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Diagnostic Decision Making on Medical Images Using Deep Learning Models

Derin Öğrenme Modelleri Kullanılarak Tıbbi Görüntülerde Tanısal Karar Verme

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ABSTRACT

According to the World Health Organization (WHO), one of every six deaths in the world is caused by cancer. Cancers of the breast, lung, prostate, colon and rectum are the most common. More than 25 percent of all types of cancer are lung and colon cancers. When the disease is detected at an early stage, the survival rate of cancer cases is importantly higher. Therefore, medical image analysis is an important field of study for cancer detection and classification. In other studies in the literature and in this study, the aim was to automate cancer diagnosis by detecting more cases in a shorter time with high performance using artificial intelligence. In this study, image processing and deep learning techniques were used to analyze histopathological colon images from the LC25000 dataset. The colon histopathological images in this dataset were resized, and data augmentation methods were used. In this study, three different CNN model architectures with 3, 6 and 8 layers were developed. In addition, the pretrained CNN architectures VGG16, VGG19, and Resnet50 CNN models were also used in this study. This study proposed a 3-layer CNN model that detects colon cancer with a high accuracy rate of 98.00%. When the results of the proposed 3-layer CNN model were examined, satisfactory performance was observed. Thus, it was concluded that the proposed method can be used for computer-aided decision making systems to diagnose colon cancer. The artificial intelligence models used and developed in this study were implemented on Colab Notebook, a Google Cloud Computing service.

Keywords: Convolution neural network (CNN), Cloud computing, Deep learning models, Diagnostic system, Medical image analysis

ÖZET

Dünya Sağlık Örgütü'ne (DSÖ) göre dünyada, her altı ölümden birinin sebebi kanserdir. En sık görülen kanserler meme, akciğer, prostat, kolon ve rektum kanserleridir. Akciğer ve kolon kanseri birlikte, tüm kanser vakalarının %25'inden fazlasını oluştururlar. Bununla birlikte, hastalığın erken bir aşamada tespit edilmesi, hayatta kalma oranını önemli ölçüde artırmaktadır. Bu yüzden, medikal görüntü analizi kanserin tespiti ve sınıflandırılması açısından önemli çalışma alanlarındandır. Hem literatürdeki yapılan diğer çalışmalarda hem de bu çalışmada, yapay zekâ kullanılarak daha kısa bir sürede daha çok vakayı yüksek başarımla tespit ederek kanser teşhisinin otomatikleştirilmesi hedeflenmiştir. Bu çalışmada, görüntü işleme ve derin öğrenme teknikleri kullanılarak LC25000 veri setindeki kolon histopatolojik görüntüleri analiz edilmiştir. Bu veri setindeki kolon histopatolojik görüntüleri yeniden boyutlandırılmış ve veri arttırma yöntemleri kullanılmıştır. Çalışmada, 3, 6 ve 8 katmanlı 3 ayrı CNN modeli mimarisi geliştirilmiştir. Ayrıca, çalışmada

önceden eğitilmiş CNN mimarileri olan VGG16, VGG19 ve Resnet50 CNN modelleri de kullanılmıştır. Bu çalışma kapsamında kolon kanserini %98.00 gibi yüksek bir başarımla tespit eden 3 katmanlı CNN modeli önerilmiştir. Önerilen 3 katmanlı CNN modeline ait sonuçlar incelendiğinde, modelin tatmin edici derecede başarımı yüksek olduğu gözlemlenmiştir. Böylece, önerilen modelin kolon kanserini teşhis etmek amacıyla bilgisayar destekli karar verme sistemleri için kullanılabileceği sonucuna varılmıştır. Bu çalışmada kullanılan ve geliştirilen yapay zekâ modelleri Google Cloud Computing hizmeti olan Colab Notebook üzerinde gerçekleştirilmiştir.

Anahtar Kelimeler: Konvolüsyonel sinir ağı (CNN), Bulut bilişim, Derin öğrenme modelleri, Teşhis sistemi, Tıbbi görüntü analizi

1. INTRODUCTION

In recent years, significant advances have been made in medicine and healthcare with the help of major advances in computer science and information systems. During this time, new techniques have been developed in the literature in the areas of disease diagnosis and pattern recognition.

Cancer is caused by irregular division and proliferation of cells in organs and tissues. According to the WHO, cancer causes the death of one every six people and ranks second among the causes of death worldwide (Mangal, et al., 2020). Colon cancer is the most common and fatal type of cancer worldwide. The high prevalence and lethality of colon cancer were the main motivations for choosing the type of cancer to be used in this study.

Cancer is a disease in which abnormal cells grow in the body as a consequence of spontaneous mutations. Once formed, these cells split abnormally and diffuse to other organs. Early detection and treatment initiation are among the biggest factors in the fight against cancer. Early diagnosis enables the patient to start treatment early. Starting treatment in the early stages of the disease will contribute positively to improving the quality of life of patients with cancer and prolonging their life expectancy. Cancer kills its victims if left untreated. Cancer treatment is expensive and requires a lengthy process. The fact that cancer causes death at an early age also reflects the social and economic development levels of nations.

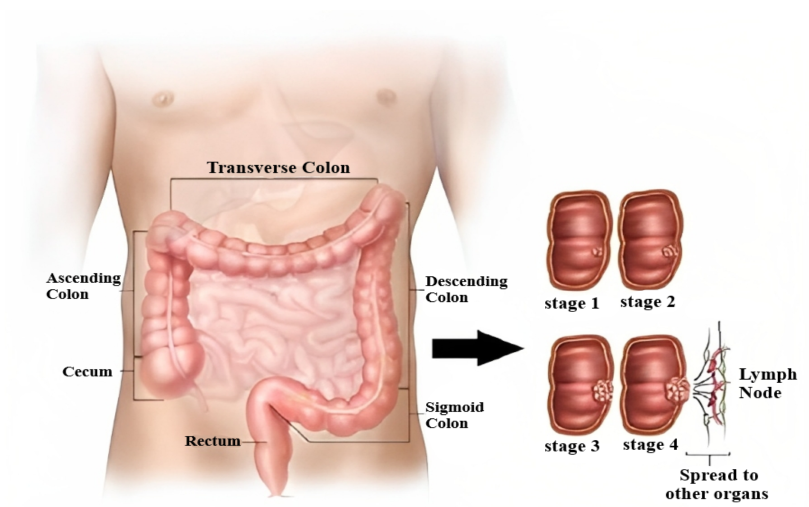

Figure 1. Colon cancer polyps (Tasnim, et. al., 2021)

All parts of the large intestine, except for the last 15-20 centimeter section (rectum) at the end, are called the colon. In this section, cancer occurring is referred to as colon cancer. Cancer of the entire large intestine is known as colorectal cancer (Yurtsever, 2019). According to the 2020 data, colorectal cancer is the third most common type of cancer in men and women in the United States. When the rates for women and men are combined, it ranks second. It also ranks third among cancer types that have resulted in death. These data are similar to those obtained in our country. According to the data, the incidence of this cancer is slightly higher in men than in women. If colorectal cancer can be diagnosed early, it is highly treatable (Siegel, et al., 2020).

Most cancers have five stages according to the Tumor Node-Metastasis (TNM) classification designed and continued by the American Joint Committee on Cancer (AJCC). These stages are called from 1 to 4. Figure 1 shows the colon cancer polyps and their stages. According to the AJCC classification, the fourth stage (stage 4) is the final stage, and the cancer has metastasized to distant parts of the body (Tasnim, et al., 2021).

Depending on the diagnosis of colon cancer, the survival rate is 70% in the first stage (stage 1) and decreases to 13% in the last stage (stage 4) (Tasnim, et al., 2021). There is currently no definitive cure for colon cancer. Therefore, the earlier the disease is detected in a person, the more important it is for doctors to plan and implement treatment for that patient in order to change the course of colon cancer. In this case, the survival rates of the patients are quite high.

In recent years, several studies have been conducted on disease detection in medical images using artificial intelligence and deep learning. Some of these studies are presented below. Mangal et al. (Mangal, et al., 2020) achieved 96% accuracy in detecting colon cancer and 97% accuracy in detecting lung cancer in their CNN study using histopathological cancer images in 2021. Lin et al (Lin, et al., 2022) proposed the Pyramidal Deep Learning Method, a plug & play module that will improve the classification performance of histopathological images in 2021.The ShuffLeNetV2, EfficientNetb0 and ResNet50 algorithms were used in the proposed method. As a result, an increase in the success rate of CNN algorithms with small training sets was observed in texture level classifications. Baranwal et al (Baranwal, et al., 2022) used ResNet50, VGG-19, Inception_ResNet_V2 and DenseNet in their study on lung cancer detection in histopathological images and achieved an accuracy rate of 99%, 92.1%, 99.7% and 99.4% respectively. Toraman et al. (Toraman, et al., 2019) proposed a study aiming to detect the probability of colon cancer using Fourier transform infrared spectroscopy signals in 2019. Various features were collected from the signals and SVM and artificial neural networks were used to categorize them. In the study, they obtained a classification accuracy of 95.7% with artificial neural networks. Urban et al. (Urban, et al., 2018) developed a method that can classify polyps in colonoscopy images with an accuracy of 96% in 2018. In their study, more than 8600 colonoscopy images of 2000 people were manually labelled and these data were used to train the CNN model. Kadirappa et al (Kadirappa, et al., 2023) obtained a classification accuracy of 99.60% on the LC25000 dataset with the Parallel, Cross-Coupled and Grouped Convolutional Deep Neural Network model they developed to obtain accurate models for classification in 2022. Raju et al (Raju and Rao, 2022) achieved 99.98% classification accuracy in their study using transfer learning on histopathological images of colon cancer in 2022. Sarwinda et al (Sarwinda, et al., 2020) proposed a feature separation method with Deep Convolutional Neural Network in 2020 and with this method, attributes were learned with ResNet50 and DenseNet121 on colon cancer data and then various popular classifiers were used. In the proposed method, 98.53% accuracy rate was obtained with KNN classifier. Yildirim et al (Yıldırım, et al., 2022) proposed a 45-layer CNN-based Ma_ColonNET model for colon cancer classification in 2021. They obtained an accuracy rate of 99.75% using the proposed new model. Masud et al (Masud, et al., 2021) achieved a classification accuracy of 96.33% in their study on histopathological images of colon and lung cancer in the LC25000 dataset with the deep learning-based classification framework they developed in 2021. Toğaçar (Toğaçar, 2021) made a new approach by using deep learning and optimisation methods together. Toğaçar separated the attributes of the images using DarkNet19 algorithm and separated the inefficient attributes using Manta Ray Foraging and Equilibrium optimization techniques. The features generated by these two optimization algorithms were then classified using the SVM method. As a result, an accuracy rate of 99.69% was achieved with this approach.

This study examines medical images for the diagnosis of colon cancer. Colon histopathology images from the LC25000 dataset were used for analysis. Colon histopathology images in this dataset were resized and data augmentation methods were utilized. The dataset was divided into two parts, 70% for training and 30% for testing. In this study, 3 different CNN model architectures with 3, 6 and 8 layers were developed and proposed. The CNN models were trained on the training dataset and tested on the test dataset. Thus, colon cancer was detected in medical images using CNN models. As a result, a promising computer-aided decision support system was proposed to be additional to the traditional approaches for colon cancer diagnosis.

This study is structured as described below. The dataset, deep learning, CNN and pre-trained CNN architectures, and performance metrics are described in Section 2. The experimental environment set up in this study is described in Section 3. The results obtained from the experimental environment set up in the study are described in Section 4. The results of the study are analyzed and compared with the literature in Section 5. The analysis of the results of the method proposed in the study is presented in Section 6.

2. MATERIAL AND METHOD

This section is structured as follows. The dataset used in this study is introduced. Deep learning has also been introduced. The CNN architecture is explained and information about its layers is provided. The pre-trained CNN architectures VGGNET and ResNet50 are described. Finally, the performance metrics used to compare the results of the CNN architectures applied in this study and the calculation of these metrics are explained.

2.1. Dataset

In this study, the dataset LC25000 (Lung and Colon Histopathological Images) (Borkowski, et al., 2019) was used. This dataset consists of 25,000 images with 5 classes. Each class was a balanced dataset consisting of 5000 images. In this study, two classes named "colon adenocarcinoma" and "colon benign" were utilized. The number of images included in the study is 10,000. The number of original images is 750 and each of these images has a size of 1024x768 pixels. These images were cropped to 768x768 pixels using an algorithm written in the Python programming language, and the number of images was increased using data duplication methods (Urban, et al., 2018). Each image was obtained at a size of 718x718 pixels (Mangal, et al., 2020; Borkowski, et al., 2019). In this study, the image size was set to 128x128 pixels. The ratios of training and test datasets were set as 70% and 30% respectively.

2.2. Deep Learning

Deep learning is a type of machine learning technique. Deep learning uses several layers of non-linear processing units to extract and transform features. Each successive layer uses the output of the previous layer as the input. Data scientists and developers use deep learning approaches for various purposes because they are generally faster and more accurate than humans. These purposes can be listed as analyzing large and complex data sets, performing complex and non-linear tasks, and extracting meaning from text, audio or images. These purposes, which have many practical applications, have enabled many modern innovations. For example, it has enabled driverless cars to process images and distinguish pedestrians from other objects, or to understand voice commands in smart home devices. Deep learning uses neural network architectures that consist of multiple layers of high-performance graphics processing units distributed in the cloud or clusters. It achieves high-performance results by using large amounts of data units to analyze very high levels of text, speech and images. As a result of its high performance and powerful processing capacity, developers have used deep learning to create digital systems that resemble human intelligence. This means that model training, which takes weeks using digital systems, can be performed much faster. Figure 2 shows an example of an artificial neural network model. In this model, the data in the dataset are passed from input layer to hidden layers. These layers are composed of cells and connections that behave like neural structures. The output layer provides information generated by passing it through intermediate layers (Toraman, et al., 2019; Osinga, 2018).

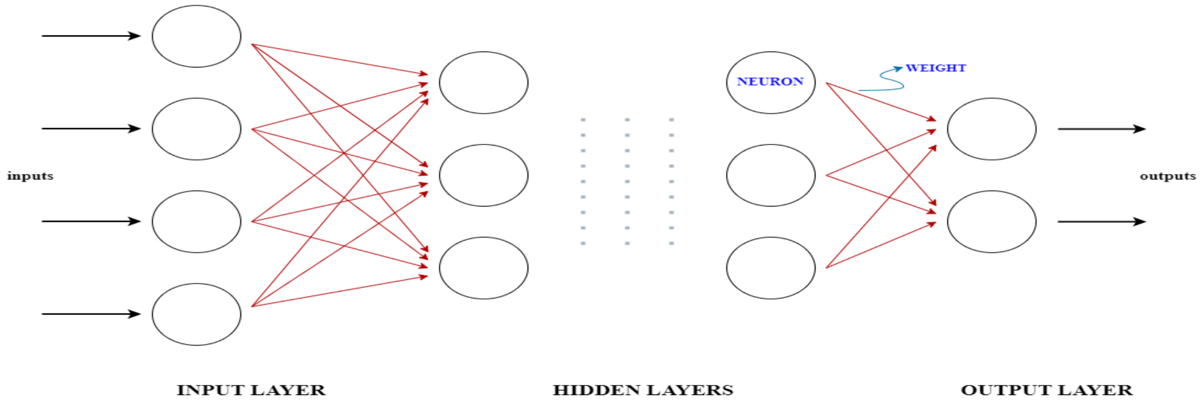

Figure 2. Artificial neural network model

2.3. Convolution Neural Network (CNN)

CNN is one of the best known and most widely used deep learning algorithms. CNN is mainly utilized in computer vision and image processing. It was inspired by the human brain's ability to process visual information. Compared to previous methods, CNN automatically identifies relevant attributes without any human supervision. This situation emerges as the biggest advantage of CNN. When CNN architectures were examined, it was observed that they consisted of three layers. These are called the Convolution Layer, Max Pooling Layer and Fully Connected Layer or Dense Layer. These layers are overlaid in various combinations to create a CNN model. A typical instance of a CNN model is shown in Figure 3 (Alzubaidi, 2021).

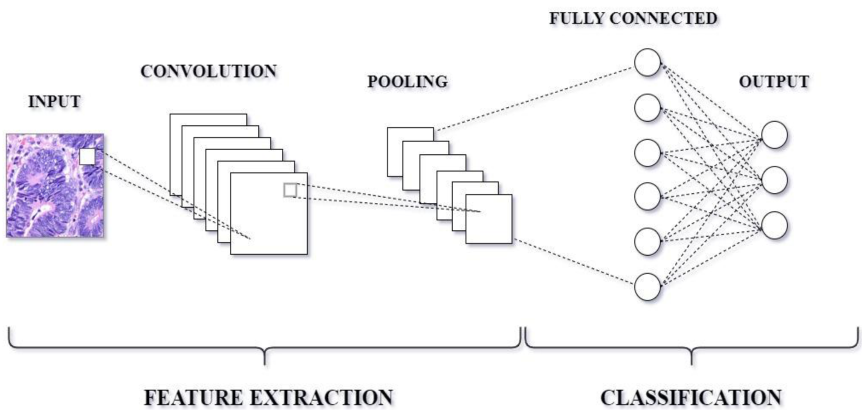

Figure 3. Structure of the CNN model

The convolutional layer is the main building block of the CNN. It is responsible for detecting the features of the image that feeds the model. In this layer, some filters are applied to the image to extract low and high level features in the images. These filters are usually multidimensional matrices. These matrices contain pixel values in the images. These matrices consist of height, width and depth information (Mangal, et al., 2020; Osinga, 2018).

The pooling layer is used to decrease the shift size of the image and the count of parameters and computations in the network. This controls the overfitting in the network. There are many pooling operations, but Max pooling is the most popular. Other algorithms that work on the similar principle are Average Pooling and L2-Norm Pooling. Max pooling obtains the largest number in the range covered by the filter. Thus, smaller outputs are utilized that include sufficient information for the neural network to decide an accurate choice. In this way, important features are used by reducing the size (Mangal, et al., 2020; Osinga, 2018).

The Flattening Layer is used to flatten the data in matrix form to prepare the data at the input of the Fully Connected Layer. Thus, the Flattening Layer transforms the multidimensional matrix data from the Convolutional and Pooling Layers into a flat vector (Mangal, et al., 2020; Osinga, 2018).

The Fully-Connected Layer is the part where the artificial neural network is located. It receives input data from the Flattening Layer. Each input is connected to every neuron in the neural network. Simultaneously, all of the neurons between the hidden layers are interconnected. Thus, the learning process was performed by the neural network (Mangal, et al., 2020; Osinga, 2018).

2.4. VGGNET

The VGGNET architecture was introduced by the VGG Group (Oxford). VGGNET is a convolutional neural network model based on the Compute Unified Device Architecture (CUDA) and supported by a graphics processing unit (GPU). VGGNET has a high success rate. However, VGGNET is difficult to process because it comprises 138 million parameters. The structure of the model is shown in Figure 4. The VGGNET network has two different structures, VGG-16 and VGG-19. The VGG-16 and VGG-19 structures occur in five blocks. The first and second blocks occur in two convolutional layers and one pooling layer. The third and fourth blocks occur in three convolution layers in the VGG-16 model, four convolution layers and one pooling layer in the VGG-19 model. The fifth block consists of three fully connected layers. In all convolutional layers, 3x3 dimensional stripe filters are used (Doğan and Türkoğlu, 2018).

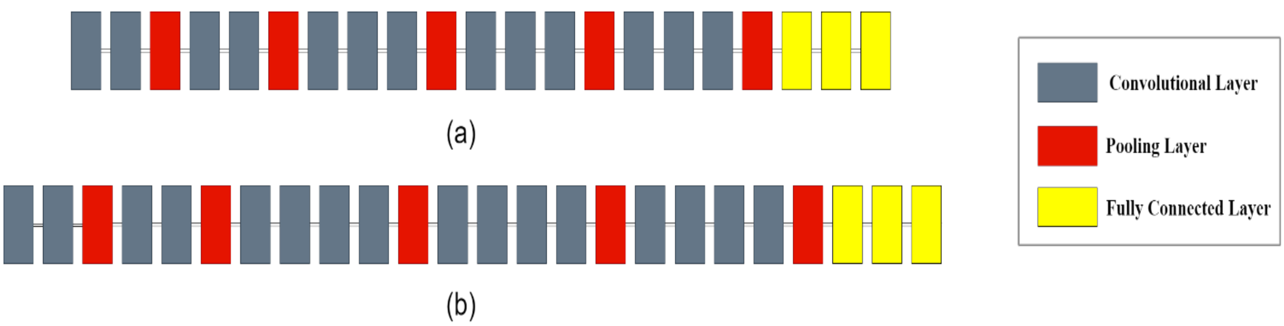

Figure 4. (a) VGG16 , (b) VGG19 (Toğaçar, et al., 2020)

2.5. ResNet50

ResNet is an abbreviation of residual neural network. The ResNet model is focuses on solving the degradation problem of CNN networks. The degradation problems occur when deep networks begin to converge. When the network depth rises, its effectiveness achieves saturation, but then presents a quick downward tendency. ResNet attaches links between layers to solve this problem. This simple idea prevents degradation as the network gets deeper. In addition, the ResNet model uses bottleneck blocks for faster training. ResNet50 comprises a network of 50 layers. Instead of using 2 (3x3) convolution layers, the ResNet model uses (1x1), (3x3), (1x1) convolution layers (He, et al. 2016).

2.6. Performance Metrics

In this study, many different metrics were used to measure the success of the proposed methods in diagnostic decision making. The metrics utilized in this study were accuracy, recall, precision and F-1 Score. To evaluate the results of the developed methods better, more than one metric was used. To calculate these metrics, true positive (TP), true negative (TN), false negative (FN) and false positive (FP) values are required. These values were obtained from the complexity matrix. The performance criteria can be calculated using the TP, TN, FN and FP values obtained from the complexity matrix. A general structure of the complexity matrix is given as an example in Table 1. When examining the complexity matrix in Table 1, it is understood that it is used to summarise and visualise the classification results of the machine learning model while predicting the actual values.

In Table 1, TP indicates that the model predicts the positive class as positive. TN indicates that the model predicts that negative class to be positive. FP indicates that the model predicts the negative class is positive. FN indicates that the model predicts the positive class as negative (Yakut, 2020; Yakut, 2023).

Table 1. General structure of the confusion matrix

	Actual Positive	**Actual Negative**
Predicted Positive	TP	FP
Predicted Negative	FN	TN

The accuracy value was calculated as the ratio of the number of samples correctly classified by the machine learning model to the total number of samples. The calculation of the accuracy value is shown in Equation (1). The accuracy value is generally used to represent the performance value of the machine learning model (Yakut, 2020; Yakut, 2023).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

The recall value was obtained by dividing the number of samples that the machine learning model determined as positive by the total number of true positive samples. The calculation of the recall value is presented in Equation (2). The recall value indicates the number of true positive samples correctly predicted by the machine learning model (Yakut, 2020; Yakut, 2023).

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

The precision value was determined by dividing the number of positive samples predicted by the machine learning model by the total number of actual positive samples. The calculation of the Precision value is given by Equation (3). The precision value specifies that the probability of the number of positive samples predicted by the machine learning model will actually be positive (Yakut, 2020; Yakut, 2023).

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

The F-1 Score value was obtained by taking the harmonic mean of the Recall and Precision values. The calculation of the Precision value is described in Equation (4). The F-1 Score showed a balance between the Recall and Precision values. The F-1 Score takes a value between 0 and 1. The F-1 Score penalizes both the extreme values. Thus, the F-1 Score represents both the Recall and Precision values symmetrically in a single metric (Yakut, 2020; Yakut, 2023).

$$F - 1\,Score = 2\,X\,\frac{Recall\ x\ Precision}{Recall + Precision} \tag{4}$$

3.EXPERIMENTAL STUDY

In this study, a CNN model architecture was developed and proposed to diagnose colon cancer. A block diagram of the proposed method is shown in Figure 5. The proposed method was developed in the Python programming language using cloud computing based Colab notebooks. In our study, the GPU support provided by Google Colab was used. Furthermore, the Python libraries TensorFlow and Keras which are commonly used for deep learning studies and are open-source were utilized. In this study, colon histopathological images from the LC25000 dataset were used to diagnose colon cancer. The images in the LC25000 dataset consisted of JPEG format images with a size of 768x768 pixels. The colon histopathological images in this dataset were resized and data augmentation methods were utilized. Thus, the images in the dataset were resized to 128x128 pixels in order to make the data to be compatible with the training and testing classifiers. The dataset was divided into two parts, 70% for training and 30% for testing. In the study, 3 different CNN model architectures with 3, 6 and 8 layers were developed and proposed. These CNN models were trained on the training dataset and tested using the test dataset. In addition, the pre-trained CNN architectures VGG16, VGG19 and Resnet50 were used in this study. CNN models with a high performance for colon cancer detection were determined. The CNN models were analyzed to diagnose colon cancer in medical images by using them in diagnostic decision making.

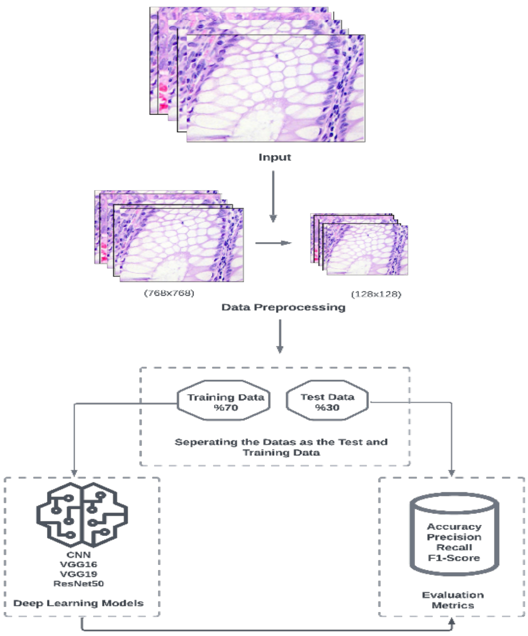

Figure 5. Block diagram of the proposed method

In this study, three different CNN model architectures with 3, 6 and 8 layers and pretrained VGG16, VGG19 and ResNet50 CNN models were utilized. The details of the hyperparameter settings of the models are presented in Table 2. The ReLu and Softmax functions were applied as activation functions in the models. Activation functions are used to transfer the output value of the neurons in one layer to another. The output value is compared to a threshold to determine whether it should be transmitted to the other layer. In the activation function, the artificial neural network cell processes the input data and receives a net output in return. The outputs are different for each function. Activation functions are generally chosen from non-linear functions. In deep learning applications, optimization methods are used to minimize possible errors to ensure a healthy learning process. Optimization methods attempt to minimize the difference between the output value produced by the network and the actual value. In this study, the Adam optimizer method was used to improve CNN models.

Table 2. Hyperparameters tuning of CNN models

Models	Layers	Parameters
VGG16	Conv1_13 Max Pooling 1_5 Dense 14-15-16	14, 731, 074
VGG19	Conv1_16 Max Pooling 1_5 Dense 17-18-19	20, 040, 770
ResNet50	7x7 Conv 1x1+2x2+3x3 Conv 2_4 Fully Connected	49, 311, 234
CNN	Conv 1_3 Max Pooling 1_3 Dropout 1-2 Dense	127, 043
CNN	Conv 1_6 Max Pooling 1_3 Dropout 1_6 Dense	39, 251
CNN	Conv 1_8 Max Pooling 1_4 Dropout 1_3 Dense	333, 998

4. EXPERIMENTAL RESULTS

Table 3. Performance results of CNN models

Models	Layers	Accuracy (%)	Recall (%)	Precision (%)	F1-Score (%)
VGG16	Conv1_13 Max Pooling 1_5 Dense 14-15-16	100.00	99.67	99.67	99.67
ResNet50	7x7 Conv 1x1+2x2+3x3 Conv 2_4 Fully Connected	100.00	99.13	99.54	99.54
VGG19	Conv1_16 Max Pooling 1_5 Dense 17-18-19	100.00	99.13	99.14	99.13
CNN	Conv 1_3 Max Pooling 1_3 Dropout 1-2 Dense	98.00	99.72	99.00	99.40
CNN	Conv 1_6 Max Pooling 1_3	92.00	94.24	95.19	94.71

	Dropout 1_6 Dense				
CNN	Conv 1_8 Max Pooling 1_4 Dropout 1_3 Dense	62.00	77.96	62.40	69.01

In this study, three different CNN model architectures were developed and proposed for colon cancer detection. In addition, three different pre-trained CNN architecture models were also used to verify and compare the results of colon cancer detection. This study utilized histopathological images of the colon from the LC25000 dataset. The prediction results of the developed CNN models are listed in Table 3. The CNN models in Table 3 were ranked from high performance to low performance.

5. DISCUSSION

When analyzing the results of the CNN models in Table 3, the pre-trained VGG16, ResNet50 and VGG19 CNN models showed high performance. Three different CNN model architectures with 3, 6 and 8 layers developed and proposed in this study were used for colon cancer detection. When the performance values obtained as a result of using these models are examined, it is clear that the models have high performance. The deep learning model with the highest performance was the 3-layer CNN model when analyzing the performance values of the CNN models developed and proposed in this study. The model with the second highest performance was the 6-layer CNN model. The model with the third highest performance was the 8-layer CNN model. As a result, the 3-layer and 6-layer CNN models showed satisfactory high performance. However, the performance of the 8-layer CNN model was relatively lower than the first two CNN models. This situation occurs when overfitting happens. In the case of overfitting, the algorithm memorizes the results on the training data and shows high performance only on that data. Because the deep learning model searches for the results memorized from the training dataset in the test dataset, it shows a low performance on the test dataset. The 8-layer CNN model in this study performed well on the training data but performed poorly on the test data. As a result, this situation we encountered in the study caused the 8-layer CNN model to show low performance due to overfitting.

Table 4. Comparison of the proposed method with other studies in literature

Models	Accuracy (%)
Proposed Method	98.00
Kadirappa et al., 2023	99.60
Raju and Rao, 2022	99.98
Yıldırım and Çınar, 2022	99.75
Baranwal, et al., 2022	99.08
Toğaçar et al., 2021	99.69
Masud et al., 2021	96.33
Sarwinda, et al., 2020	98.53
Mangal, et al., 2020	96.61
Siegel, et al., 2020	94.63

Analyzing the CNN models developed in this study, the 3-layer CNN model is a deep learning model with satisfactory performance. Within the scope of this study, a 3-layer CNN architecture model is proposed to diagnose colon cancer. When analyzing the results of this model, it is observed that it is close to the results of the VGG16, ResNet50 and VGG19 models, which are well-known pre-trained CNN models in the literature and have performance results in the same range. Thus, it is concluded that the proposed 3-layer CNN architecture model is promising as an assistant to the traditional approaches in colon cancer diagnosis and is suitable for use in computer-aided decision making systems.

The results of other studies in the literature using artificial intelligence and deep learning technologies for colon cancer detection are presented in Table 4. By analyzing the accuracy rates of the proposed method and other studies in Table 4, it can be concluded that the proposed method has a satisfactorily good performance. At the same time, it is believed that the accuracy of the model in colon cancer detection can be increased by making improvements and enhancements in the data multiplication, feature selection and classification stages of the proposed method.

CONCLUSION

In this study, a CNN-based deep learning model was developed to provide fast results by reducing the workload of experts in processing colon cancer images. Colon histopathological images from the LC25000 dataset were used to detect colon cancer. Colon histopathological images in this dataset were resized and data augmentation methods were used. In this study, three different CNN model architectures with 3, 6 and 8 layers were developed using cloud computing based Colab notebooks. In addition, pre-trained CNN architectures VGG16, VGG19 and Resnet50 CNN models were also used in the study. The 3-layer CNN model was determined as the model that detected colon cancer with the high accuracy. The 3-layer CNN model proposed in this study showed a performance in the same range and close to the other models in the literature. Therefore, it was concluded that the proposed method can be used for computer-aided decision making systems for the diagnosis of colon cancer. In future studies, a larger cancer diagnosis system can be developed by combining more data and datasets containing more types of diseases by incorporating other deep learning approaches.

REFERENCES

Alzubaidi L., Zhang J., Humaidi A. J., Al-Dujaili A., Duan Y., Al-Shamma O., Farhan L. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. Journal of big Data, 8, 1-74. https://doi.org/10.1186/s40537-021-00444-8

Baranwal N., Doravari P., Kachhoria R. (2022). Classification of histopathology images of lung cancer using convolutional neural network (CNN). Shinde S. V., Mahalle P. N., Bendre, V., Castillo O. (Eds.), Disruptive Developments in Biomedical Applications, (pp. 75-89). Florida: CRC Press. https://doi.org/10.48550/arXiv.2112.13553

Başaran E., Cömert Z., Çelik Y., Velappan S., Toğaçar M. (2020). Determination of tympanic membrane region in the middle ear otoscope images with convolutional neural network based YOLO method. Dokuz Eylül Üniversitesi Mühendislik Fakültesi Fen ve Mühendislik Dergisi, 22(66), 919-928. https://doi.org/10.21205/deufmd.2020226625

Borkowski A. A., Bui M. M., Thomas L. B., Wilson C. P., DeLand L. A., Mastorides S. M. (2019). Lung and colon cancer histopathological image dataset (lc25000). arXiv preprint, 1-2.

https://doi.org/10.48550/arXiv.1912.12142

Doğan F., Türkoğlu İ. (2018). Derin öğrenme algoritmalarının yaprak sınıflandırma başarımlarının karşılaştırılması. Sakarya University Journal of Computer and Information Sciences, 1(1), 10-21.

Eker A. G., Duru N. (2021). Medikal görüntü işlemede derin öğrenme uygulamaları. Acta Infologica, 5(2), 459-474. https://doi.org/10.26650/acin.927561

Gazel S. E. R., Bati C. T. (2019). Derin sinir ağları ile en iyi modelin belirlenmesi: mantar verileri üzerine Keras uygulaması. Yuzuncu Yıl University Journal of Agricultural Sciences, 29(3), 406-417. https://doi.org/10.29133/yyutbd.505086

Hatuwal B. K., Thapa H. C. (2020). Lung cancer detection using convolutional neural network on histopathological images. Int. J. Comput. Trends Technol, 68(10), 21-24. https://doi.org/10.14445/22312803/IJCTT-V68I10P104

He K., Zhang X., Ren S., Sun J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition. Las Vegas, NV, USA. https://doi.org/10.1109/CVPR.2016.90

Kadirappa R., Subbian D., Ramasamy P., Ko S. B. (2023). Histopathological carcinoma classification using parallel, cross-concatenated and grouped convolutions deep neural network. International Journal of Imaging Systems and Technology, 33(3), 1048-1061. https://doi.org/10.1002/ima.22846

Lin J., Han G., Pan X., Liu Z., Chen H., Li D., Han C. (2022). PDBL: Improving Histopathological Tissue Classification with Plug-and-Play Pyramidal Deep-Broad Learning. IEEE Transactions on Medical Imaging, 41(9), 2252-2262. https://doi.org/10.1109/TMI.2022.3161787

Mangal, S., Chaurasia, A., Khajanchi, A. (2020). Convolution neural networks for diagnosing colon and lung cancer histopathological images. arXiv preprint, 1-10. https://doi.org/10.48550/arXiv.2009.03878

Masud M., Sikder N., Nahid A. A., Bairagi A. K., AlZain M. A. (2021). A machine learning approach to diagnosing lung and colon cancer using a deep learning-based classification framework. Sensors, 21(3), 748. https://doi.org/10.3390/s21030748

Osinga D. (2018). Deep learning cookbook: practical recipes to get started quickly. California : O'Reilly Media, Inc.

Öztürk K., Şahin M. E. (2018). Yapay sinir ağları ve yapay zekâ'ya genel bir bakış. Takvim-i Vekayi, 6(2), 25-36.

Raju M. S. N., Rao B. S. (2022, December). Classification of colon cancer through analysis of histopathology images using Transfer Learning. In 2022 IEEE 2nd International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC). Gunupur, Odisha, India. https://doi.org/10.1109/iSSSC56467.2022.10051631

Rathore S., Hussain M., Ali A., Khan A. (2013). A recent survey on colon cancer detection techniques. IEEE/ACM Transactions on computational biology and bioinformatics, 10(3), 545-563. https://doi.org/10.1109/TCBB.2013.84

Sarwinda D., Bustamam A., Paradisa R. H., Argyadiva T., Mangunwardoyo W. (2020, November). Analysis of deep feature extraction for colorectal cancer detection. In 2020 4th International Conference on Informatics and Computational Sciences. Semarang, Indonesia. https://doi.org/10.1109/ICICoS51170.2020.929899

Seyyarer E., Ayata F., Uçkan T., Karci, A. (2020). Derin öğrenmede kullanilan optimizasyon algoritmalarinin uygulanmasi ve kiyaslanmasi. Computer Science, 5(2), 90-98.

Shandilya S., Nayak S.R. (2022). Analysis of Lung Cancer by Using Deep Neural Network. Mishra M., Sharma R., Kumar Rathore A., Nayak J., Naik B. (Eds) Innovation in Electrical Power Engineering, Communication, and Computing Technology, Lecture Notes in Electrical Engineering, (pp. 427-436). Singapore: Springer. https://doi.org/10.1007/978-981-16-7076-3_37

Siegel R. L., Miller K. D., Goding Sauer A., Fedewa S. A., Butterly L. F., Anderson J. C., Jemal A. (2020). Colorectal cancer statistics, 2020. CA: a cancer journal for clinicians, 70(3), 145-164. https://doi.org/10.3322/caac.21601

Tasnim Z., Chakraborty S., Shamrat F. M. J. M., Chowdhury A. N., Nuha H. A., Karim A., Billah M. M. (2021). Deep learning predictive model for colon cancer patient using CNN-based classification. Int. J. Adv. Comput. Sci. Appl, 12, 687-696. https://doi.org/10.14569/IJACSA.2021.0120880

Toğaçar M., Ergen B., Özyurt F. (2020). Evrişimsel Sinir Ağı Modellerinde Özellik Seçim Yöntemlerini Kullanarak Çiçek Görüntülerinin Sınıflandırılması. Fırat Üniversitesi Mühendislik Bilimleri Dergisi, 32(1), 47-56. https://doi.org/10.35234/fumbd.573630

Toğaçar M. (2021). Disease type detection in lung and colon cancer images using the complement approach of inefficient sets. Computers in Biology and Medicine, 137, 104827. https://doi.org/10.1016/j.compbiomed.2021.104827

Toraman S., Girgin M, Üstündağ B., Türkoğlu İ. (2019). Classification of the likelihood of colon cancer with machine learning techniques using FTIR signals obtained from plasma. Turkish Journal of Electrical Engineering and Computer Sciences, 27(3), 1765-1779. https://doi.org/10.3906/elk-1801-259

Urban G., Tripathi P., Alkayal, T., Mittal M., Jalali F., Karnes W., Baldi P. (2018). Deep learning localizes and identifies polyps in real time with 96% accuracy in screening colonoscopy. Gastroenterology, 155(4), 1069-1078. https://doi.org/10.1053/j.gastro.2018.06.037

Yakut Ö., (2020). Comparison of clustering methods for early stage diabetes risk prediction using cloud computing. International Black Sea Coastline Countries Symposium-5, Zonguldak, Turkey.

Yakut, Ö. (2023). Diabetes Prediction Using Colab Notebook Based Machine Learning Methods . International Journal of Computational and Experimental Science and Engineering , 9 (1), 36-41. https://doi.org/10.22399/ijcesen.1185474

Yıldırım M., Çınar A. (2022). Classification with respect to colon adenocarcinoma and colon benign tissue of colon histopathological images with a new CNN model: MA_ColonNET. International Journal of Imaging Systems and Technology, 32(1), 155-162. https://doi.org/10.1002/ima.22623

Yurtsever U., (2019). Bölütlenmiş histopatolojik görüntüler üzerinde derin öğrenme yöntemiyle kolon kanseri tespiti, (Doctoral Dissertation), Sakarya Universitesi, Turkey.