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Research Article

Classification and Segmentation of Alzheimer Disease in MRI Modality using the Deep Convolutional Neural Networks

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Abstract

In the study, classification and segmentation tasks were implemented for analysis of Alzheimer's disease. In classification task, 7 different models were tested using transfer learning. The GoogLeNet model achieved the best classification performance with the accuracy of 0.9467, sensitivity of 0.9474, specificity of 0.9811, and F1-score of 0.9467. In segmentation task, U-Net architecture design was used for the segmentation of Alzheimer's disease. U-Net model achieved the dice of 0.874, IoU of 0.776, sensitivity of 0.868, specificity of 0.999, precision of 0.879, and accuracy of 0.999. In order to create the pipeline, classification and segmentation models were used together. Consequently, a computer vision-assisted decision support system was created.

Keywords: Alzheimer, Classification, Segmentation, GoogLeNet, U-Net.

Derin Evrişimli Sinir Ağlarını Kullanarak MRG Modalitesinde Alzheimer Hastalığının Sınıflandırılması ve Segmentasyonu

Öz

Çalışmada Alzheimer hastalığının analizi için sınıflandırma ve segmentasyon görevleri uygulanmıştır. Sınıflandırma görevinde transfer öğrenme kullanılarak 7 farklı model test edilmiştir. GoogLeNet modeli 0.9467 doğruluk, 0.9474 duyarlılık, 0.9811 özgüllük ve 0.9467 F1 skoru ile en iyi sınıflandırma performansını elde etmiştir. Segmentasyon görevinde, Alzheimer hastalığının segmentasyonu için U-Net mimari tasarımı kullanılmıştır. U-Net modeli 0.874 zar skoru, 0.776 IoU, 0.868 duyarlılık, 0.999 özgüllük, 0.879 kesinlik ve 0.999 doğruluk elde etmiştir. Pipeline oluşturmak için sınıflandırma ve segmentasyon modelleri birlikte kullanılmıştır. Sonuç olarak, bilgisayarlı görü destekli bir karar destek sistemi oluşturulmuştur.

Anahtar Kelimeler: Alzheimer, Sınıflandırma, Segmentasyon, GoogLeNet, U-Net.

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1. Introduction

Alzheimer's disease is a type of dementia that causes problems with mind, thinking, and behavior. Symptoms usually progress slowly and get worse over time. The biggest known risk factor is age. If Alzheimer's disease is not diagnosed early, the quality of life of patients may be shortened and the number of diseases resulting in death may increase. While it is estimated that there are 50 million Alzheimer's patients today, this number is expected to triple in 30 years (Alp Eren et al., 2021).

Nowadays, there is no treatment for Alzheimer's disease, so it is vital to take precautions together with early diagnosis (Öziç & Özşen, 2020). Therefore, auxiliary diagnostic systems are needed. The most important of these diagnostic systems is artificial intelligence applications. The most important artificial intelligence sub-research area in health is computer vision. Continuously developing medical imaging systems are pointed out as one of the most important reasons for this. Magnetic resonance imaging (MRI), computed tomography (CT) and X-ray modalities can be given as examples of those that are frequently used in medical imaging systems. Especially MRI and CT are imaging systems that are frequently used in the diagnosis of Alzheimer's disease. The inclusion of computer vision applications in these imaging systems is a very important research area (Hong et al., 2019; John & Kunju, 2018; Khvostikov et al., 2018).

It has been suggested by many scientific researchers that various classification and segmentation techniques can be used for Alzheimer's disease. Allioui et al., (Allioui et al., 2019), aimed to perform the segmentation of alzheimer's diseases by using MRI images. U-Net model was performed on Online Aerospace Supplier Information System (OASIS) data set. Accuracy of 92.71%, Sensitivity of 94.43%, and Specificity of 91.59% were achieved by U-Net model. Ahmed et al. (Ahmed et al., 2019), aimed to perform the classification of alzheimer's diseases by using MRI images. Gwangju Alzheimer's and Related Dementia (GARD) cohort data set was used. A novel ensemble learning based classification method was proposed. The ensemble classifier achieved accuracy of 90.05%. Vieria et al. (Vieira et al., 2017), aimed to perform the classification of alzheimer's diseases by using MRI images. ADNI data set which is includes the three classes was used. In the study, accuracy of 83.03% was achieved.

The aim of the paper is to diagnose Alzheimer's disease, which negatively affects human life. Therefore, classification and segmentation processes were used together in this study. In both processes, MR images were used in the training of the classification and segmentation models. After, these models were used as pipeline structure. At this stage, firstly the images were classified and then segmented. As a result, a computer vision-assisted decision support system was created for Alzheimer's disease.

The contributions of this proposed study are summarized as follows:

1. A novel pipeline was proposed.

2. A computer aided diagnosis (CAD) system was created using classification and segmentation for the diagnosis of Alzheimer's disease.

The rest of this paper is organized as follows. In Section 2, the utiliezed methodologies have been detailed. In Section 3, obtained results have been discussed. In Section 4, concluding remarks have been reported.

2. Methodology

The utilized methodology in the study is presented under the subtitles data sets, classification and segmentation networks and performance evaluation metrics.

2.1. Data sets

Two different data sets were used for classification and segmentation tasks.

In classification task, data set includes four classes namely, Non Demented, Very Mild Demented, Mild Demented, and Moderate Demented (*Alzheimer's Dataset (4 Class of Images) | Kaggle*, n.d.). The data set consists of total of 7,093 MRI images. The data set includes 1699, 235, 1699, and 3460 images for Mild Demented, Moderate Demented, Very Mild Demented, and Non Demented classes, respectively. The size of the images in the data set is 256 by 256 pixels. Training and testing size of data set is %90 and %10, respectively.

In segmentation task, Alzheimer's Disease Neuroimaging Initiative (ADNI) data set was used (*ADNI | Alzheimer's Disease Neuroimaging Initiative*, n.d.). The data set consists of 135 MRI images of patients. The total number of labeled images which are the right and left hippocampus regions in the data set is 3586. The format of the images in the data set is DICOM, so DICOM data was converted to PNG format. The images and masks in the data set were resized to 128 by 128 pixels. After, min-max normalization was applied. Lastly, the training and testing size of the data set were determined as 90% and 10%, respectively.

2.2. Classification and Segmentation Networks

In image classification task, transfer learning method was used. At this stage, models trained on the ImageNet data set were used. DenseNet121, EfficientNet, GoogLeNet, MobileNet version 3, ResNet101, ResNext101, and ShuffleNet models were used for the Alzheimer's disease classification. In the training phase of image classification models; cross entropy was used as loss function, Adam was used as optimizer, batch size was set as 16, and epoch was set as 20. 1e-3 was set as the learning rate. Google Colab integrated development environment (IDE) was used in the experiment. PyTorch framework in Python programming language was used in the coding stage. The experiment was implemented on the NVIDIA Tesla T4 graphics card.

In segmentation task, U-Net (Weng & Zhu, 2021), a state-of-the-art segmentation network, was used. U-Net architecture design is shown in Figure 1. In the training phase of U-Net model; the compound form of the cross entropy and dice loss functions was used as loss function, RMSprop was used as optimizer, batch size was set as 2, and epoch was set as 50. 1e-4 was set as the initial learning rate. If segmentation performance of U-Net is not improvement for during the 15 epochs, the learning rate was multiplied by 0.1. Spyder IDE was used in the experiment. PyTorch framework in Python programming language was used in the coding stage. The experiment was implemented on the NVIDIA GeForce RTX 3060 graphics card.

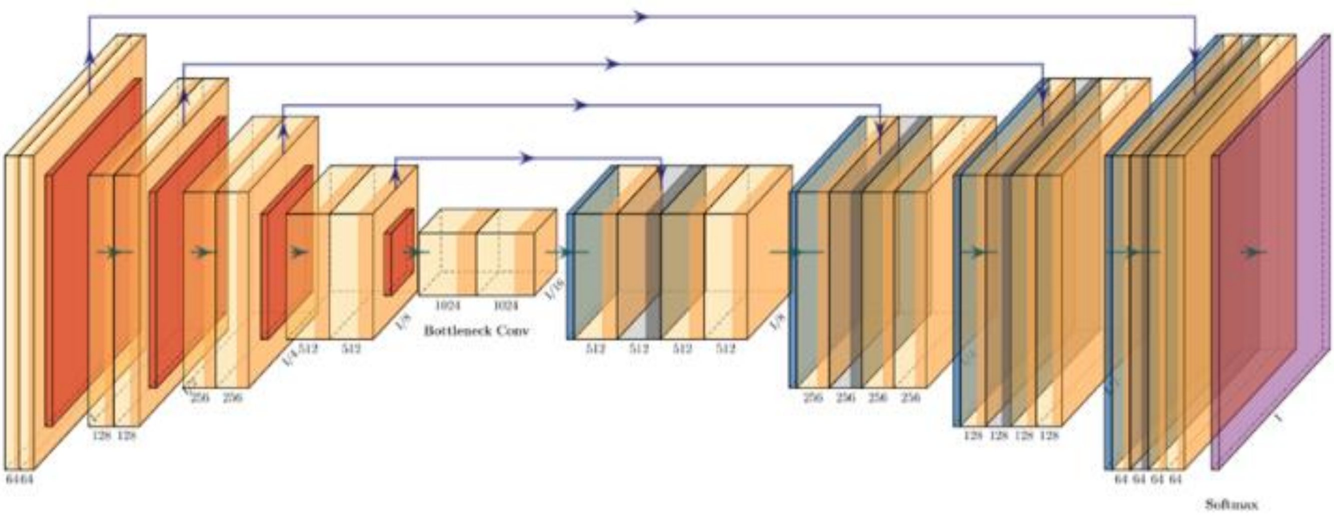

Figure 1. U-Net architecture design (Iqbal, 2018)

2.3. Performance Evulation Metrics

In this study, accuracy, sensitivity, specificity, F1-score, dice and IoU performance evaluation metrics were used for the performance analysis of the classification models and U-Net. Formulations of accuracy, precision, sensitivity, specificity, F1-score, dice and IoU performance evaluation metrics are shown in this section from equation 1 to equation 7. True Positive (TP) indicates to number of correctly classified positive class. True Negative (TN) indicates number of correctly classified negative class. False Positive (FP) indicates incorrectly classified positive class. False Negative (FN) indicates number of the incorrectly classified negative class.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (1)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (2)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (4)$$

$$\text{F1} - \text{Score} = \frac{2 \text{ x Precision x Sensitivity}}{\text{Precision} + \text{Sensitivity}} \quad (5)$$

$$\text{Dice} = \frac{2 \text{ x TP}}{2 \text{ x TP} + \text{FP} + \text{FN}} \quad (6)$$

$$\text{IoU} = \frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN}} \quad (7)$$

3. Results and Discussion

From Table 1, Densenet121 model achieved accuracy of 90.4388, sensitivity of 89.8414, specificity of 96.5833 and F1-Score of 88.5524. The training time of Densenet121 model is 16 minutes and 45 seconds. EfficientNet model achieved accuracy of 92.6332, sensitivity of 92.8281, specificity of 97.4071 and F1-Score of 92.1447 The training time of EfficientNet model is 35 minutes and 40 seconds. GoogLeNet model achieved accuracy of 94.6708, sensitivity of 94.7475, specificity of 98.1175 and F1-Score of 94.6708 The training time of GoogLeNet model is 10 minutes and 01 seconds. MobileNet_v3 model achieved accuracy of 91.5360, sensitivity of 90.7704, specificity of 97.0899 and F1-Score of 89.8757 The training time of MobileNet model is 9 minutes and 35 seconds. ResNet101 model achieved accuracy of 87.9310, sensitivity of 81.8456, specificity of 95.7228 and F1-Score of 83.5871 The training time of ResNet101 model is 30 minutes and 42 seconds. ResNext101 model achieved accuracy of 82.9135, sensitivity of 77.8572, specificity of 93.8420 and F1-Score of 78.3370 The training time of ResNext101 model is 45 minutes and 34 seconds. ShuffleNet model achieved accuracy of 92.3197, sensitivity of 92.7022, specificity of 97.3556 and F1-Score of 90.2638 The training time of ShuffleNet model is 29 minutes and 34 seconds.

The best three classification performances were achieved by GoogLeNet, EfficientNet, and ShuffleNet. The three shortest training times were achieved by MobileNet_v3, GoogLeNet, and DenseNet121, respectively. Figure 2 shows accuracy of models and training times. Figure 3 shows performance evaluation metrics results of models and training times. Figure 4 shows confusion matrix for GoogLeNet model. Figure 5 shows the used number of 9 input images and the output images achieved by the GoogLeNet model.

U-Net model achieved the dice of 0.874, IoU of 0.776, sensitivity of 0.868, specificity of 0.999, precision of 0.879, and accuracy of 0.999. The results obtained by U-Net are given in Figure 6.

Figure 7 shows the used number of 2 input images and the output images achieved by pipeline of the combination of the GoogLeNet and U-Net models.

Table 1. Results obtained using classification models

Models	Accuracy	Sensitivity	Specificity	F1-score	Training Time
DenseNet121	90.4388	89.8414	96.5833	88.5524	16.45
EfficientNet	92.6332	92.8281	97.4071	92.1447	35.40
GoogLeNet	94.6708	94.7475	98.1175	94.6708	10.01
MobileNet_v3	91.5360	90.7704	97.0899	89.8757	09.35
ResNet101	87.9310	81.8456	95.7229	83.5871	30.42
ResNext101	82.9135	77.8572	93.8420	78.3370	45.34
ShuffleNet	92.3197	92.7022	97.3556	90.2638	29.34

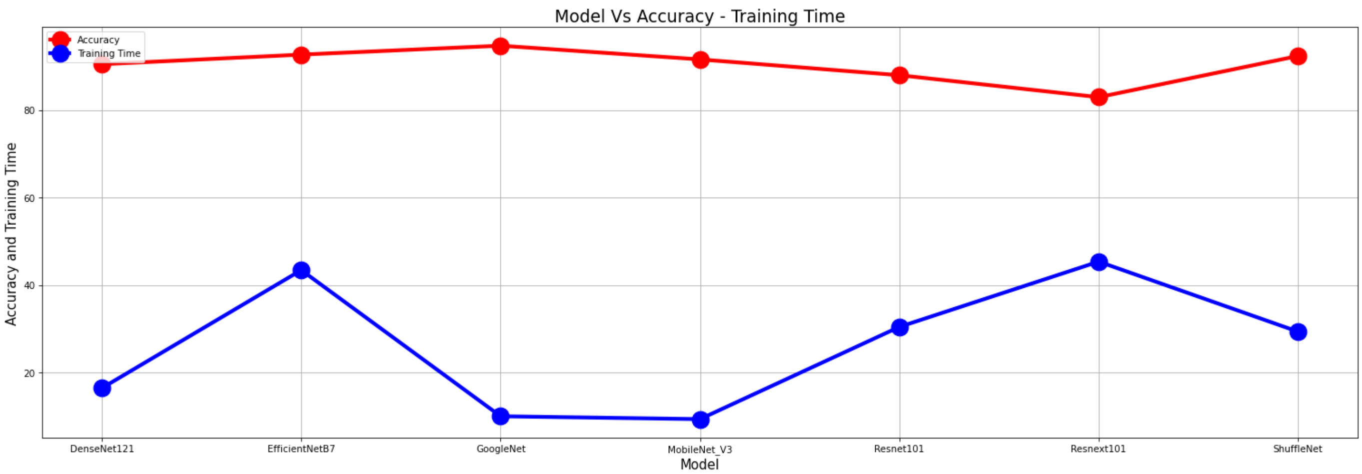

Figure 2. Accuracy of models and training times

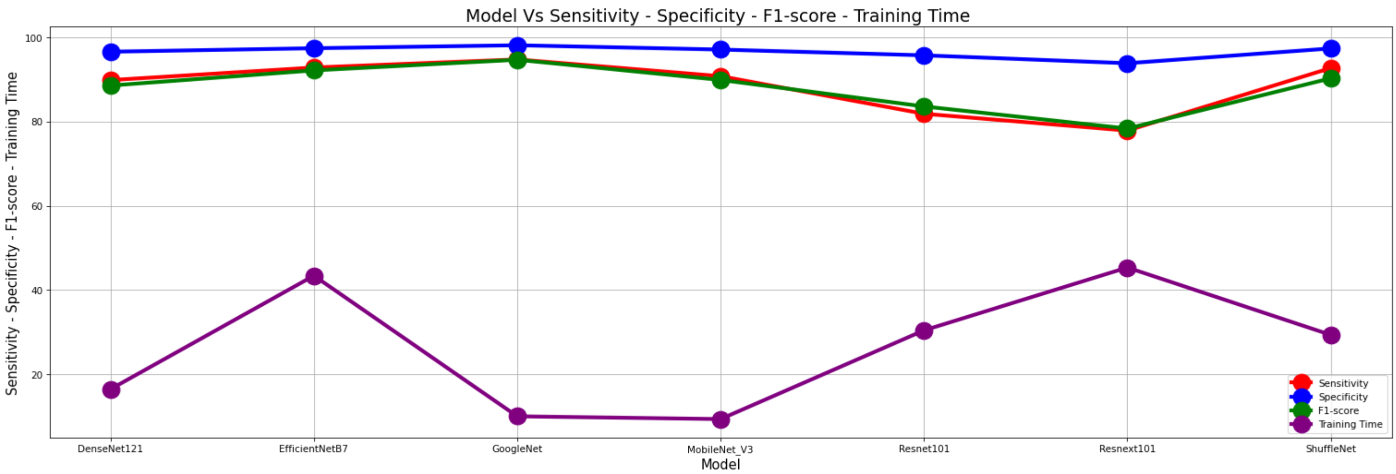

Figure 3. Performance evaluation metrics results of models and training times

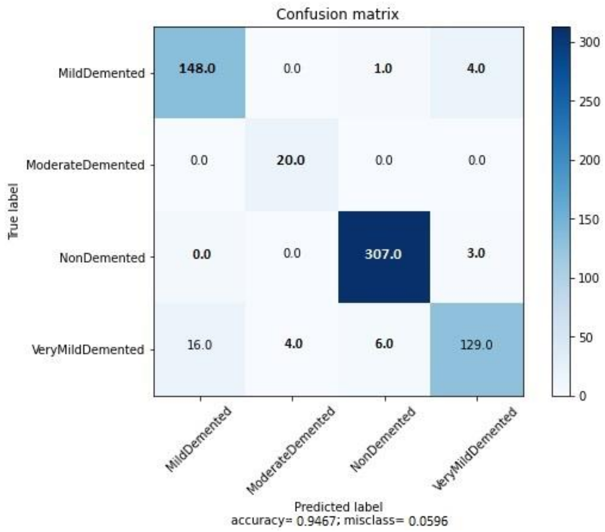

Figure 4. Confusion matrix for GoogLeNet model

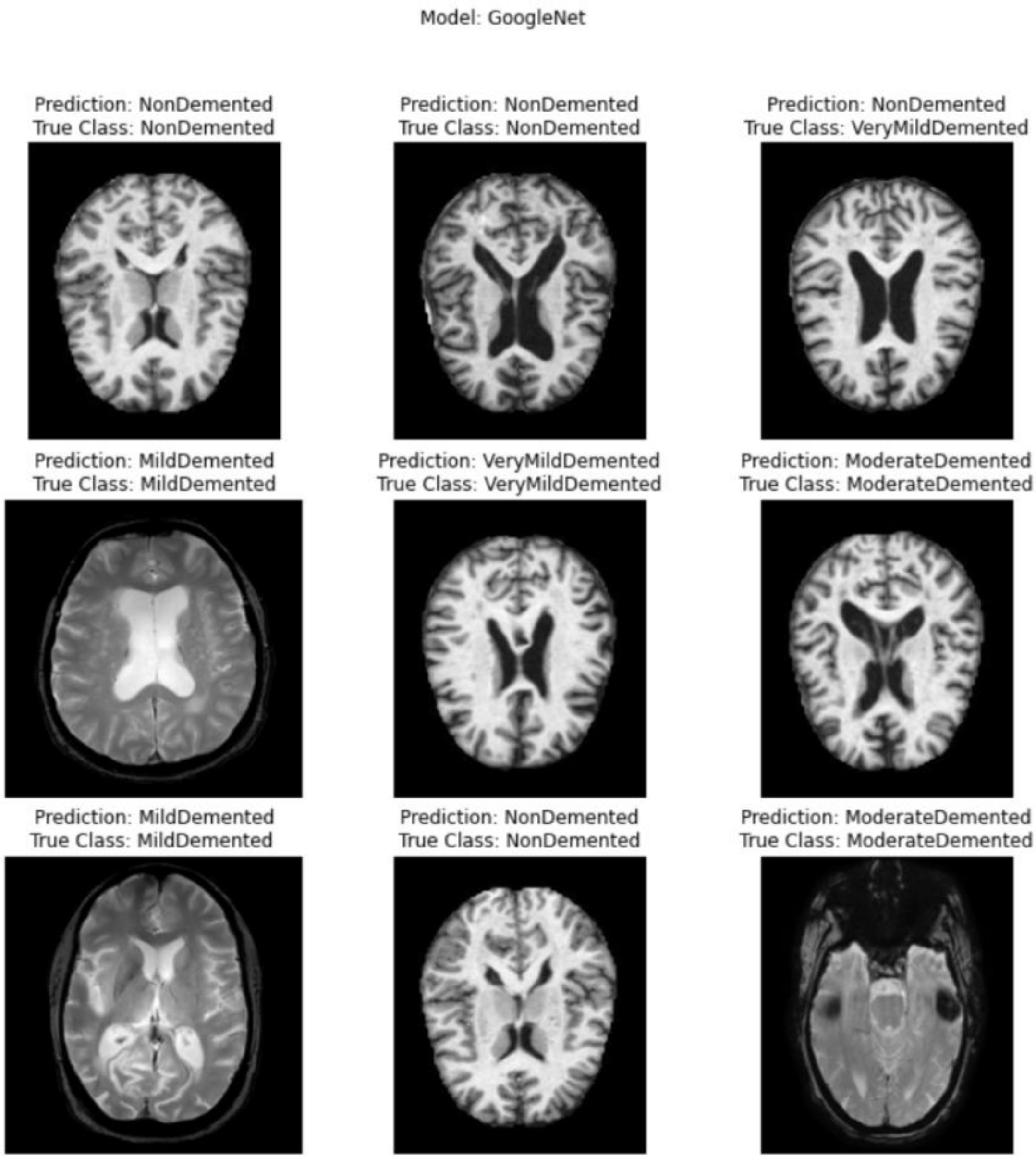

Figure 5. Predictions obtained by GoogLeNet

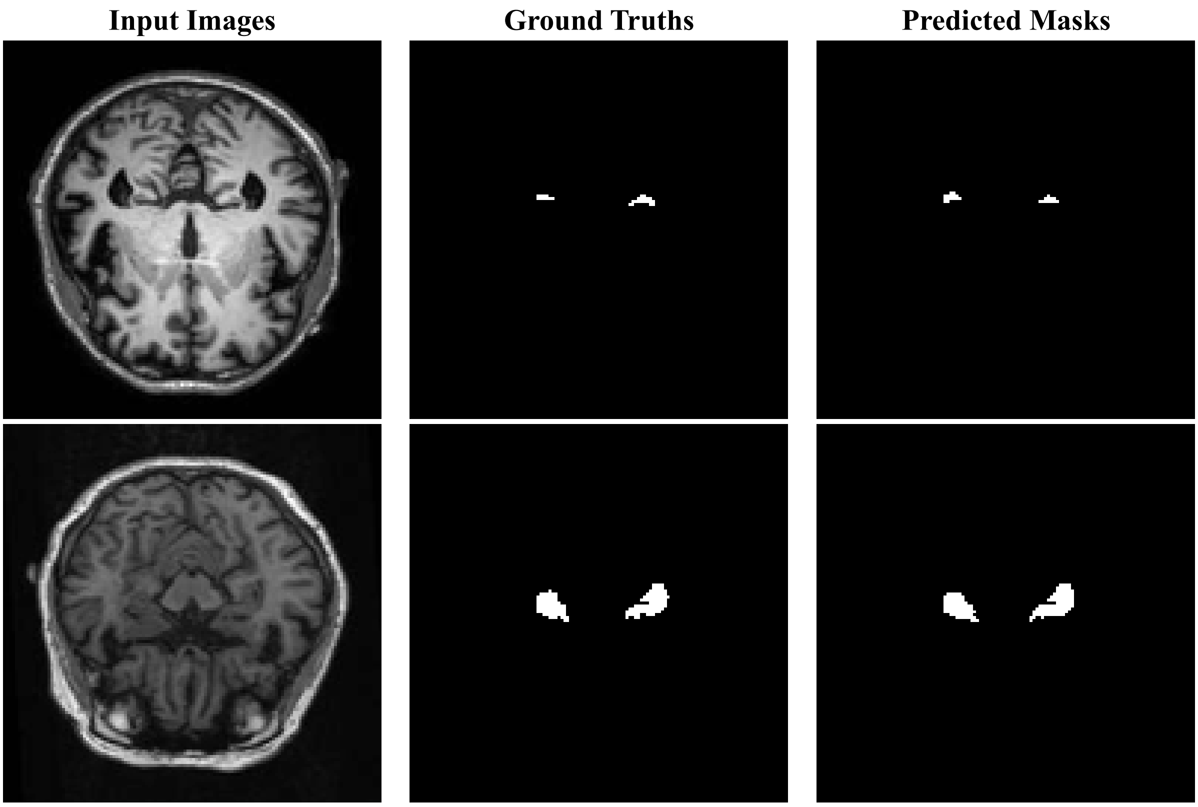

Figure 6. Predictions obtained by U-Net

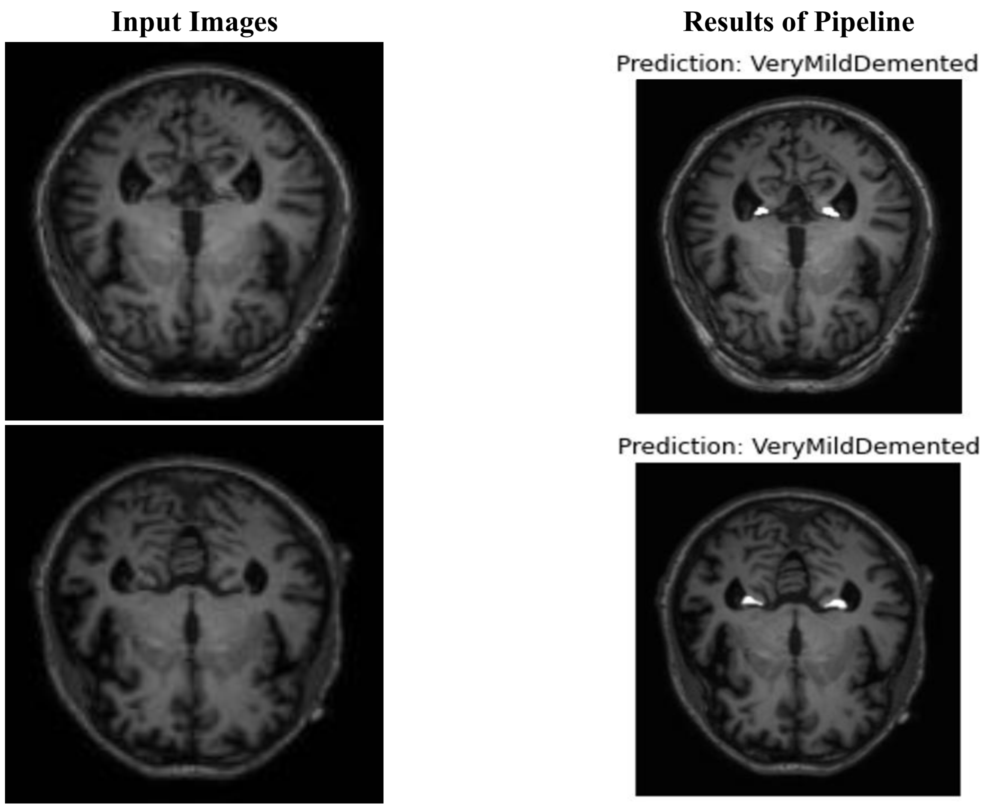

Figure 7. Results of Pipeline

4. Conclusions

In this study, several classification models were used to perform alzheimer classification. It is attempted to present a suggestion to other researchers on the classification performances of the models by comparing DenseNet121, EfficientNetB7, GoogLeNet, MobileNet_V3, Resnet101, Resnext101 and ShuffleNet. The GoogLeNet classification model has outperformed other classification models with the accuracy of 0.9467, sensitivity of 0.9474, specificity of 0.9811, and F1-score of 0.9467. The U-Net model achieved the dice of 0.874, IoU of 0.776, sensitivity of 0.868, specificity of 0.999, precision of 0.879, and accuracy of 0.999. Subsequently, pipeline was created by using classification and segmentation models. As a result, with the help of computer vision assisted CAD system, the workload of radiologists can be reduced. In addition, Alzheimer's disease can be detected early using the proposed pipeline.

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