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Classification of Alzheimer's disease with EfficientNetB3

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ABSTRACT

Alzheimer's disease (AD) is a condition that manifests as a loss of consciousness and cognitive dysfunction, eventually leaving the individual incapable of performing basic functions. The process culminates in death. The brain anomalies caused by the disease can be monitored using magnetic resonance imaging (MRI). This study aims to assist in the clinical diagnosis of AD and proposes a hybrid model to classify the stages of the disease. The magnetic resonance (MR) images used in the study were obtained from the Kaggle database and categorized into four classes: non-demented, very mild dementia, mild dementia, and moderate dementia. Background removal was applied to the images, followed by segmentation using the k-means clustering method. By combining EfficientNet B3 and the Gray Level Co-Occurrence Matrix (GLCM) feature extractor, this hybrid model was trained to perform the classification task. The model was trained five times, and experimental results were recorded. During training, the batch size was set to 18, the number of epochs to 20, and the learning rate to 0.0001. Experimental results showed an average training accuracy of 99.99% and a testing accuracy of 99.67%. Additional performance metrics, such as precision, recall, and F1-score, were also reported.

Alzheimer hastalığının EfficientNet B3 ile sınıflandırılması

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ÖZET

Alzheimer Hastalığı (AH), bilinç kaybı ve bilişsel işlev bozukluğu olarak ortaya çıkan ve sonunda bireyi temel işlevleri yerine getiremez hale getiren bir durumdur. Süreç ölümle sonuçlanır. Hastalığın neden olduğu beyin anomalileri manyetik rezonans görüntüleme (MRI) kullanılarak izlenebilir. Bu çalışma, AH' nin klinik teşhisine yardımcı olmayı amaçlamakta ve hastalığın evrelerini sınıflandırmak için hibrit bir model önermektedir. Çalışmada kullanılan manyetik rezonans (MR) görüntüleri Kaggle veri tabanından elde edilmiş ve dört sınıfa ayrılmıştır: demans olmayan, çok hafif demans, hafif demans ve orta derecede demans. Görüntülere arka plan kaldırma işlemi uygulanmış ardından k-means kümeleme yöntemi kullanılarak görüntülere segmentasyon işlemi uygulanmıştır. EfficientNet B3 ve Gri Seviye Eş Oluşum Matrisi (GLCM) özellik çıkarıcısını birleştiren bu hibrit model, sınıflandırma görevini yerine getirmek üzere eğitilmiştir. Model beş kez eğitilmiş ve deneysel sonuçlar kaydedilmiştir. Eğitim sırasında yığın boyutu 18, epok sayısı 20 ve öğrenme oranı 0.0001 olarak ayarlanmıştır. Deneysel sonuçların ortalamasına göre eğitim doğruluğu %99,99, test doğruluğu ise %99,67 olarak elde edilmiştir. Kesinlik, geri çağırma ve F1-skoru gibi ek performans ölçümleri de rapor edilmiştir.

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1. INTRODUCTION

Nowadays, predictions about diseases can be made using computer-aided decision support systems [1]. Analyzing and classifying diseases with computational methods, such as image processing and machine learning applied to medical images, is a frequently studied topic in the literature [2]. Medical images can also be utilized for predicting Alzheimer's disease (AD). AD is a neurodegenerative condition that begins with mild memory loss and progresses to cognitive dysfunction, psychiatric and behavioral disorders, and disruption of daily activities [3]. In the later stages of the disease, individuals lose bodily functions, and death is expected to occur within 3 to 9 years from the date of diagnosis, depending on the rate of disease progression [4]. As with any disease, early diagnosis of AD is crucial for delaying progression and alleviating symptoms.

Magnetic resonance imaging (MRI), positron emission tomography (PET), and cerebrospinal fluid (CSF) analysis are used in clinical settings to diagnose Alzheimer's disease [5]. Research on the diagnostic prediction of AD using MRI data and machine learning techniques is extensive. For example, Sisodi and colleagues [6] classified MRI data using ResNet50, VGG19, Xception, DenseNet201, and EfficientNetB7 methods to detect various stages of AD. The validation accuracies for the DenseNet201, ResNet50, VGG19, Xception, and EfficientNetB7 models were recorded as 96.59%, 93.52%, 95.08%, 89.77%, and 83.20%, respectively. Sanjay et al. [7] used a combined DenseNet and MobileNet structure to classify MRI scans, achieving 98.87% accuracy, 98.95% precision, and 98.99% recall. Sharen et al. [8] applied a transfer learning model with the EfficientNetB7 architecture to classify the Kaggle brain MRI dataset, which includes four classes: mild dementia, moderate dementia, no dementia, and very mild dementia. Their proposed model achieved improved accuracy and F1 scores of 89.7% and 0.91%, respectively. Sethi et al. [9] obtained an accuracy level of 91.36% and an AUC of 83% using the EfficientNet model to classify AD and Cognitive Normal (CN) based on MRI scans. Mujahid et al. [10] proposed EfficientNet-B2 and VGG-16 for early-stage diagnosis of AD in MRI datasets, achieving 97.35% accuracy and 99.64% AUC for multi-class datasets and 97.09% accuracy and 99.59% AUC for binary-class datasets. Pranata et al. [11] designed a method using the MRI-based EfficientNet architecture and a Convolutional Neural Network (CNN). They reported the highest values as follows: accuracy 0.97, precision 0.97, recall 0.97, F1-score 0.97, and loss 0.1104.

This study aims to contribute to the early diagnosis of AD. MR images of Alzheimer's patients are enhanced with image processing techniques and classified with the EfficientNet B3 model. To improve the classification performance, the EfficientNet B3 model is combined with GLCM, a feature extraction method. The study has yielded significant results for the classification problem.

2. MATERIALS and METHOD

The methodology of the study is illustrated in the diagram provided in Figure 1.

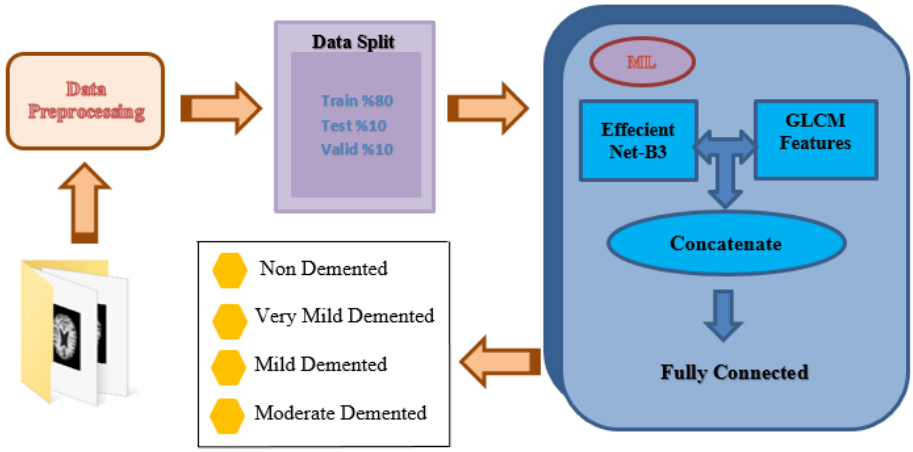

Figure 1. Proposed model general representation

2.1. Data

In this study, a four-class dataset from Kaggle was used [12]. The dataset contains augmented MR images of four classes: mild dementia, moderate dementia, non-demented, and very mild dementia. Table 1 displays the number of images for each class in the dataset.

Table 1. Alzheimer's Disease dataset

Mild Dementia	Moderate Dementia	Very Mild Dementia	Non-Demented
8960	6464	9600	8960

2.2. Data Preprocessing

Background removal and k-means segmentation methods were applied to the images for classification.

- *Remove Images Backgrounds*

In this study, edge detection and contour detection methods were used to separate images from their backgrounds. The images were converted to grayscale, and Canny edge detection was applied. This method identifies object boundaries by detecting pixels that fall within a specific threshold as edges. The pixels forming these boundaries were then identified using the contour detection function, and a mask was created. To smooth the edges, a Gaussian filter was applied to the mask [13]. Figure 2 shows the original image and the background image for the moderate demented class.

Converting the image to greyscale results in an image with the greyscale value of each pixel, calculated by Equation 1. Here the variables x and y represent the horizontal (width) and vertical (height) positions of the pixel in the image. The Canny edge detection method uses gradient calculations to identify edges in an image. The mathematical formula of the gradient calculation is expressed in Equation 2. The mathematical equivalent of the Gaussian filter used to smooth edges is shown in Equation 3 [14].

$$I(x,y) \tag{1}$$

$$G(x,y) = \sqrt{\left(\frac{\partial I(x,y)}{\partial x}\right)^2 + \left(\frac{\partial I(x,y)}{\partial y}\right)^2} \tag{2}$$

$$G(x,y) = \frac{1}{2\pi\sigma^2} exp\left(-\frac{x^2 - y^2}{2\sigma^2}\right) \tag{3}$$

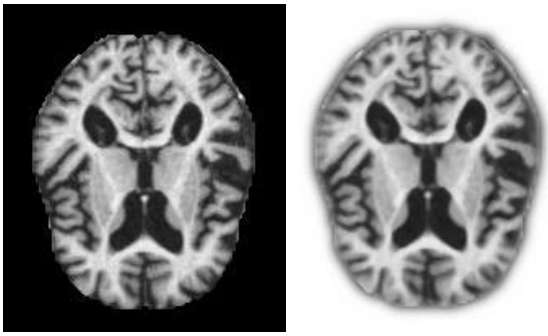

Figure 2. The original image and the image with the background removed

- K-Means Segmentation

The K-means clustering algorithm, an image processing technique, is based on the similarities between pixels. This algorithm assigns each pixel to one cluster, and as a result, the similarities within clusters are expected to be higher than those between clusters. The number of clusters, determined externally, is initially assigned randomly to the cluster centers. All pixels are then assigned to the cluster with the closest features, and the cluster centers are recalculated. This process of assigning pixels to clusters continues until the cluster centers no longer need to be reassigned [15].

In Figure 3, the original image, the image with the background removed for the moderate demented class, and the images segmented using the K-means clustering method are shown.

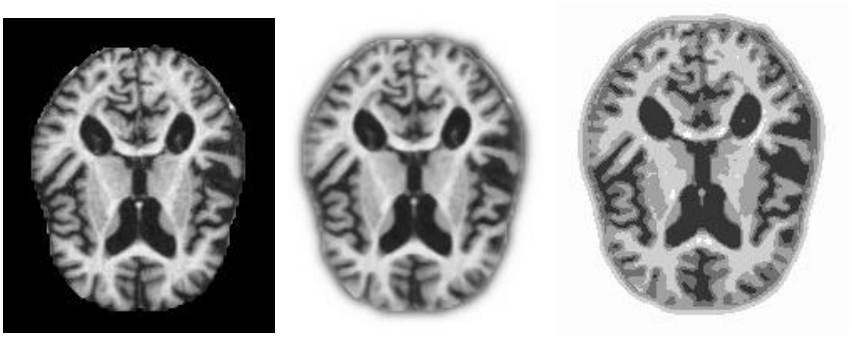

Figure 3. Original image, image with background removed, and segmented image

2.3. Classification Method

For the pre-processed images, 25 features were extracted using the gray level co-occurrence matrix, and these features were integrated into the EfficientNetB3 model for classification.

- *Gray Level Co-Occurence Matrix*

The Gray Level Co-occurrence Matrix (GLCM) is a statistical technique used for processing remote sensing data in texture analysis. It extracts spatial features from grayscale images by analyzing the relationship between the luminance values of a central pixel and its neighboring pixels, as defined by a kernel or window size. This relationship is represented in the form of a matrix, which records the frequency of ordered pairs of pixel values occurring together in a specified direction. This method enables GLCM to generate various sets of texture information depending on the grayscale, kernel size, and direction.

In this study, the features considered are contrast, homogeneity, dissimilarity, energy, and correlation [16]. Contrast refers to the difference between the highest and lowest pixel values in the image. Homogeneity, also known as the inverse difference moment, measures uniformity in an image, with larger values indicating smaller differences in grey tones between pairs of elements. Dissimilarity is a linear measure of local variations in the image. Energy is calculated as the square root of the angular second moment, representing the textural uniformity. Correlation measures the linear dependencies between the grey tones of an image [17].

Each of the textural features is calculated using Equations (4) to (8) [18]:

$$CONTRAST = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-j)^2 \tag{4}$$

$$HOMOGENEITY = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{P(i,j)}{1+(i-j)^2} \tag{5}$$

$$DIFFERENCE = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}P(x,y)x|i-j| \tag{6}$$

$$ENERGY = \sqrt{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}P(i,j)^2} \tag{7}$$

$$CORRELATION = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma)_i(\sigma)_j}} \tag{8}$$

In the mathematical expressions, N represents the number of gray levels, and P(i,j) is the normalized value of the sum of the grayscale at position i and j within the kernel, which equals 1. For each image, a total of 25 features were generated for each texture feature, using distances of 1, 3, and 5 pixels, and at angles of 0 degrees (horizontal), 45 degrees (diagonal), and 90 degrees.

- *EffecientNet-B3*

Tan and Le proposed seven models, EfficientNetB0 to EfficientNetB7, which they referred to as EfficientNet CNN models. These models aim to achieve better classification accuracy with fewer parameters [19]. The methods scale the width, depth, and resolution dimensions proportionally using predefined coefficients [20].

The EfficientNet-B3 model automatically scales depth and width based on the resolution of the input image. With more filters per layer and higher spatial resolution, the model can capture finer details in the input images. The architecture includes convolutional layers, batch normalization layers, and ReLU activation functions. Feature maps are computed using depthwise convolutions, which reduce the number of parameters by performing one convolution per channel. The model consists of 26 convolution blocks, each followed by a convolution layer activated by batch normalization. Mobile Inverted Bottleneck Convolution is used as an inverted residual block, consisting of a convolution layer, a depthwise convolution, and another convolution layer, with skip connections at both the beginning and end. Finally, the dimensions are reduced by global average pooling [21].

2.4. Evaluation

EfficientNet B3 belonging to the EfficientNet model family was used in this study. The model is loaded with weights previously learnt by training on the ImageNet dataset. EfficientNet B3 is designed to process three-channel (RGB) images. The images used in this study are grey-scale (single channel) images, which were converted into three channels (124x124x3) by using a Lambda layer to adapt to the model.

A Multilayer Perceptron (MLP) model was designed to process the 25-dimensional inputs obtained by feature extraction methods. This model contains two dense layers: The first layer consists of 8 neurons and the second layer consists of 4 neurons and both layers use the ReLU activation function. The outputs of the MLP and EffecientNet B3 models are combined in a concatenate layer to allow the model to handle various features.

The concatenated inputs are passed through a dense layer with a ReLU activation function. Finally, a 4 neuron output layer with softmax activation function is added to perform the classification process.

Recall precision, accuracy, F1 score and recall metrics are used to measure the performance of the proposed hybrid model.

Accuracy (Acc) is one of the mainly applied metrics in such domain. This metric calculates the number of true predictions that the model was able to detect. It is calculated by dividing the sum of true negatives and true positives by the Acc is calculated by Equation (6). Acc expresses the ratio of the ratio of the number of people that can be properly predicted and categorised. The term Sensitivity (Sens) denotes the proportion of correctly identified patients in the overall number of patients and is calculated by Equation (7). The term Specificity (Spec) denotes the proportion of correctly identified healthy individuals relative to the total number of individuals without any health issues, computed as outlined in Equation (8). Precision, recall, and F1-score are measures that analyse the performance of classification models. The areas where the model makes correct predictions are expressed as True Positive (TP) and True Negative (TN). The areas where the model makes incorrect predictions are False Positive (FP) and False Negative (FN). Precision indicates the accuracy of Positive class predictions, calculated as the ratio of True Positives to all Positive predictions. Recall (Rec) is a metric that shows how much of what is expected to be positively predicted is positively predicted. The F1 Score represents the harmonic mean of Precision and Recall. Metrics are calculated using Equation (9) to (14):

$$Acc = \frac{TN + TP}{TN + TP + FN + FP} \tag{9}$$

$$Sens = \frac{TP}{TP + FN} * 100 \tag{10}$$

$$Spec = \frac{TN}{TN + FP} * 100 \tag{11}$$

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

$$Rec = \frac{TP}{TP + FN} \tag{13}$$

$$F_1 = 2 * \frac{Precision * Rec}{Precision + Rec} \tag{14}$$

The data set is divided into 80% training, 10% validation and 10% test data. The model was trained in TPU environment with the hyperparameter values specified in Table 2.

Table 2. Hyperparameters of the proposed model

Hyperparameter	Value
Input Shape	(124, 124, 3)
Optimizer	Adam
Loss	Categorical Crossentropy
Metrics	Accuracy
Learning Rate	0.0001
Epoch	20
Batch Size	18

3. RESULTS

This study, which aims to assist in the diagnosis of Alzheimer's disease, has achieved significant success in the classification task. In this section, we describe the experimental results. The hybrid model used to classify the stages of Alzheimer's disease was trained five times, and the results were recorded. As shown in Table 3, the model was trained with a batch size of 18, for 20 epochs, and a learning rate of 0.0001.

When training the model, the data is processed in parts. Backpropagation updates the weights based on the performance of each part. This process is repeated in each training step to calculate the appropriate weight values for the model. Each of these steps is called an epoch. Batch size refers to the number of data points the model processes simultaneously. In this study, various combinations of epoch and batch size parameters were tested, and the highest-performing values were selected. To ensure the model converged to a stable and optimum result, the initial learning rate was set as low as 0.0001. If no improvement occurred for 2 consecutive epochs during training, the learning rate was reduced by a factor of 0.1.

Two methods were applied to avoid overfitting in the model: data augmentation and the early stopping function. The data used in the study is an augmented version of the AD dataset. Since the raw version of the dataset contains unbalanced class distributions and an insufficient number of samples, which may cause the model to overfit, using a larger, augmented dataset is more logical. Additionally, early stopping was employed as another method. In this approach, the validation accuracy and validation loss values obtained at the end of each epoch are analyzed, and training is halted based on the model's validation Performance [22]. Table 3 presents the test accuracy values obtained during training.

Table 3. Results of the model

Number of experiment	Train Accuracy	Test Accuracy
1	%100	%99.60
2	%99.99	%99.80
3	%99.99	%99.68
4	%100	%99.59
5	%100	%99.70

The mean values of the experimental results were calculated as 99.99% for training accuracy and 99.67% for test accuracy. The precision, recall, and F1-score results obtained from the experiments are shown in Table 4.

Table 4. Precision, recall and F1-score results of the model

Disease		Precision	Recall	F1- Score
Non-Demented	1	1.00	1.00	1.00
	2	1.00	1.00	1.00
	3	1.00	1.00	1.00
	4	1.00	1.00	1.00
	5	1.00	1.00	1.00
Very Mild Dementia	1	1.00	1.00	1.00
	2	1.00	1.00	1.00
	3	1.00	1.00	1.00
	4	1.00	1.00	1.00
	5	1.00	1.00	1.00
Mild Dementia	1	1.00	0.99	0.99
	2	1.00	1.00	1.00
	3	1.00	1.00	1.00
	4	1.00	0.99	1.00
	5	1.00	0.99	0.99
Moderate Dementia	1	0.99	1.00	0.99
	2	1.00	1.00	1.00
	3	0.99	1.00	0.99
	4	0.99	0.99	0.99
	5	0.99	0.99	0.99

Based on the results obtained from the experiments, it can be concluded that the proposed model yields consistent results on the test data and is successful.

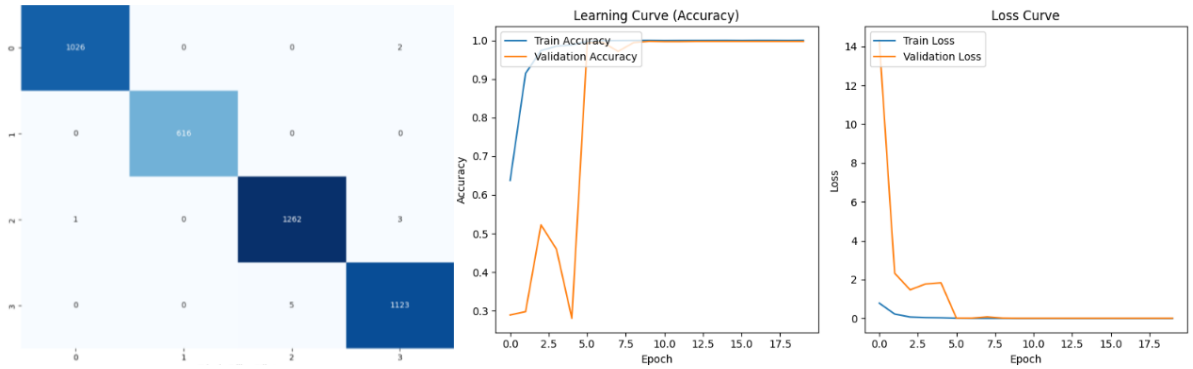

Figure 4. Confusion matrix, learning curve and loss curve of Experiment 1

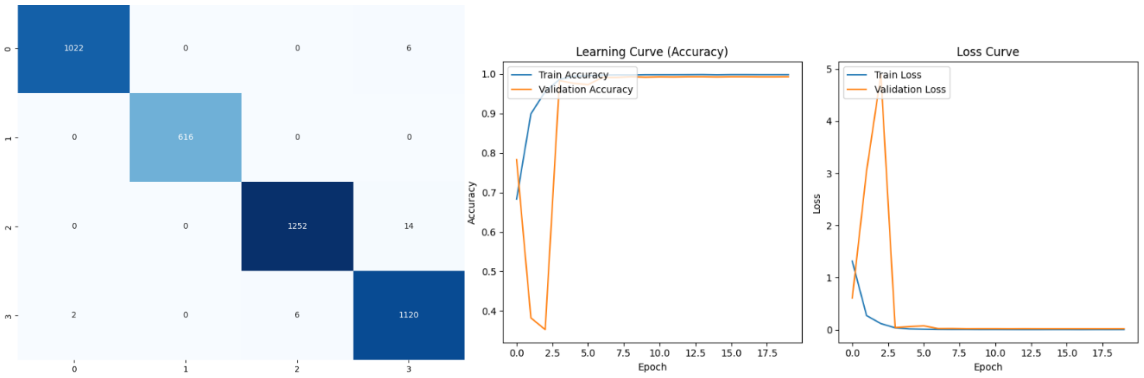

Figure 5. Confusion matrix, learning curve and loss curve of Experiment 2

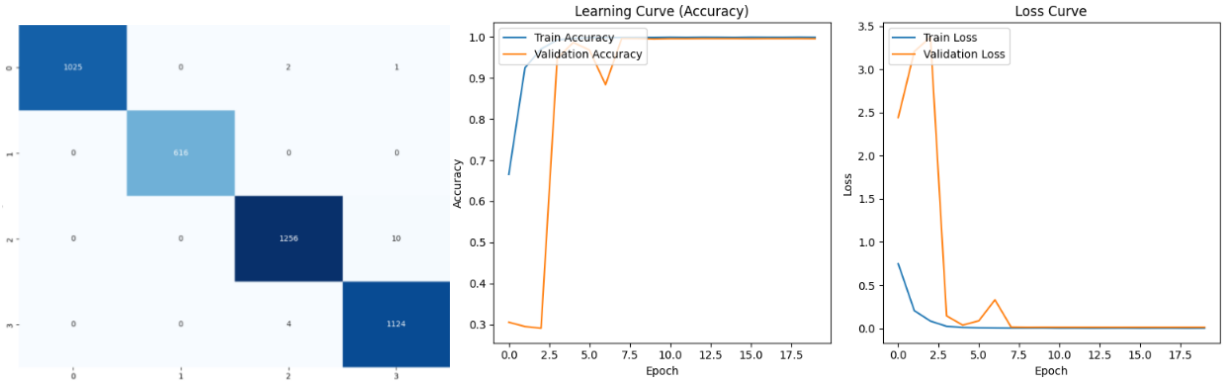

Figure 6. Confusion matrix, learning curve and loss curve of Experiment 3

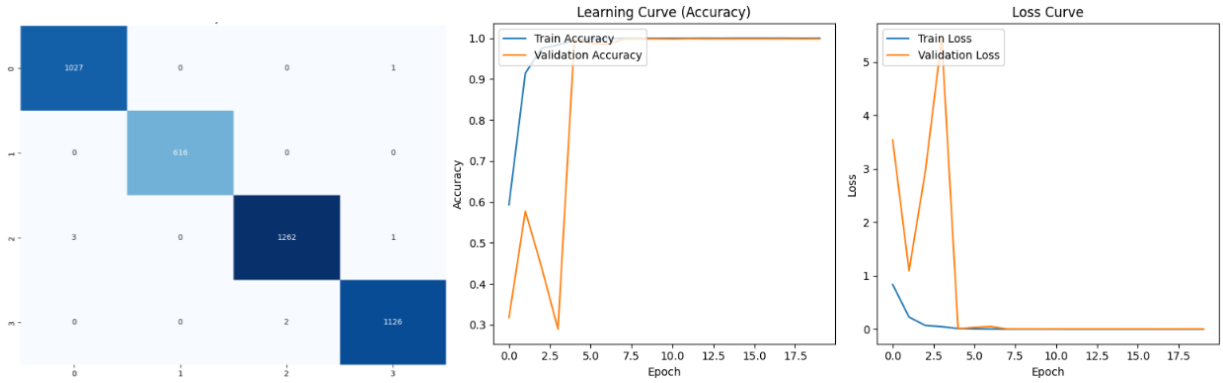

Figure 7. Confusion matrix, learning curve and loss curve of Experiment 4

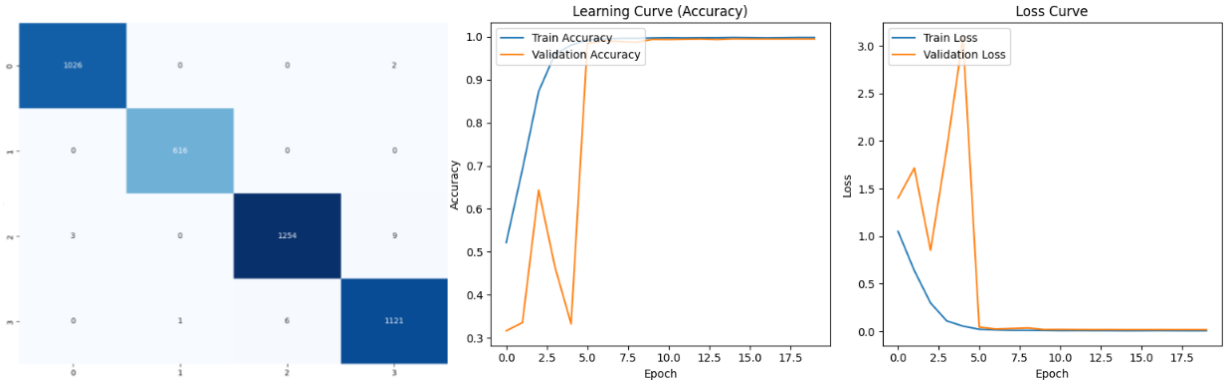

Figure 8. Confusion matrix, learning curve and loss curve of Experiment 5

The confusion matrices, as well as the learning and loss curves from the experiments, are shown in Figures 4-8. In the confusion matrices, the class labels are as follows: 0 - Non-Demented, 1 - Very Mild Demented, 2 - Mild Demented, and 3 - Moderate Demented. In the matrices, the horizontal axis represents the predicted labels, and the vertical axis represents the true labels. The model's classification performance can be evaluated by examining these confusion matrices. The curves illustrate the behavior of the validation and training data during model training.

4. DISCUSSION

Table 5 can be used to compare the performance of the proposed work with similar studies in the literature. The studies listed in the table share two common aspects with the proposed work: the classification of AD stages and the use of MR images. Additionally, these studies employed the EfficientNet method, which is also utilized in this study. An analysis of the table indicates that this study has achieved greater success compared to the other studies.

Table 5. Performance analysis of this model compared to other models

Method	Year	Dataset	Accuracy (%)
EfficientNetB7[6]	2023	Alzheimer's Disease Dataset(ND,VMD, MD, MOD)- MRI	83.20
Merged DenseNet and MobileNet [7]	2023	MRI Neuroimaging Data (EMCI, LMCI, AD, MCI, & NC)-MRI	98.87
EfficientNetB7[8]	2022	Alzheimer's Disease Dataset(ND,VMD, MD, MOD)- MRI	89.70
EfficientNet AD diagnostic (ENetAD) [9]	2022	ADNI Dataset (CN, AD)-MRI	91.36
EfficientNet-B2 and VGG-16[10]	2023	Alzheimer's Disease Dataset(ND,VMD, MD, MOD)- MRI	97.35
CNN model with Efficient-Net [11]	2023	Alzheimer's Disease Dataset(ND,VMD, MD, MOD)- MRI	97.00
This Study	**2024**	**Augmented Alzheimer's Disease Dataset(ND,VMD, MD, MOD)- MRI**	**99.67**

In our study, neurological images of the disease underwent a comprehensive image processing workflow. The studies referenced in Table 5 did not employ extensive image processing techniques. Image processing plays a crucial role in our study, with its primary objective being to enhance the images and highlight disease-specific features. The number of images, or dataset size, is beneficial during the training phase, as it allows the model to be trained under varying conditions to produce robust results. In our study, approximately 34,000 images were used, which is a larger dataset than those in other studies.

The textural features of the images were extracted and integrated into the EfficientNet B3 model. This approach combined the features extracted by the EfficientNet B3 model for classification with the textural features extracted using the GLCM. As a result, classification was performed using a richer set of features. Compared to other studies, our model has a more complex architecture. Our study demonstrated superior performance compared to other models in terms of accuracy, and it outperformed other variations of the EfficientNet family.

5. CONCLUSION

Early diagnosis of diseases is crucial for the timely initiation of treatment. Early diagnosis of AD is particularly valuable, as it enables treatments that can slow the progression of the disease or stabilize its condition. In this study, we proposed a model for the early diagnosis of Alzheimer's disease. We combined pre-processed MRI images with a machine learning algorithm and a GLCM feature extractor for classification. This study demonstrates the effectiveness of the proposed hybrid model in classifying the stages of Alzheimer's disease.

Across five different experiments, the model achieved an average training accuracy of 99.99% and a testing accuracy of 99.67%, demonstrating its generalizability across different data sets. The model’s performance in classifying different stages of AD was validated using metrics such as precision, recall, and F1 score, and the results for each class were reported. In the Non-Demented and Very Mild Demented classes, precision, recall, and F1 score values were recorded as 1.00. For the Mild and Moderate Demented classes, values ranged between 0.99 and 1.00.

Strategies such as data augmentation and early stopping, used to prevent overfitting, played a critical role in ensuring the stability of the model. In all five experiments, the training and loss curves indicate that the model effectively fits the validation data while avoiding overfitting.

Overall, the model is a reliable and effective tool for the early diagnosis and classification of AD, providing a consistent and accurate approach that can assist in clinical diagnoses. Future improvements to this study may include incorporating additional feature extractors, applying various image processing techniques, and utilizing a larger dataset.

AUTHOR CONTRIBUTIONS

Ruken Tekin and Tuğba Özge Onur, conceptualization, validation, visualization. Ruken Tekin, software, investigation, resources, writing-orginal draft preparation. Tuğba Özge Onur, supervision, methodology, formal analysis, data curation, writing-review and editing. All authors have read and agreed to the published version of the manuscript.

CONFLICT OF INTEREST

The authors declare that they have no competing interests.

ETHICS

There is no ethical problem in the publication of this article.

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