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Research Article

A Model Suggestion For Alzheimer's Disease Diagnosis By Using Deep Learning

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Abstract

Alzheimer's disease is one of the greatest health problems of our time. Since there is no cure, it is necessary to diagnose the disease in the early stages and to apply preventive treatments. However, early diagnosis of the disease is very difficult, so most people can be diagnosed after significant and irreversible effects occur. Various studies are carried out by researchers around the world for the early diagnosis of the disease. Deep learning has recently gained importance in the early diagnosis of Alzheimer's disease. With the use of models created using deep learning, the success of early diagnosis has reached high levels. In this study, the stages of Alzheimer's disease and the changes that occur were examined. A literature review was conducted for various techniques used in the diagnosis of Alzheimer's and the use of imaging techniques in the early diagnosis of Alzheimer's was investigated. Due to its widespread use, the MRI technique has been emphasized, and mostly studies using MRI have been examined. Concepts used in deep learning are explained, innovations and results are presented. The architectures used in deep learning and the innovations they bring to this field are revealed, and deep learning models that have been created and tested in current studies are examined. The innovations and success rates brought by various studies have been revealed. Efforts have been made to develop a fast, efficient and successful model that provides ease of use. For this, the scheduler structure, MONAI framework, Data loader structure and various techniques are presented with simple use. Also, the model is optimized to run smoothly on Google Colab. In addition, the tools in the FSL library, which are very important in preprocessing, were studied and optimal parameters were found for the "Bias field and Neck Clean Up", "Standard Brain Extraction Using BET2" and "Robust Brain Center Estimation" tools. By using this library, optimal brain images can be obtained for any model. The DenseNet121 model was used as a basis in the model and it was presented in a structure that can be easily changed. The model can directly use 3D MR images, thus preventing the loss of various spatial information.

Keywords: Alzheimer's Disease, Deep Learning, Image Recognition, Early Diagnosis, Artificial Intelligence

Derin Öğrenme ile Alzheimer Hastalığı Teşhisi İçin Model Önerisi

Öz

Alzheimer hastalığı çağın en büyük sağlık problemlerinden biridir. Bir tedavisi bulunmaması nedeniyle hastalığın erken evrelerde teşhis edilmesi ve önleyici tedavilerin uygulanması gerekmektedir. Ancak hastalığın erken teşhisi oldukça zordur, bu nedenle çoğu kişide belirgin ve geri dönüşsüz etkiler oluştuktan sonra teşhis yapılabilmektedir. Hastalığın erken teşhis edilmesi için dünyada araştırmacılar tarafından çeşitli çalışmalar yapılmaktadır. Deep learning, Alzheimer hastalığının erken teşhisinde son zamanlarda oldukça önem kazanmıştır. Deep learning ile oluşturulmuş modellerin kullanılmasıyla erken teşhis yapılabilme başarısı yüksek

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seviyelere ulaşmıştır. Bu çalışmada Alzheimer hastalığının oluşum evreleri ve oluşan değişiklikler incelenmiştir. Alzheimer's teşhisinde kullanılan çeşitli teknikler için literatür taraması yapılmış ve görüntüleme tekniklerinin Alzheimer's erken teşhisinde kullanımı araştırılmıştır.

Yaygın kullanımı nedeniyle MRI tekniği üzerinde durulmuş, çoğunlukla MRI kullanılan çalışmalar incelenmiştir. Deep learning'te kullanılan kavramlar açıklanmış, yenilikler ve sonuçlar ortaya konmuştur. Deep learning'te kullanılan mimariler ve bu alanda getirdikleri yenilikler ortaya konmuş, mevcut çalışmalarda oluşturulmuş ve test edilmiş deep learning modelleri incelenmiştir. Yapılan çeşitli çalışmaların getirdiği yenilikler ve başarı oranları ortaya konmuştur. Kullanım kolaylığı sağlayan ve hızlı, performanslı ve başaırılı bir model geliştirilmesi için çalışılmıştır. Bunun için scheduler yapısı, MONAI yapısı, "Data loader" yapısı ve çeşitli teknikler basit bir kullanımla sunulmuştur. Ayrıca model Google Colab üzerinde sorunsuz şekilde çalışması için optimize edilmiştir. Ayrıca görüntü önişlemede oldukça önemli olan FSL kütüphanesindeki toollar ile çalışılmış ve "Bias field and Neck Clean Up", "Standard Brain Extraction Using BET2" ve "Robust Brain Center Estimation" toolları için optimal parametreler bulunmuştur. Bu kütüphane ile herhangi bir model için optimal beyin görüntüleri elde edilebilmektedir. Modelde temel olarak DenseNet121 modeli kullanılmıştır ve kolaylıkla model değiştirilebilen bir yapıda sunulmuştur. Model 3 boyutlu MR görüntülerini doğrudan kullanabilmektedir ve bu sayede çeşitli uzaysal bilginin kaybının önüne geçilmiştir.

Anahtar Kelimeler: Alzheimer Hastalığı, Derin Öğrenme, Görüntü Tanıma, Erken Teşhis, Yapay Zeka

1. Introduction

Alzheimer's disease is a neurodegenerative disease characterized by irreversible deterioration of cognitive and memory functions. Symptoms develop progressively towards the advanced stages of the disease and affect the daily life of the patient. The disease causes irreversible damage to brain cells and in advanced stages the disease is fatal. AD is the most common type of dementia and accounts for approximately 50% to 80% of total dementia cases [1]. The average expected life expectancy of people with Alzheimer's disease is between 3 years and 10 years. This expectation varies according to the age at which the disease occurs. As age increases, life expectancy also decreases[1]. For people older than 65 years, the risk of Alzheimer's doubles every 5 years [2]. Mild Cognitive Impairment (MCI) is a stage in which cognitive functions are impaired and dementia symptoms appear mildly, unlike healthy people of similar age. In other words, it can be said that it is the intermediate stage between a healthy person and a person with dementia. MCI has language, thinking and decision-making problems, and memory problems, and these are much more serious than normal age-related problems. Symptoms can be seen on tests, but they do not yet affect daily life like dementia. MCI is a factor that increases the risk of developing dementia. In fact, the risk of Alzheimer's disease increases when memory problems predominate in MCI. Some MCI patients can develop into AD. Some studies have found that between 10% and 15% of people with MCI develop AD each year [3][4]. Correctly detecting the possible conversion from MCI to AD is very important for the diagnosis of AD in the early stages.

The most used techniques in the early diagnosis of Alzheimer's disease in recent years are imaging methods. The images obtained by imaging methods like Functional MRI(fMRI), Structural MRI (sMRI), Diffusion Tensor Imaging (DTI) and Positron Emission tomography (PET) are processed with various models and meaningful results are obtained. Many studies have been conducted to improve success rates, and a variety of models have been tested on these students. First of all, the imaging technique to be used should be selected. MRI is one of the most used imaging techniques. This is because the MRI technique has many advantages over other imaging techniques. One of the studies in which the functional MRI technique is preferred is the study [5]. Resting-State fMRI (RS-fMRI), a type of functional MRI, was used in studies [6] and [7]. Volumetric MRI (vMRI) was used in the study [8], structural MRI (sMRI) was used in [9] and 4D fMRI is used in [10]. There are also studies using imaging techniques other than MRI. In one of these studies [11], 18F-FDG PET technique, a type of positron emission tomography, was used. In [12] and [8], Diffusion Tensor Imaging (DTI) technique was used.

According to experiments, Convolutional Neural Networks are the best deep learning method for image recognition and processing. For this reason, high success rates have been obtained in studies using this method. In the study [10] using 4D fMRI, 3D convolutional neural networks were used. 4D imaging such as fMRI encompasses the time dimension, among other dimensions, so much more information can be obtained from imaging. However, since there is not enough and suitable 4D algorithm, 4D images that can be led by various imaging techniques are transformed into 2D and 3D. A model for processing 4D images is presented in the article. This model is the C3d-LTSM model and is created by combining 3D convolutional neural networks. Temporal and spatial features can be extracted from 3D images in fMRI images. Consequently, it is an excellent approach for processing 4D fMRI images. As a result experiments and comparisons, C3d-LTSM gave much better results than 2D imaging, 3D imaging and functional connectivity methods that are currently used under the same conditions.

In recent studies, it has been seen that better results are obtained by using more than one method together. Much better results will be obtained by combining CNN, which is a very successful method, with other methods. Finding the best combination of these is the main challenge. Such a study was conducted with convolutional neural networks in [13] and early diagnosis of dementia and Alzheimer's disease, and separation of MCI and Alzheimer's patients were studied. In the study, an ensemble of 3D densely connected convolutional networks (3D-DenseNets) model is proposed for the diagnosis of Alzheimer's disease and MCI patients. 1000 iterations were made to select the best from different 3D-DenseNets models, and as a result, the best 5 3D-DenseNets models were selected as the base classifier. Then, a probability-based fusion method was applied and 3D-DenseNets were combined with different architectures and an ensembled model was created. The accuracy rating of this ensembled model is 97.52 percent. This is better than a stand-alone 3D-DenseNet. It was seen that the probability-based ensemble model and the majority voting approach used in the study performed quite well and could give better results than the state-of-art models. It has also been determined that combining multiple classifiers reduces the error rate and increases the success rate. The probability-based ensemble model which is proposed in the study performed much better than the majority voting method. The proposed model gave an accuracy rate of 98.83% in distinguishing Alzheimer's patients from normal individuals, and an accuracy rate of 93.61% in discriminating Alzheimer's Disease/Mild Cognitive Impairment. It also outperformed Demet on other thorny classification missions. It was concluded that the proposed ensemble 3D-DenseNet model is an effective way to distinguish and diagnose Alzheimer's diseases and MCI.

The availability of proper data is one of the most crucial challenges in the early diagnosis of Alzheimer's disease. Deep learning methods need data consisting of a large number of images. If there are not enough images, an overfitting problem may occur. Various techniques exist to solve this problem like data augmentation and transfer learning and have been used in various studies. In a transfer learning application study [14], accuracy results are increased by using data augmentation. This shows the importance and benefit of data augmentation. In addition, data augmentation plays a key role in preventing the overfitting problem. In addition to the necessity of having sufficient data, it is also necessary to preprocess the data used correctly. Preprocessing of MR images is a very challenging issue for researchers. For this, various methods have been tried in this study.

2. Materials and Method

2.1. Dataset

Various imaging techniques are used in the diagnosis of Alzheimer's. It is very difficult for researchers to collect and organize the images obtained with these techniques. For this reason, various organizations have been established to collect and standardize Alzheimer's disease data. One of these is the Alzheimer's Disease Neuroimaging Initiative (ADNI) [15]. In addition to MRI, PET images, genetic and biospecimen data are also included and these data are shared with researchers free of charge. In this study, MR images were studied due to its prevalence and ease of use, and trials were conducted using the ADNI1:Baseline 3T and ADNI1:Complete 1Yr 1.5T4 datasets. There are 3 classes in these datasets and they are Control Normal (CN), Mild Cognitive Impairment (MCI) and Alzheimer's Disease (AD). It also has various information about the people with the images, such as gender, age and number of visits. The ADNI database contains data of 3208 people from various age groups and different genders. Despite the large number of data available, not every patient has all types of data. Images in the ADNI database have undergone certain processes to establish a certain standard. All exams in the ADNI1 database are intensity normalized and gradient un-warped T1 images. The distribution of the data in the ADNI database is shown in Table 1. NC: Normal Control, MCI: Mild Cognitive Impairment, EMCI: Early MCI, LMCI: Late MCI, AD: Alzheimer's Disease

Table 1. Age distributions of people in ADNI [16]

Age Group	CN	MCI	EMCI	LMCI	AD
Under 2	1	0	0	0	0
2-11	0	0	0	0	0
12-18	0	0	0	0	0
19-29	0	0	0	0	0
30-39	0	0	0	0	0
40-49	0	0	0	0	0
50-59	39	31	18	10	24
60-69	282	170	133	54	85
70-79	422	343	137	95	216
80-89	114	144	51	24	119
Above 89	6	5	1	2	12
Unknown	0	0	0	0	0

2.2. FMRIB Software Library (FSL)

Although the MR images in the ADNI database have undergone certain processes, they still need various processes to enter the model. The most critical ones are clearing the neck area from the image and removing the skull from the image. As a result of these procedures, the regions in the MR image that are unnecessary for the model are deleted, leaving only the brain regions. In this way, various errors that may occur are prevented.

There are various methods and tools used in this field. One of them is Fsl [17][18][19], which is a very comprehensive library of analysis tools. It can be used on Windows, macOs and Linux. The tools used for MR images in Alzheimer data are “Bias field and Neck Clean Up”, “Standard Brain Extraction Using BET2” and “Robust Brain Center Estimation” [20][21]. With Bias Field and Neck Clean Up process, various irrelevant areas in the MR image are deleted such as neck, nose, sinuses and eyes. In this way, the performance increases and the learning rate increases while training the deep learning model. After this process, Standard Brain Extraction Using BET2 is applied and skull stripping is performed. In this way, the skull around the brain is erased and a very clean brain image is obtained. Alternatively, the Robust Brain Center Estimation process can be applied, which aims to give the best result by applying the BET2 tool several times to obtain a more accurate image.

2.3. Convolutional Neural Network (CNN)

Convolutional Neural Network is a type of Multi-Layer Perceptron (MLP). The CNN algorithm, which is a forward-looking neural network, was inspired by the visual center of animals. In Convolutional Neural Networks, convolutional layers are used as an essential part. A CNN consists of one or more convolutional layers, a subsampling layer, followed by one or more fully connected layers such as a standard multilayer neural network. The purpose of CNNs is the same as neural networks. With the various transformations of the inputs, representations of a more abstract level are obtained [22]. Conversely, convolutional layers use local connectivity instead of full connectivity and perform calculations and transformations between input and hidden neurons. Another component of the CNN is the pooling layer. They are usually found between a convolutional layer and the next one. The main purpose of the pooling layers is to reduce the dimensions, that is, the features, and while doing this, to protect the information as much as possible. They do this with various pre-specified pooling methods. The pooling layer works with various hyperparameters and makes dimension reduction with these parameters. There are various pooling methods. For example, averaging-pooling, stochastic pooling, max-pooling, etc. According to [23] the method that gives the best results with images is the max pooling method, so it is the most used pooling method.

The first CNN network is the architecture called LeNet, which was introduced by Yann LeCun in 1988 and continued to be improved until 1998 [24]. In the LeNet network, the sublayers consist of cascading convolution and maximum pooling layers. The next upper layers correspond to the fully connected conventional MLP. CNN algorithms are applied in many different fields such as natural language processing (NLP), medical image processing, especially in the fields of image and sound processing. In particular, the best results have been obtained in the field of image processing. In the ImageNet Competition in 2014, all of the teams that received the best scores in object classification and detection with millions of images and hundreds of object classes used modifications of CNN algorithms [25]. In a 2015 study, CNN demonstrated success in capturing faces in wide-angle ranges, including reversed faces. This network is trained on a database of 200,000 images containing faces from various angles and orientations, and another 20 million images without faces [26]. Apart from these examples, CNN has been used in many areas.

2.3.1 Supervised Learning

In supervised learning, each data in the used dataset has a label. Each feature creates a dimension and the vector created by the features is called the feature vector. A label can be of many different types like integer, real number, matrix, vector, classes, etc. The purpose of supervised learning is to produce a model that uses a dataset. The model uses the features taken from the feature vector as input and produces output. With these outputs, label deducing is done for the feature vector [27]. Diagnosing Alzheimer's using MRI images is a type of supervised learning. Using MR data, each of which has a label, the deep learning model is trained and the success of classification for the test data is measured. Supervised learning is more widely used than unsupervised learning. The most well-known supervised network methods are Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Deep Neural Network (DNN) [28]. The most successful method among them is the convolutional neural network. Many CNN models can successfully perform AD classification. Examples of these are the models VGNet, AlexNet [29][30][31][32], ResNet [33][34], DenseNet [35][36] and Inception [37][38].

There have been many studies using these models, and many have achieved high accuracy rates. For example, in one study [39], a feature map was created using the improved PCANet model and this map was used as an input in the DenseNet model. Thanks to the dense connections in DenseNet, image classification was made in a fast and high-performance way. Although CNN is a very successful model and is considered better than traditional feature extraction methods, it requires a large number of image data for training. Also, a CNN model needs more time to train properly than other methods [28]. As can be seen in the studies carried out, the lack of medical image has always been a big problem. Various methods such as data augmentation and transfer learning have been created to overcome this problem. With the techniques tried in the proposed model, the time spent on preprocessing and training has been reduced. In addition, an optimal model has been tried to be created with the infrastructure of proven architectures such as DenseNet and ResNet. Various data augmentation methods such as adding noise, Gaussian offset and image flipping are also available in the model. The DLTK library is used for this [40].

2.3.2 Voxel-based Feature Extraction

In this method, feature extraction is done over voxels. The method is to extract the activated voxel values in preprocessed images utilizing statistical methods. These voxel values are features. If a three-dimensional analysis is desired like the diagnosis of Alzheimer' Disease by using MR images, it is the method that can be applied most directly. In this way, quantitative analysis of the brain can be done directly using voxels. With the voxel-based feature extraction method, even very small changes in the brain can be noticed and quantitatively analyzed. In addition, this process can be easily done for certain areas of the brain.

In a study, Voxel-Based Morphometry (VBM) obtained from MR images was used to distinguish between AD and normal control individuals [41]. Since there are too many voxels in MR images and computational costs will be high if all of them are used, some methods have been applied to reduce the number of features. The “t-algorithm” was used in a study to reduce the calculation amount and computational cost and to increase the performance. With this algorithm, appropriate voxels are selected and other voxels are excluded [42].

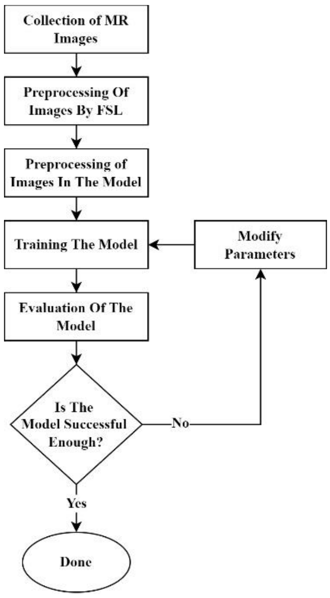
2.4. Google Colab

Google Colab is a platform established by Google to provide free resources to researchers [43]. This platform, which can be used for many different purposes such as machine learning and deep learning applications, has specially optimized hardware. Thus, it provides convenience and time savings in the studies carried out. Since it is free, its resources are limited and its use needs to be managed correctly. On average, 12.5 GB of RAM is available for system RAM usage. The use of GPU provides very high performance in the field of image recognition. That's why it's important to properly manage GPU usage. On average, 12.5 GB of GPU RAM is available for free use. The disk space available for free is 70 GB on average. The model used uses an average of 11 GB of GPU RAM. The remaining GPU RAM is insufficient to use all images. For this reason, it is necessary to insert images into the model in batches, not all at once.

2.5. Proposed Method

The main purpose of the proposed model is to find solutions to various problems that researchers encounter while establishing or applying a deep learning model, and thus to lead the way in the creation of more successful and performance models. For this reason, various tools and techniques that provide ease of use have been researched and tested in the model to be easily used by other researchers. PyTorch framework is preferred in the model. This is because of the open-source and easily modifiable nature of PyTorch builds. Successful architectures such as DenseNet264 and ResNet can easily be used instead of DenseNet121 used in the model. The MONAI framework [44][45] was used as the infrastructure in the model. It has been preferred because it provides ease of use and is easy to understand. 3D images can be used directly in the model and feature extraction is voxel-based. The model is openly shared on Github and researchers can access it easily on Github. The process of preparing the data and applying the model is shown in Figure 1.

Figure 1. Process of Data and Model



2.5.1. Scheduler Structure

Optimal parameter selection in deep learning models is a very important and difficult issue. In the proposed model, the "Scheduler" structure is used to find the optimal value of the "Learning Rate" parameter. With this structure, the learning rate changes automatically and gradually, and the success rates can be followed on the graph. By default, the initial learning rate=1e-7 and the max learning rate=1e-5 are given in the model. The amount of learning rate increase is calculated depending on the size of the training data and the number of epochs.

2.5.2. Data loader Structure

Each of the MR images used is 42 MB on average and contains a lot of data. Therefore, RAM usage is high. It causes problems, especially in Google Colab and prevents the model from working. For this reason, the data loader structure, which is a structure that puts images into the model piece by piece, not all at once, was used and RAM usage was significantly reduced. The batch size can be adjusted according to the amount of free RAM available and the model can work optimally. In this way, low RAM capacity or high image count is no longer a problem. Due to the usage limits of Google Colab, the optimal batch size=7 for the training data is determined and the model can work without any problems. It is possible to easily change the batch size according to the changing sources.

3. Results and Discussion

In the skull stripping process, which is an important preprocessing step, the optimal parameter (Fractional Intensity Threshold) for the ADNI dataset was found to be f=0.5 as a result of approximately 300 trials for the "Bias field and Neck Clean Up" tool. By using this value, neck and nose parts can be wiped optimally. Since only the brain is used in the diagnosis of Alzheimer's disease using MR images, the performance and accuracy of the model increase with this process. The second operation is the accurate deletion of the skull around the brain in the image with the neck, nose and eye parts removed. The point to be considered in this process is to protect the brain regions while wiping the skull, and therefore the correct parameter usage is very important. For “Standard Brain Extraction Using BET2”, approximately 700 images were tested and the optimal value was found to be f=0.15. In the experiments performed on the same images with the "Robust Brain Center Estimation" tool, the optimal parameter for this tool was found to be f=0.1. Figure 2 shows the sagittal plane image of an MR image taken from the ADNI database. The sagittal plane view of the image formed as a result of the operations performed with the Bias field and Neck Clean Up tool is shown in Figure 3. The last image created with the Standard Brain Extraction tool is shown in Figure 4 and it is seen that the brain is successfully separated from other regions. With the FSL processing, the regions outside the brain were deleted and a brain MR image was created which is ready to enter the deep learning model. To process these images, a model was created that can directly use 3D images. In this way, three-dimensional images such as MR can be used directly without the need for any slice operation and loss of information. In addition, with the new brain extracted images, training time is reduced by approximately 35% compared to normal MR images.

One of the benefits of the model is that it greatly reduces the need for RAM by using a data loader. Most models store all images on RAM, which results in performance degradation. Thanks to the data loader structure used in the proposed model, the images are used in batches and provide improvements in terms of performance and resource usage. Due to the usage limits of Google Colab used in the study, it is very important to manage the resource usage correctly and a great improvement has been achieved with this structure.

Figure 2. Magnetic Resonance Image From ADNI [15]

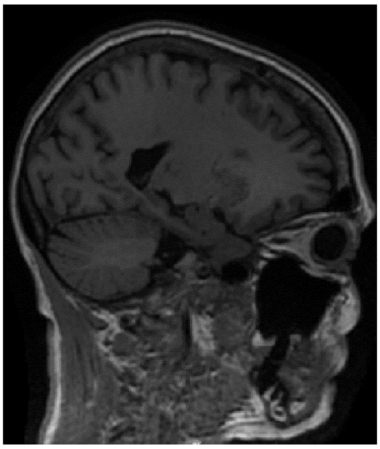


Figure 3. Neck, Nose and Eye Removed

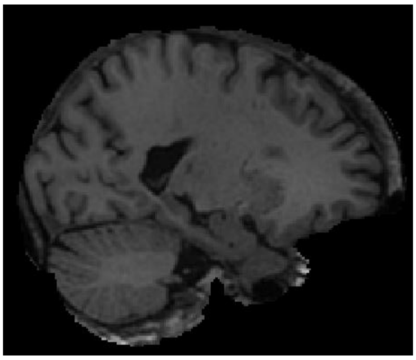
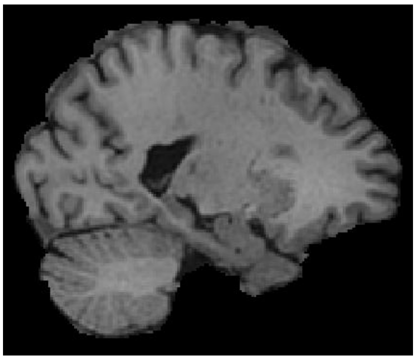


Figure 4. Brain Extracted (Skull Stripped)



To provide a standard for images, they are first resized to 128*128*128. All images are normalized within the model and pixel values are drawn between zero and one. Different normalization options are also available in the model and can be easily arranged as desired. Various data augmentation methods such as adding noise, Gaussian offset and image flipping are also included in the model and can be used. The DLTK library was used for data augmentation and normalization [40]. In addition, DenseNet121 infrastructure is used in the model. The infrastructure can be easily changed with minor modifications, thus providing great convenience in new works that can be done. Using proven infrastructures promises high accuracy and success rates. With the data to be prepared with the aforementioned Fsl tools, both ease of use, high performance and economical resource use, as well as high success can be achieved. In this sense, all the tools mentioned in this study work seamlessly in harmony and overcome various difficulties in use.

The scheduler structure used in the model is one of the most important features used in the model. This structure is a structure that aims to facilitate parameter management, which is quite time-consuming. Without the need for any processing, the "Learning Rate" in the model is constantly changing within the specified range and the optimal learning rate is found much faster. In addition, The Tensorboard library is used for visualization and parameters can be monitored simultaneously with the model.

The advantage of using 3D images directly in the model is that the loss of information is at a minimum level. Spatial information loss occurs when 3D images are converted by various methods. Preserving this valuable information will increase the success of potential studies using the proposed model. In addition, converting 3D images and inserting them into the model in different ways means extra time and resource usage. With the proposed model, these processes are not required and time and resource savings are provided.

4. Conclusions and Recommendations

In the study, a new model is proposed to be used in the diagnosis of Alzheimer's and to provide an infrastructure for new models. In the proposed model, various techniques that increase success and performance are presented in an easy-to-use and customizable manner. The main purpose of the model is to present the techniques that can be simply used in future research and to support the researchers at the points where they have difficulties. It was aimed and succeeded to provide improvement in the fields of image preprocessing, model construction, optimal determination of parameters, and efficient use of resources. As a result of the trials with the ADNI dataset, approximately 35% reduction in training time was achieved. The most important reason for this is that the unused voxels are cleaned from the MR image with the FSL library. In the study, optimal parameters were found for three tools in the FSL library. With the data loader structure, the limited resources in Google Colab were used effectively and the model was run without any problems. With the scheduler structure, the learning rate parameter has changed automatically and it has been possible to find the optimal parameter quickly and easily. All of these developments are presented in a proposed model with easy use and it is aimed to reduce the difficulties in new studies.

In future studies, using the techniques in the proposed model will save researchers from many difficulties and save time and resources. In addition, the use of the PyTorch framework will also provide ease of work due to its more open structure. Researchers can easily develop their models or use parts of the proposed model in the future.

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