortunately, patients are exposed to some radiation in the MRI method. Considering these situations, the need for simpler and different applications is important in the early diagnosis of cancer patients [12-14].

In recent years, there is a need to develop computer-based methods because of the increasing workload, the accuracy of pathologists and radiologists, and the difficulty of workflow efficiency in improving patient care with the use of these classical methods [15]. Artificial Intelligence (AI), one of the highest levels of today's technological developments, in modeling human intelligence; It is a technology formed by bringing together systems and machines that perform actions such as reasoning and making sense [16,17]. Deep Learning (DL) is a subgroup of artificial intelligence developed by utilizing the neurologic multilayered neural network structure of the brain. Convolutional Neural Network (CNN), a very popular type of deep learning, is a method used to obtain a series of remarkable research results such as object detection and classification of images.

With deep learning and CNN technologies in the health sector, researchers and medical specialists have had the opportunity to analyze diseases in more detail by using medical data. In recent years, important steps have been taken especially in the diagnosis of cancer with the use of deep learning methods. With the increase in advanced technological studies in this field, a large amount of cancer data can be collected to be used effectively in medical research [18,19].

In the medical sciences, recent advances have been made in classification analysis using computer-assisted methods for imaging tumor histopathology [20]. Although cancer histopathological images are quite rich, the data are not fully clarified [21]. It has been reported that with the developed computer-assisted imaging analyzes, it has been detected with an accurate, efficient, and consistent determination for diagnosis [22].

In this study, histopathological images of colon and lung cancer were classified using DenseNet121, DenseNet169, and DenseNet201 methods, deep learning techniques and outstanding successful in

classification success rates. While performing the classification process, the LC25000 dataset [23,24]. was used and the colon and lung images in this dataset were handled both separately and together, and the classification process was carried out. During the classification process, DenseNet versions accepted in the literature, and 3 novel models obtained by making improvements to these versions were used and compared. The training and testing of DenseNet versions was carried out using the transfer learning technique.

The remainder of the text is organized as follows. In Chapter 2, studies in the field of classification of colon and lung cancer with histopathological images are given. Materials and methods are covered in Chapter 3, and experimental analyzes and discussions from histopathological images of colon and lung cancer are included in Chapter 4. Chapter 5 discusses the results and future work.

2. Related work

Researchers have used DL based learning algorithms in almost all types of a cancer diagnosis. Since our study belongs to the field of diagnosis and classification of lung and colon cancer, we will consider the methods reported in these two fields. These approaches vary depending on the type of images used, the techniques applied to these images, and the DL model used for cancer identification.

In 2018 Selvanambi et al., used Recurrent Neural Network (RNN) as the Learning algorithm in a Lung cancer prediction method based on firefly swarm optimization (GSO) using images from multiple sources and achieved 98% accuracy [25]. de Carvalho Filho et al., proposed CNN-based lung cancer identification method on more than 50,500 CT scan images and achieved 92.63% accuracy, 90.7% sensitivity, 93.47% specificity rates [26]. In 2020, Suresh and Mohan announced a method of diagnosing lung cancer using the CNN model. They achieved 93.9% accuracy with the CNN-based classification method on CT scan images [27]. Masud et al., proposed a CNN-based automated pulmonary nodule detection and classification system using the Lung Image Database Consortium (LIDC). With this method they suggested, they achieved an accuracy rate of 97.9% [28]. Bębas et al., used various classification methods including SVM, kNN, RF, deep learning in PET/MR lung images and achieved 75.48% efficiency in adenocarcinoma and squamous cell carcinoma classification [29].

Tasnim et al., developed the maximum pooling and average pooling layers and MobileNetV2 models, CNN models that they trained and tested in different epochs to analyze colon cell images. Among these methods, The MobileNetV2 model was found to be superior to the other 2 models with 99.67% higher accuracy and 1.24% lower data loss rate [30]. Qasim et al., produced a CNN model to predict colon cancer with a small number of parameters in the Visual geometry group (VGG16) model. They reported that the accuracy of the proposed model was 99.6% and the VGG16 was 96.2% [31]. Godhindi et al., used CNN, Random Forest, and KNN machine learning algorithms to detect polyps in colon cancer in their study, achieving 87%, 85%, and 83% accuracy, respectively. They showed that they achieved better results in deep learning models compared to classical machine learning models [32]. Vuong et al., developed a procedure to classify colon cancer images using deep-learning architectures. They achieved 85.91% accuracy with the DenseNET121 model and emphasized that the classification of different types of tumor tissues in colon cancer is an important study in the field of pathology [33]. Yuan et al., used the CNN-based AlexNet technique in their research and achieved an accuracy rate of 91.47% in the classification of polyps in colonoscopic film images [34]. Masud et al., performed classification studies on histological images using CNN and Digital Image Processing (DIP) methods to distinguish two benign and three malignant colon cancer tissues. As a result of the study, they reported that they could detect cancer tissues with an accuracy of up to 96.33% [3]. Postavaru et al., achieved 91.4% accuracy with the 5 convolution layers of the CNN method in order to make an automatic diagnosis on a series of histopathological images of individuals with colorectal cancer [35].

3. Materials and Methods

In this part of the study, detailed information is given about the dataset, dataset preprocessing, system structure, model structures, and training parameters used to obtain successful classification results in the histopathological images of colon and lung cancer from the DenseNet algorithm.

3.1. Dataset and image pre-processing

In the study, a dataset containing histopathological images of 2-class colon cancer and 3-class lung cancer, frequently used in the literature and downloaded from the internet, was used [23,24]. This dataset includes colon adenocarcinoma and colon benign tissue types in colon cancer and lung adenocarcinoma, lung benign tissue, and lung squamous cell carcinoma types in lung cancer. There are 25000 images in total in the dataset. Of these, 10000 are histopathological images of colon cancer types, and 15000 are histopathological images of lung cancer types (Table 1).

Table 1. Colon and lung cancer histopathological image numbers in the dataset

Datasets	Colon Adenocarcinoma	Colon Benign Tissue	Lung Adenocarcinoma	Lung Benign Tissue	Lung Squamous Cell Carcinoma	Total
Image Numbers	5000	5000	5000	5000	5000	25000

The dimensions of the colon and lung cancer histopathological images in the dataset is 768×768×3. In order to get successful results from the deep learning methods discussed in the study, each image in the dataset was rearranged by adjusting it to 64×64×3 pixels. Example images of colon and lung cancer histopathological images in the dataset are given in Figure 1.

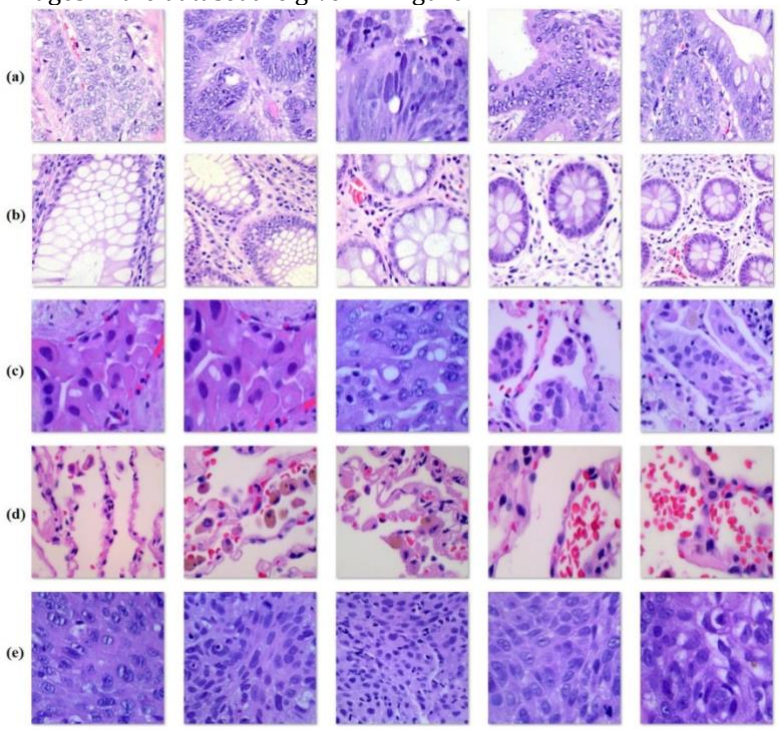


Figure 1. Histopathological images of colon and lung cancer in the dataset (a) Colon Adenocarcinoma (b) Colon Benign Tissue (c) Lung Adenocarcinoma (d) Lung Benign Tissue (e) Lung Squamous Cell Carcinoma

3.2. System Structure

In the study, Python programming language was used for both training and testing of DenseNet deep learning algorithm versions on histopathological images of colon and lung cancer. In order to analyze the results obtained, Google Colaboratory [36] with NVIDIA Tesla K80 graphics processor was used.

3.3. Model Structures

In the study, the DenseNet algorithm was preferred in order to obtain successful classification results from histopathological images of colon and lung cancer. While performing the classification process, DenseNet121 [37], DenseNet169 [38], and DenseNet201 [39] model structures were used. However, using these model structures, 3 novel improved models have been proposed, namely DenseNet121_Improved, DenseNet169_Improved, and DenseNet201_Improved. In Table 2, the model structures of the DenseNet algorithm versions and the model structures of 3 novel models obtained by making improvements in these model structures were given.

Table 2. Model Structures

Models	Frozen Status	Cut-Point Layer	Deducted Blok	Auxiliary Layers	Total Params	Feature
DenseNet121	Yes	None	None	None	7,04M	1024
DenseNet121 Improved		conv4_block24_concat	1	Conv2D(256, (3, 3) BatchNormalization MaxPool2D(2, 2) Dropout(0.2) Dense(64) Dropout(0.20))	6,70M	1024-256
DenseNet169		None	None	None	12,65M	1664
DenseNet169 Improved		conv4_block32_concat	1	Conv2D (256,(3, 3) + BatchNormalization + MaxPool2D(2, 2) + Dropout(0.2) + Dense(64) + Dropout(0.20))	8,78M	1280 - 256
DenseNet201		None	None	None	18,33M	1920
DenseNet201 Improved		conv4_block48_concat	1	Conv2D(256, (3, 3) + BatchNormalization + MaxPool2D(2, 2) + Dropout(0.2) + Dense(64) + Dropout(0.20))	13,77M	1792 - 256

When the model structures given in Table 2 were examined, firstly, to the DenseNet121, DenseNet169, and DenseNet201 models used in the study, without cutting blocks (Cut-Point Layer) and adding layers, the transfer model structure was used by applying the frozen status process only to the last layers. Later, to DenseNet121, DenseNet169, and DenseNet201 models one block cut operation, Auxiliary Layers (256 convolutions with 3x3 filter size, respectively, BatchNormalization, Maximum Pooling with 2x2 filter size), 20% Dropout, 64 Full Connection, and 20% Dropout layers were added and frozen operation was applied. Improved DenseNet121_Improved, DenseNet169_Improved, and DenseNet201_Improved models were proposed, respectively. One block was cut considering the feature extraction and the number of parameters to be reduced.

A novel DenseNet121_Improved model with 6.70M parameters was proposed by cutting one block and adding Auxiliary Layers to the DenseNet121 model with 7.04M parameters. Similarly, novel DenseNet169_Improved models with 8.78M parameters and DenseNet201_Improved models with 13.77M parameters were proposed by cutting one block and adding Auxiliary Layers to DenseNet169 with 12.65M parameters and DenseNet201 with 18.33M parameters. In each proposed model structure, model complexity was reduced by using fewer parameters than the original DenseNet versions. Therefore, in these models, certain layers were frozen to use pre-trained weights so that not all of the model parameters were re-trained. It was only used for feature extraction.

3.4. Model Training Parameters

In order to obtain successful results from colon and lung cancer histopathological images, the dataset used in the study was divided into training, testing, and validation datasets. First, 15% of the 25000 images in the dataset were reserved for the validation dataset, and the remaining 85% was used for training and testing. Stratified 5k-fold cross-validation was applied to the data used in the training and testing process. In this way, the training dataset had a 68% split and the test dataset had a 17% split. The number of images belonging to the datasets were presented in detail in Table 3. In addition, the model training parameters given in Table 4 were used to compare the success accuracy of each model discussed in the study.

Table 3.Training, testing, and validation datasets of colon and lung cancer histopathological

Cancer Type	Classification Type	Train (%68)	Test (%17)	Validation (%15)	Total (%100)
Colon	Adenocarcinoma	3400	850	750	5000
	Benign	3400	850	750	5000
Lung	Adenocarcinoma	3400	850	750	5000
	Benign	3400	850	750	5000
	Squamous Cell Carcinoma	3400	850	750	5000
Total		**17000**	**4250**	**3750**	**25000**

Table 4. Models training parameters

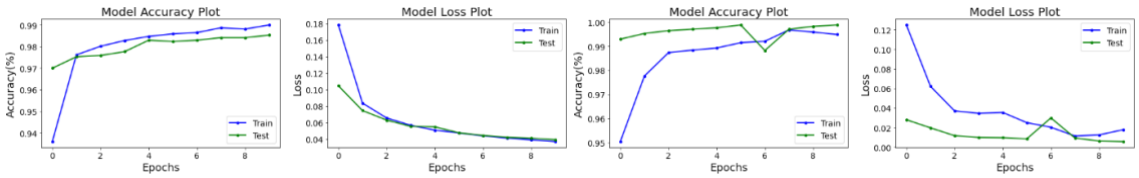
Parameters	Value
Stratified K-Fold	5
Epoch	10
Mini Batch Size	8
Activation Function	Softmax
Optimization Algorithm	Adamax
Loss Function	Categorical Crossentropy

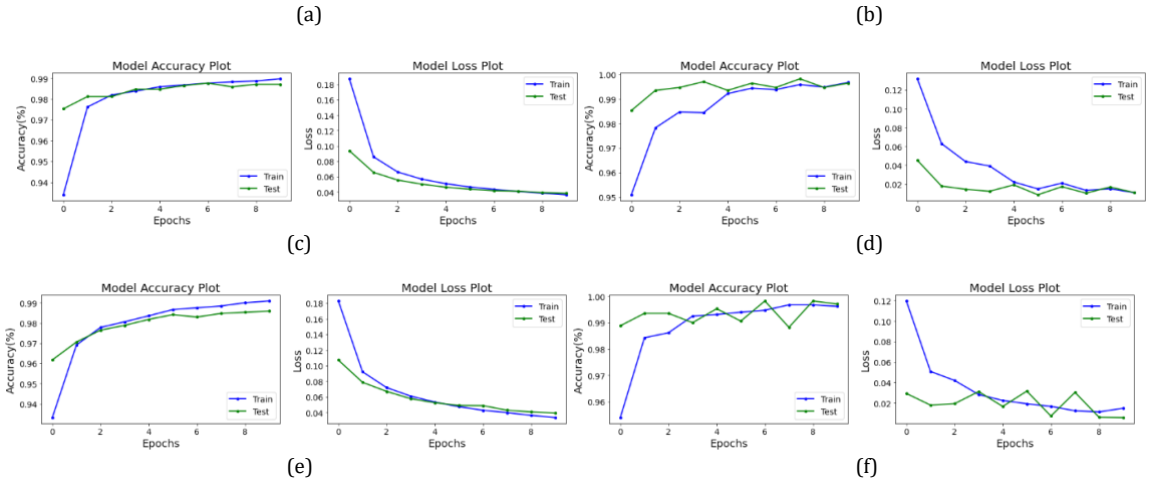
4. Results and Discussion

In the study, the versions of the DenseNet algorithm and the training and testing of 3 novel models obtained as a result of the improvement of these versions were carried out. The training and testing of each model were first applied to only the 2-class colon cancer dataset, secondly to the 3-class lung cancer dataset, and thirdly to the combined 5-class colon and lung cancer dataset. Stratified 5k-fold cross-validation method was used in order to make the training test process more consistent and to distribute the dataset more evenly. First, training was conducted by applying the stratified 5k-fold cross-validation method to each model using a 2-class colon cancer dataset. The loss values and accuracy rates obtained as a result of this training were given in Table 5 comparatively. The models with the lowest loss and the highest accuracy rate obtained as a result of the stratified 5k-fold cross-validation method were determined, and the accuracy and loss graphs of the training and test results of these models were given in Figure 2.

Table 5. The loss values and accuracy rates obtained as a result of the trainings made by applying stratified 5k-fold cross-validation to each model using the colon cancer training-test dataset.

Models	Loss/Acc	K-Fold 1	K-Fold 2	K-Fold 3	K-Fold 4	K-Fold 5	Avg
DenseNet121	Loss	0.043233	0.043100	0.043452	0.043927	**0.039264**	0.042595
	Acc	0.984706	0.985294	0.984118	0.983529	**0.985294**	0.984588
DenseNet121_Improved	Loss	0.012774	0.017161	0.012139	0.022865	**0.009374**	0.014863
	Acc	0.995294	0.994118	0.995294	0.993529	**0.997059**	0.995059
DenseNet169	Loss	0.053334	0.043686	**0.038386**	0.041599	0.041581	0.043717
	Acc	0.984118	0.987647	**0.987059**	0.988235	0.985882	0.986588
DenseNet169_Improved	Loss	0.041271	0.030986	0.026230	0.012195	**0.010951**	0.024326
	Acc	0.985882	0.990000	0.992941	0.994706	**0.996471**	0.992000
DenseNet201	Loss	0.040173	0.044651	**0.039421**	0.046195	0.039509	0.041990
	Acc	0.990000	0.984706	**0.985882**	0.983529	0.987647	0.986353
DenseNet201_Improved	Loss	**0.006036**	0.006460	0.009007	0.012791	0.006338	0.008126
	Acc	**0.998235**	0.997647	0.998235	0.994706	0.997059	0.997176





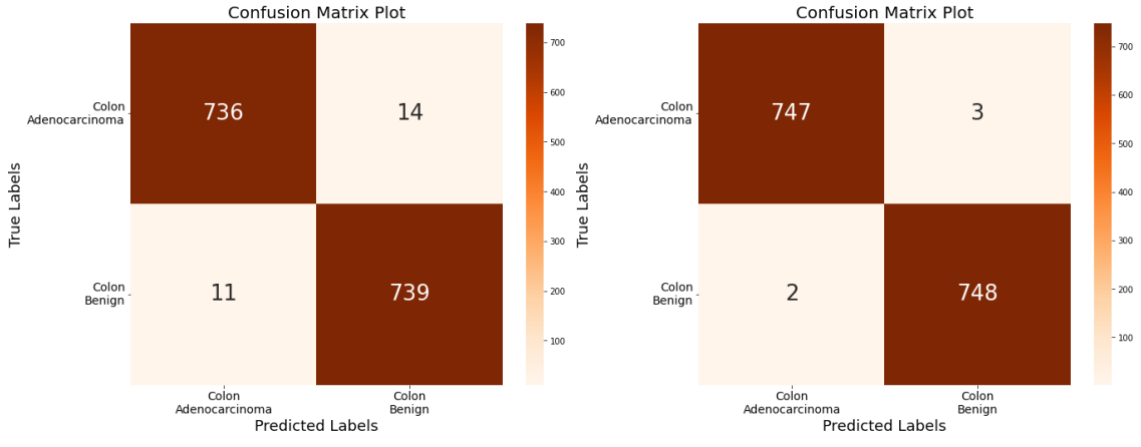
Şekil 2. Accuracy and loss graphs of the models with the lowest loss and the highest accuracy rate obtained as a result of the stratified 5k-fold cross-validation method using the colon cancer training-test dataset. (a) DenseNet121 (b) DenseNet121_Improved (c) DenseNet169 (d) DenseNet169_Improved (e) DenseNet201 (f) DenseNet201_Improved

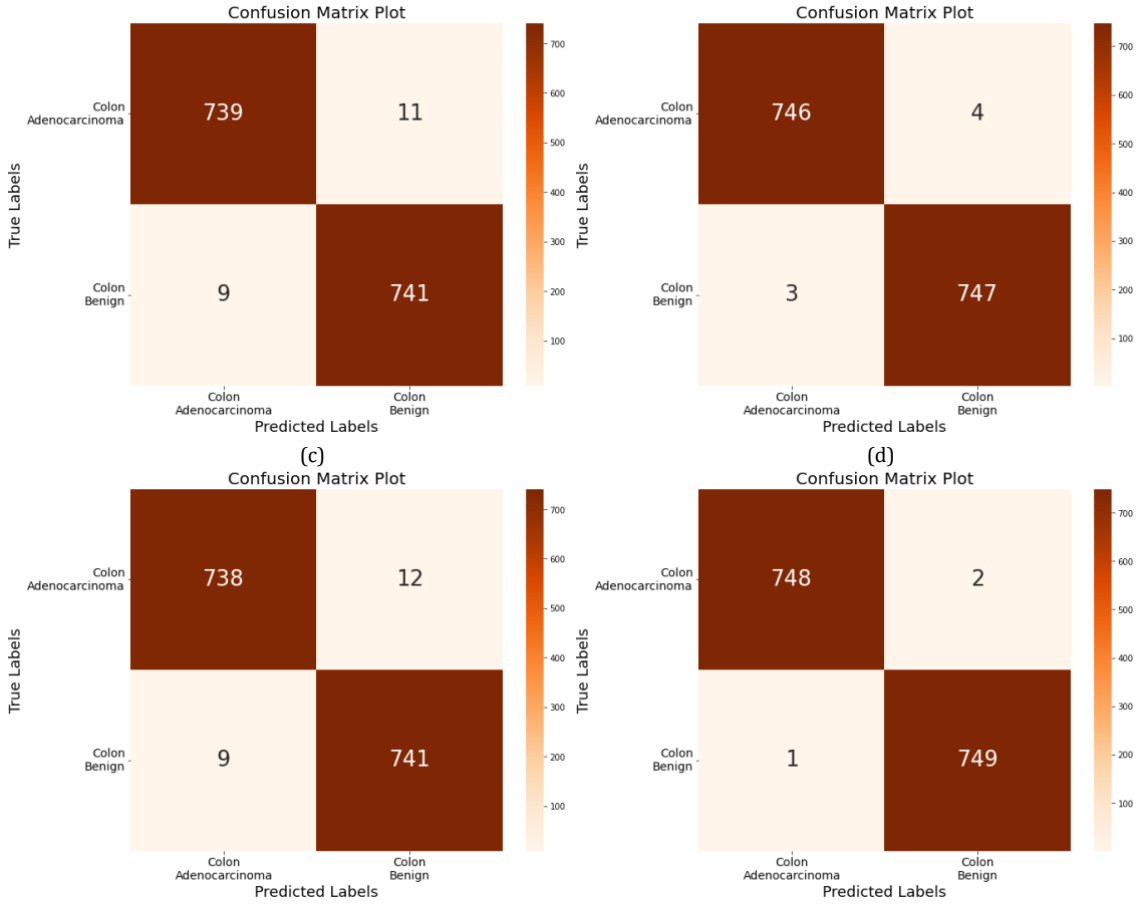
When the best models given in Table 5 and the accuracy and loss graphs of these models given in Figure 2 were examined, the training-test success of approximately 98.50% has been achieved in colon cancer classification for each of the DenseNet121, DenseNet169, and DenseNet201 models. For each of the proposed DenseNet121_Improved, DenseNet169_Improved, and DenseNet201_Improved models, a training-test success rate of over 99.50% was achieved in classifying colon cancer. Hence, it has been observed that more successful learning was achieved with the model structuresproposed in colon cancer classification.

In addition, the accuracy, loss, precision, recall, f1-score, and support values obtained as a result of using the validation dataset from the models with the lowest loss and highest accuracy rate given in Table 5 were shown in Table 6, and the confusion matrix graphics were shown in Figure 3.

Tablo 6. Accuracy, loss, precision, recall, f1-score, and support values obtained with the colon cancer validation dataset

Models	Accuracy	Loss	Precision	Recall	F1-Score	Support
DenseNet121	0.9833	0.0475	0.98	0.98	0.98	1500
DenseNet121_Improved	0.9967	0.0097	1.00	1.00	1.00	
DenseNet169	0.9867	0.0400	0.99	0.99	0.99	
DenseNet169_Improved	0.9953	0.0109	1.00	1.00	1.00	
DenseNet201	0.9860	0.0491	0.99	0.99	0.99	
DenseNet201_Improved	0.9980	0.0063	1.00	1.00	1.00	





Şekil 3. Confusion matrix graphics from the colon cancer validation dataset (a) DenseNet121 (b) DenseNet121_Improved (c) DenseNet169 (d) DenseNet169_Improved (e) DenseNet201 (f) DenseNet201_Improved

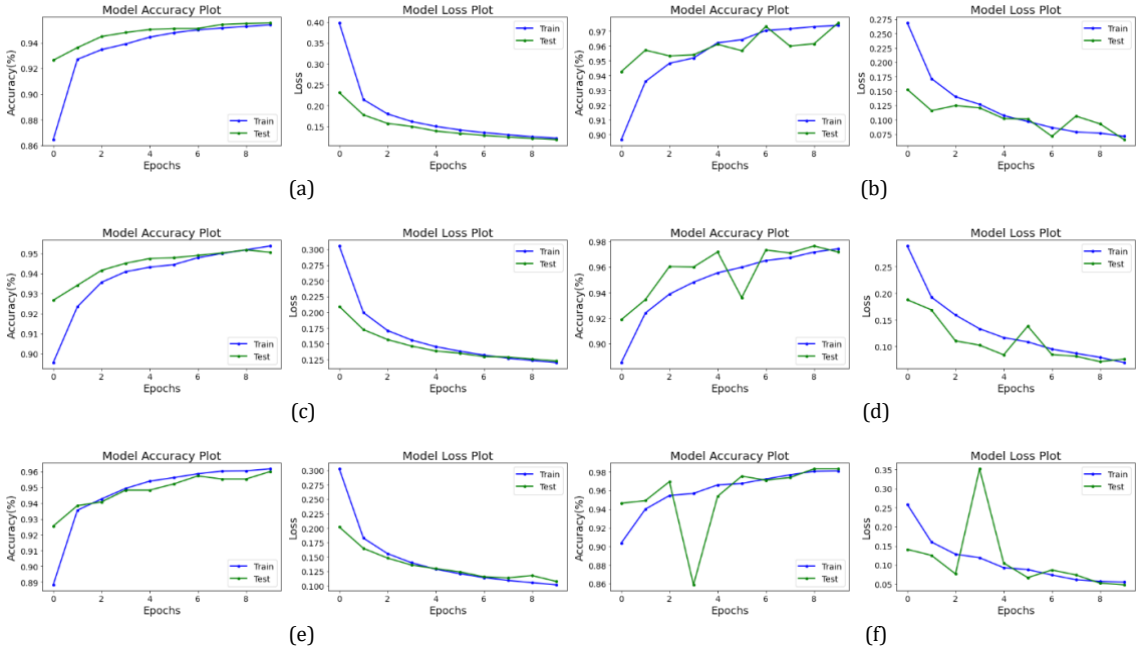
According to the findings obtained as a result of using the validation dataset in Table 6 and Figure 3, it was determined that the best model in colon cancer classification was DenseNet201_Improved with a success rate of 99.80%.

Secondly, using the 3-class lung cancer dataset, each model was trained by applying the stratified 5k-fold cross-validation method, and the loss values and accuracy rates obtained as a result of this training were given comparatively in Table 7. The models with the lowest loss and the highest accuracy rate obtained as a result of the stratified 5k-fold cross-validation method were determined, and the accuracy and loss graphics of the training and test results of these models were given in Figure 4.

Table 7. Loss values and accuracy rates obtained as a result of training made by applying stratified 5k-fold cross-validation to each model using the lung cancer training-test dataset.

Models	Loss/Acc	K-Fold 1	K-Fold 2	K-Fold 3	K-Fold 4	K-Fold 5	Avg
DenseNet121	Loss	**0.118990**	0.125507	0.137259	0.132939	0.136850	0.130309
	Acc	**0.955294**	0.946275	0.945882	0.947843	0.948235	0.948706
DenseNet121_Improved	Loss	0.084376	0.068029	**0.065528**	0.073664	0.076446	0.073609
	Acc	0.967843	0.972941	**0.975686**	0.972941	0.969804	0.971843
DenseNet169	Loss	**0.122635**	0.132274	0.139209	0.131915	0.138912	0.132989
	Acc	**0.950588**	0.943922	0.945882	0.945490	0.945490	0.946275
DenseNet169_Improved	Loss	**0.076120**	0.083975	0.082406	0.076933	0.145721	0.093031
	Acc	**0.971765**	0.969020	0.970980	0.967843	0.955294	0.966980
DenseNet201	Loss	0.115518	0.113036	0.123033	**0.107590**	0.124477	0.116731
	Acc	0.958824	0.956863	0.952941	**0.960000**	0.953726	0.956471
DenseNet201_Improved	Loss	0.081638	**0.047858**	0.079767	0.053291	0.062214	0.064954

	Acc	0.969804	**0.983137**	0.969412	0.980000	0.976863	0.975843



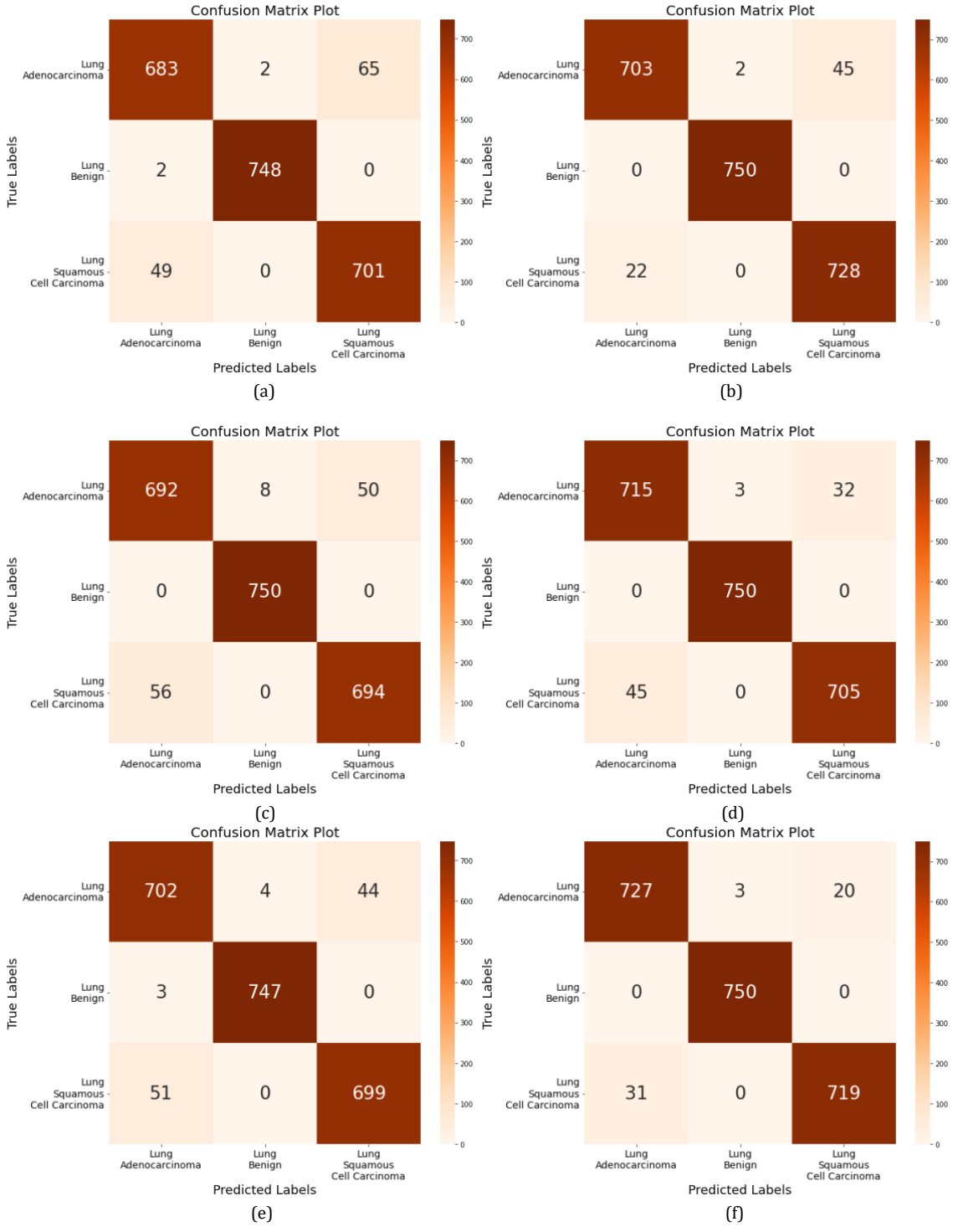
Şekil 4. Accuracy and loss graphics of the models with the lowest loss and the highest accuracy rate obtained as a result of the stratified 5k-fold cross-validation method using the lung cancer training-test dataset. (a) DenseNet121 (b) DenseNet121_Improved (c) DenseNet169 (d) DenseNet169_Improved (e) DenseNet201 (f) DenseNet201_Improved

When the best models given in Table 7 and the accuracy and loss graphs of these models in Figure 4 were examined, the training-test success of approximately 95.50% has been achieved in the classification of lung cancer for each of the DenseNet121, DenseNet169, and DenseNet201 models. For each of the proposed DenseNet121_Improved, DenseNet169_Improved, and DenseNet201_Improved models, a training-test success of approximately 97.50% was achieved in the classification of lung cancer. Therefore, it has been also observed that more successful learning is achieved with the model structures that we have suggested in the classification of lung cancer.

In addition, the accuracy, loss, precision, recall, f1-score, and support values obtained as a result of using the validation dataset from the models with the lowest loss and highest accuracy rate given in Table 7 were shown in Table 8, and confusion matrix graphics were shown in Figure 5.

Tablo 8. Accuracy, loss, precision, recall, f1-score, and support values obtained with the lung cancer validation dataset

Models	Accuracy	Loss	Precision	Recall	F1-Score	Support
DenseNet121	0.9476	0.1468	0.95	0.95	0.95	2250
DenseNet121_Improved	0.9693	0.0785	0.97	0.97	0.97	
DenseNet169	0.9493	0.1387	0.95	0.95	0.95	
DenseNet169_Improved	0.9644	0.0967	0.96	0.96	0.96	
DenseNet201	0.9547	0.1237	0.95	0.95	0.95	
DenseNet201_Improved	0.9760	0.0668	0.98	0.98	0.98	



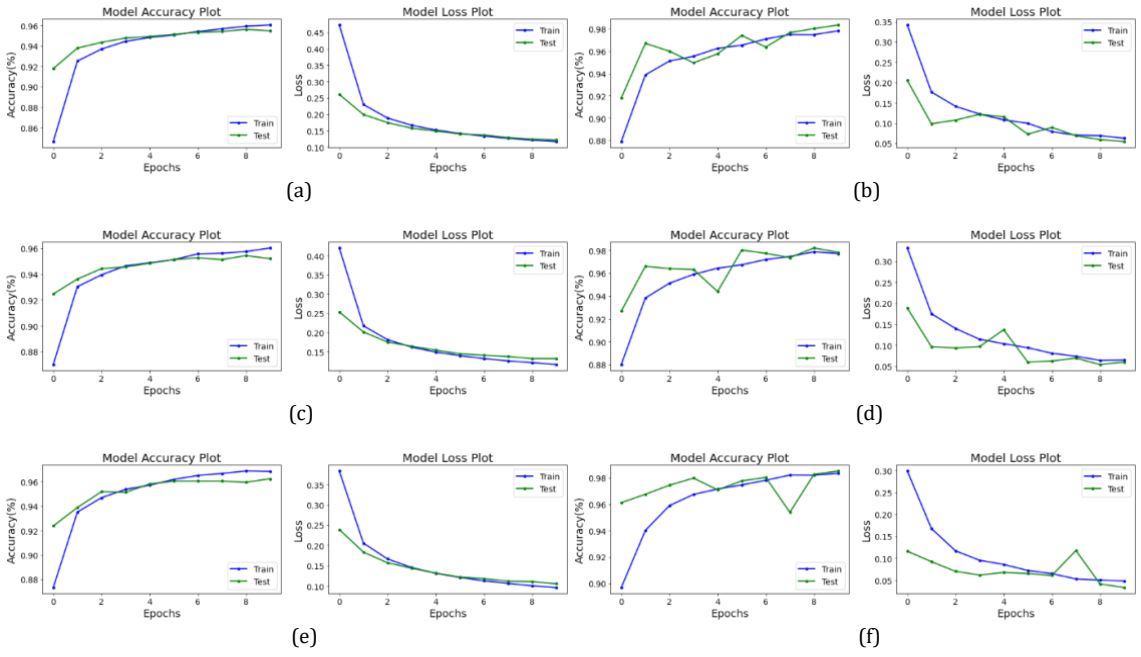
Şekil 5. Confusion matrix graphics from the lung cancer validation dataset (a) DenseNet121 (b) DenseNet121_Improved (c) DenseNet169 (d) DenseNet169_Improved (e) DenseNet201 (f) DenseNet201_Improved

According to the findings obtained as a result of using the validation dataset in Table 8 and Figure 5, it was seen that the best model in lung cancer classification was DenseNet201_Improved with a success rate of 97.60%.

Finally, trainings were made by applying the stratified 5k-fold cross-validation method to each model by using the combined 5-class colon and lung dataset, and the loss values and accuracy rates obtained as a result of these trainings were given in Table 9. The models with the lowest loss and the highest accuracy rate obtained as a result of the stratified 5k-fold cross-validation method were determined, and the accuracy and loss graphs of the training and test results of these models were given in Figure 6.

Table 9. The loss values and accuracy rates obtained as a result of the trainings made by applying stratified 5k-fold cross-validation to each model using the colon and lung cancer training-test dataset

Models	Loss/Acc	K-Fold 1	K-Fold 2	K-Fold 3	K-Fold 4	K-Fold 5	Avg
DenseNet121	Loss	**0.121511**	0.125670	0.133395	0.127864	0.126793	0.127047
	Acc	**0.954824**	0.955059	0.949412	0.955765	0.956000	0.954212
DenseNet121_Improved	Loss	0.060804	**0.054704**	0.082608	0.057553	0.055825	0.062299
	Acc	0.979294	**0.983529**	0.964000	0.980000	0.977412	0.976847
DenseNet169	Loss	**0.132124**	0.134749	0.132855	0.138284	0.136952	0.134993
	Acc	**0.952000**	0.954353	0.948941	0.950118	0.949882	0.951059
DenseNet169_Improved	Loss	0.061095	0.089922	**0.054158**	0.058737	0.064675	0.065718
	Acc	0.976471	0.966118	**0.982118**	0.979059	0.978118	0.976376
DenseNet201	Loss	0.107979	0.122740	0.116832	**0.105459**	0.114872	0.113576
	Acc	0.961647	0.957647	0.960471	**0.962353**	0.956941	0.959812
DenseNet201_Improved	Loss	0.060194	0.054367	**0.033474**	0.094753	0.043791	0.057316
	Acc	0.982353	0.981882	**0.985176**	0.966118	0.983294	0.979765



Şekil 6. Accuracy and loss graphics of the models with the lowest loss and the highest accuracy rate obtained as a result of the stratified 5k-fold cross-validation method using the colon and lung cancer training-test dataset. (a) DenseNet121 (b) DenseNet121_Improved (c) DenseNet169 (d) DenseNet169_Improved (e) DenseNet201 (f) DenseNet201_Improved

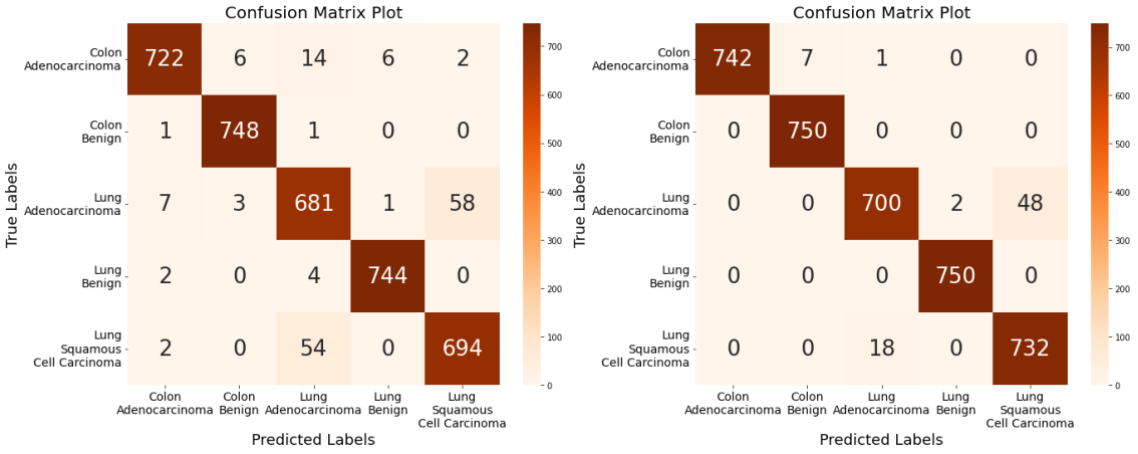
When the best models given in Table 9 and the accuracy and loss graphs of these models given in Figure 6 were examined, the training-test success of approximately 95.50% was achieved in the classification of colon and lung cancers for each of the DenseNet121, DenseNet169, and DenseNet201 model. For each of the proposed DenseNet121_Improved, DenseNet169_Improved, and DenseNet201_Improved models, the training-test success of over 98.20% was achieved in the classification of colon and lung cancer. Consequently, it was also determined that more successful learning was achieved with the model structures that we have suggested in the classification of colon and lung cancer.

In addition, the accuracy, loss, precision, recall, f1-score, and support values obtained as a result of

using the validation dataset from the models with the lowest loss and highest accuracy rate given in Table 9 were shown in Table 10, and the confusion matrix graphics were shown in Figure 7.

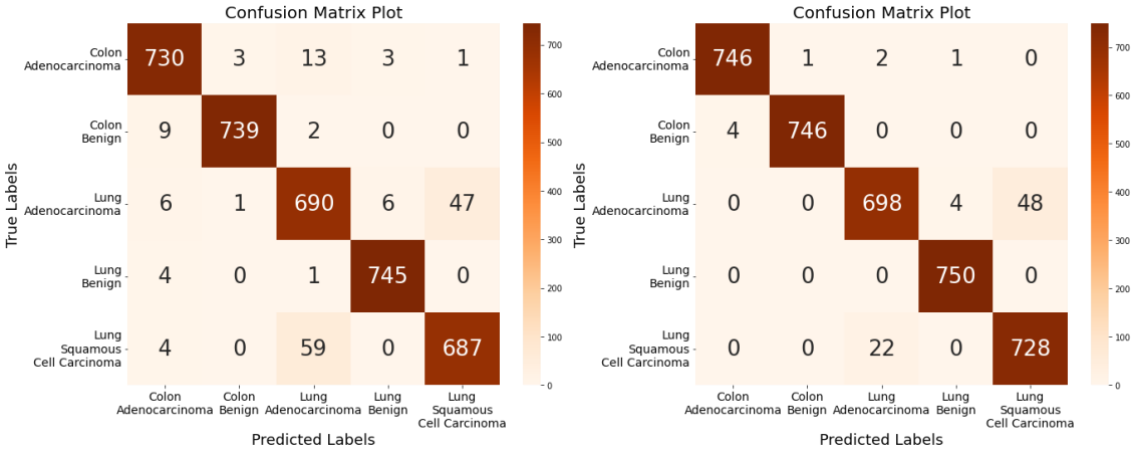
Tablo 10. Accuracy, loss, precision, recall, f1-score, and support values obtained with colon and lung cancer validation dataset

Models	Accuracy	Loss	Precision	Recall	F1-Score	Support
DenseNet121	0.9571	0.1295	0.96	0.96	0.96	3750
DenseNet121_Improved	0.9797	0.0592	0.98	0.98	0.98	
DenseNet169	0.9576	0.1261	0.96	0.96	0.96	
DenseNet169_Improved	0.9781	0.0589	0.98	0.98	0.98	
DenseNet201	0.9635	0.1134	0.96	0.96	0.96	
DenseNet201_Improved	0.9848	0.0420	0.98	0.98	0.98	



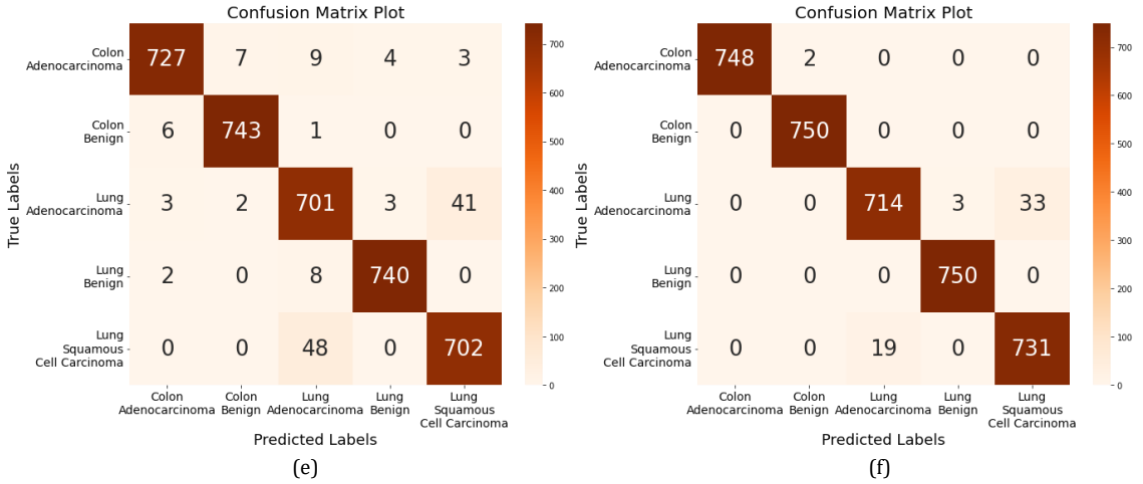
(a)

(b)



(c)

(d)



Şekil 7. Confusion matrix graphics from the colon and lung cancer validation dataset (a) DenseNet121 (b) DenseNet121_Improved (c) DenseNet169 (d) DenseNet169_Improved (e) DenseNet201 (f) DenseNet201_Improved

According to the findings obtained as a result of using the validation dataset in Table 10 and Figure 7, it was seen that DenseNet201_Improved was the best model in colon and lung cancer classification with an accuracy rate of 98.48%.

When the success accuracy rates obtained from the 2-class colon cancer validation dataset given in Table 6, the 3-class lung cancer validation dataset given in Table 8, and the 5-class colon and lung cancer validation dataset given in Table 10 were evaluated, it was determined that the best performance achievements were observed in the DenseNet201_Improved, DenseNet121_Improved, and DenseNet169_Improved models in order of success in all datasets. Therewithal, the DenseNet201_Improved model achieved the best performance with an accuracy of 99.80% in the colon cancer dataset, 97.60% in the lung cancer dataset, and 98.48% in the colon and lung cancers dataset.

We demonstrated the classification of lung and colon histopathological images with deep learning technique, one of the advanced machine learning techniques and does not require feature extraction by field experts but is a self-learning technique of the model. Since quite different novel models are proposed in the study, it is not possible to directly compare the results we obtained with those in the cited literature. However, since the objectives of the studies were the same, they were discussed comparatively.

The methods we proposed outperformed most of the other cancer identification methods in terms of maximum classification accuracy [40-43][38-41]. Among these studies, Bukhari et al., used only the dataset containing colon cancer and obtained a lower accuracy rate than the proposed method [41]. Mangal et al., and Hatuwal and Tapha used the LC25000 dataset in their classification studies, but they proposed a model on 3-class lung cancer and 2-class colon cancer and achieved a lower accuracy rate (96.61% and 97.2%) [42,43]. However, no information was given about the classification results in terms of precision and recall data. On the other hand, similar to our research, Masud et al. also classified five types of lung and colon cancers. However, they showed a less successful performance than the proposed model with a maximum accuracy rate of 96.33% [3].

In general, it was seen that deep learning-based methods gave successful results in previous studies, and the proposed method was comparable to previous studies in terms of accuracy. Chehade et al. proposed six models of XGBoost, SVM, RF, LDA, MLP, and LightGBM, by using machine learning and image processing techniques, to classify histopathological images of lung and colon cancers in the LC25000 dataset. They studied these models on both colon and lung cancer with 5 classes, but they achieved 99% success only with the XGBoost model [44]. Coudray et al. trained the Inception V3 model, one of the deep learning models, on all slide images obtained from the Cancer Genome Atlas. The model they trained only for lung cancer classification, with a success rate of 97%, obtained data lower than the success rate of the model we proposed [45]. D. Sarwinda et al. proposed DenseNet-121's previously trained deep-featured KNN classifier only for colon tissues. They obtained an accuracy of 98.53% with the model they proposed. However, they were unable to sample lung cancer tissues with their models and did not provide any information [46].

4. Conclusion

Around the world, colon and lung cancers are the most common types of cancer diagnosed in adults aged 65 and over. In these cancer types, which have different biology, risk factors, and survival outcomes, the 5-year survival rate of colon cancer ranges from 59% to 71%, and lung cancer from 15% to 22% [47]. This study used a dataset containing histopathological images of 2-class colon cancer and 3-class lung cancer to classify colon and lung cancer types. In order to obtain successful results from this dataset, classification processes were carried out first with the versions of the DenseNet algorithm, and then with 3 novel models by making block cutting (cut-point layer), adding an auxiliary layer, and frozen status improvements to these versions. Each model was first trained on a dataset containing only colon cancer histopathological images and the best classification success rate was obtained with DenseNet201_Improved with 99.80%. Secondly, each model was trained on the dataset containing only lung cancer histopathological images, and the best classification success was obtained with DenseNet201_Improved with 97.60%. Finally, each model was trained on the dataset containing both colon and lung cancer, and the best classification success was obtained with DenseNet201_Improved with 98.48%. As a result, considering the experimental analyzes and comparisons obtained in the study, the best success rate in classifying colon and lung cancer types using 3 datasets was obtained with the developed DenseNet201_Improved. In future research, experiments with different deep learning algorithms will be performed by using the dataset containing more cancer types.

Author Contribution

The authors' contribution rates in the study are equal.

Conflict of Interest Statement

The authors declare that there is no conflict of interest.

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