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Enhanced Dementia Severity Discrimination through Deep Learning Assisted Methodology

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Abstract

Alzheimer's Disease (AD) remains the leading cause of dementia worldwide. It gradually progresses from mild -severe, limiting one's capacity to do any task without help. It begins to outpace owing to population ageing and the diagnostic schedule. It has a significant negative impact on affected individuals and their quality of life. An early diagnosis can help them manage their healthcare demands much more effectively. In the past few years, there has been an increased focus on the development of automated approaches for the identification of different illnesses, leveraging advances in artificial intelligence. This study focuses on Alzheimer’s disease detection, which combines U-Net for segmentation and CNNs for classification, has the potential to significantly advance Alzheimer's disease diagnostics. ADNI dataset is used in this study and the model achieves an accuracy rate of 93% after the process of pre-processing and segmentation.

Keywords: Alzheimer's Disease, U-Net, CNN, Image pre-processing, Performance Metrices.

1. Introduction

Alzheimer's disease (AD) is a progressive neurological disorder marked by cognitive decline and memory loss. The area of the brain that controls learning is where Alzheimer's disease usually starts to alter. Alzheimer's disease causes symptoms to worsen as it spreads throughout the brain [11]. These symptoms include disorientation, mood swings, and behavioural abnormalities; increasing confusion about event, time suspicions about loved

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ones, acquaintances, and carers; more severe memory loss and behavioural abnormalities; and trouble swallowing, speaking, and walking [12].

Early identification is critical to effective diagnosis and therapy. Deep learning algorithms have recently showed tremendous promise in terms of enhancing the accuracy and efficiency of Alzheimer's disease identification utilising brain imaging data. Early identification and exact diagnosis are critical for effective Alzheimer's disease therapy and care [13]. Magnetic resonance imaging (MRI) is an excellent tool for detecting morphological and functional brain abnormalities associated with Alzheimer's disease. Deep learning approaches have showed great promise in the diagnosis and severity discrimination of dementia. The Figure 1 shows the difference between the healthy and the Alzheimer’s brain [14].

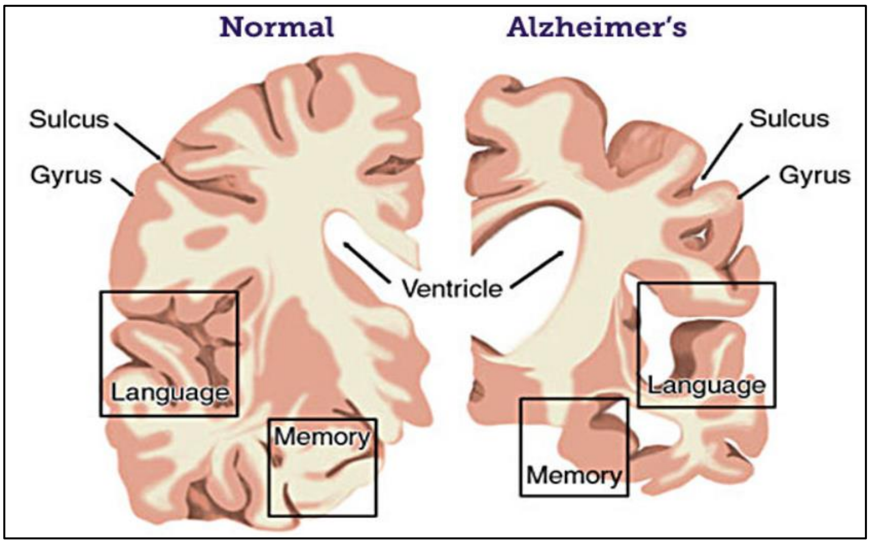


Figure 1. Difference Between Normal and Alzheimer’s Brain [1]

In the field of medical imaging, reliable identification and classification of abnormal features is essential for early diagnosis and therapy planning. Alzheimer's disease, a progressive neurodegenerative disorder, poses major diagnostic hurdles due to its gradual onset and intricate brain alterations [15]. Recent advances in deep learning, notably in image segmentation and classification, provide potential methods for improving diagnostic accuracy and efficiency in Alzheimer's disease imaging research [7].

This technical article describes an innovative approach that combines U-Net, a deep learning model for image segmentation, with convolutional neural networks (CNNs) for image classification. The suggested technique seeks to use the benefits of both designs to enhance the detection and classification of Alzheimer's disease-related alterations in brain imaging data.

2. Literature Review

In deep neural network-based technique, a DNN/scaled PCA, accurately predicts Alzheimer using health behaviour and medical service consumption data, offering an early pre-screening tool for both patients and clinicians. The suggested approach achieves 85.5% of the area under the curve (AUC), which is higher than the results obtained using previous algorithms [1].

The suggested technique performs well in distinguishing between various stages and kinds of cognitive impairment, indicating its potential as an early diagnostic tool for Alzheimer's disease. This early identification is critical because it enables possibly simpler and more effective therapies. The approach obtains an accuracy of up to 0.90 and an AUC of 0.95 in discriminating between normal controls (NC) and Alzheimer's Disease (AD) patients.[2]

The work shows that elastic net penalization in creating reliable and efficient models for predicting MCI to AD conversion using multimodal MRI data. The methodology's capacity to manage collinear predictors and integrate multiregional data makes it an effective tool for early detection and treatment planning in Alzheimer's disease. Logistic regression models predict conversion status with up to 72% cross-validated accuracy, which is equivalent to the performance using non-linear support vector machine (SVM) classification.[3]

The study successfully develops and deploys ADNet, an advanced deep learning-based system capable of automatically and accurately categorising brain images into AD, MCI (Mild Cognitive Impairment and NC categories using MRI data. This approach has tremendous potential for early detection and biomarker identification in Alzheimer's disease, outperforming a benchmark challenge and laying the groundwork for future medical imaging applications. In the challenge, ADNet-DA outperformed numerous current techniques in the literature, scoring 52.3% accuracy.[4]

The CNN is a technique for detecting AD and forecasting the course of MCI, making it appropriate for use by untrained operators. The approach is expected to generalise to previously unreported patient data, indicating that it has the potential for extensive therapeutic application. The methodology achieved 99% accuracy employing only the ADNI dataset as well as 98% accuracy with the combined ADNI and non-ADNI datasets. Achieved 75% accuracy with no noticeable difference between ADNI and non-ADNI images.[5]

The research study presents an advanced deep learning strategy based on 3D-DenseNets to overcome the issues of identifying Alzheimer's disease and moderate cognitive impairment using 3D MRI data. The method improves feature extraction and model efficiency, displaying higher performance on the ADNI dataset and giving a reliable tool for early diagnosis and treatment planning in dementia.[6]

3. Methodology

3.1 Dataset Collection

The dataset is divided into two files: Training and Testing. Each file contains around 160 images classified by Alzheimer's severity. The dataset consists of four sub-stages. The are divided into Mild, very mild, moderate, and nondemented. The block diagram of the proposed method is shown in the Figure 2 below.

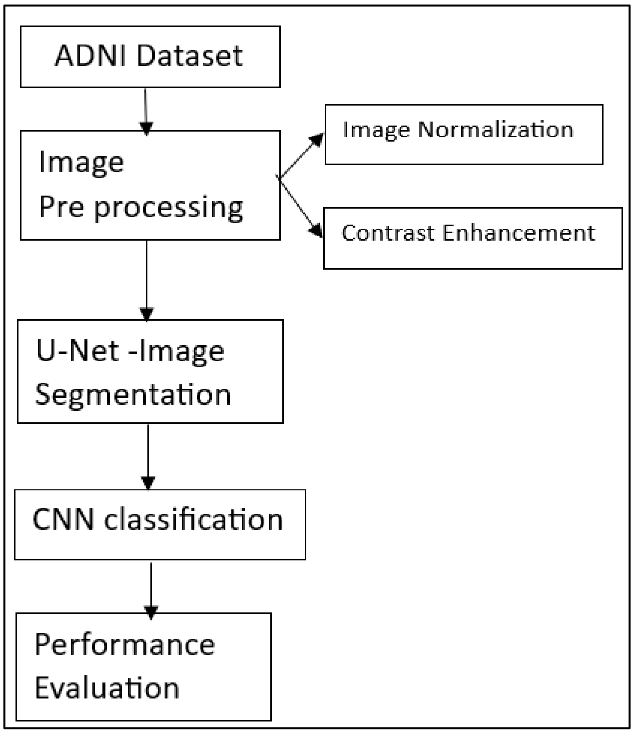


Figure 2. Block diagram of the proposed model

3.2 Data Pre-processing

The following are the pre-processing steps carried on in image pre-processing

3.2.1 Image normalization

Image normalisation is an important preparing step in image processing, particularly for machine learning and deep learning applications. Normalisation standardises the input images, ensuring that the model learns effectively and efficiently. Normalisation aims to change the pixel values such that they follow a comparable data distribution. This can make the training process fast while also reducing the model's sensitivity to feature scale.

Here Min-Max Normalization Method is used.

3.2.2 Feature Scaling (Min-Max Normalization)

This approach adjusts pixel values to a predetermined range, usually 0 to 1. It is accomplished by removing the minimum value of the pixel and dividing by the range of the pixel values.

$$Normalized = \frac{pixel - \min(Pixel)}{\max(pixel) - \min\,(pixel)}$$

3.2.3 Image Enhancement:

Image enhancement is an essential preprocessing step in image processing, especially for machine learning and computer vision. It entails increasing the quality of images in order to make them more appropriate for analysis or processing. The proposed work uses adaptive histogram equalization for image enhancement.

A version of histogram equalisation in which the image is partitioned into tiles and histogram equalisation is done to each one. This approach is more suited for increasing local contrast and edge definition.

The transformation function of AHE may be expressed as follows:

$$T(X) = \int_0^x P_r\,(r)dr$$

where P(r): probability density function of the pixel values within a local region around.

AHE is commonly used in medical imaging to improve the visibility of features. It assists in detecting small variations in tissue characteristics, which are critical for correct diagnosis.

3.2.4 Segmentation and Model Preparation

- U-Net for Image Segmentation

U-Net, which was originally designed for biomedical image segmentation, has a unique architecture that comprises a contracting path to record context and a symmetric expanding path for exact localization. The model uses input images to generate pixel-wise segmentation masks that emphasise regions of interest (ROIs) such as atrophy or amyloid plaques associated with Alzheimer's disease. The segmentation stage is critical because it distinguishes significant characteristics from normal brain structures, increasing the specificity of the subsequent classification method. The Figure 3 illustrates the U-Net architecture

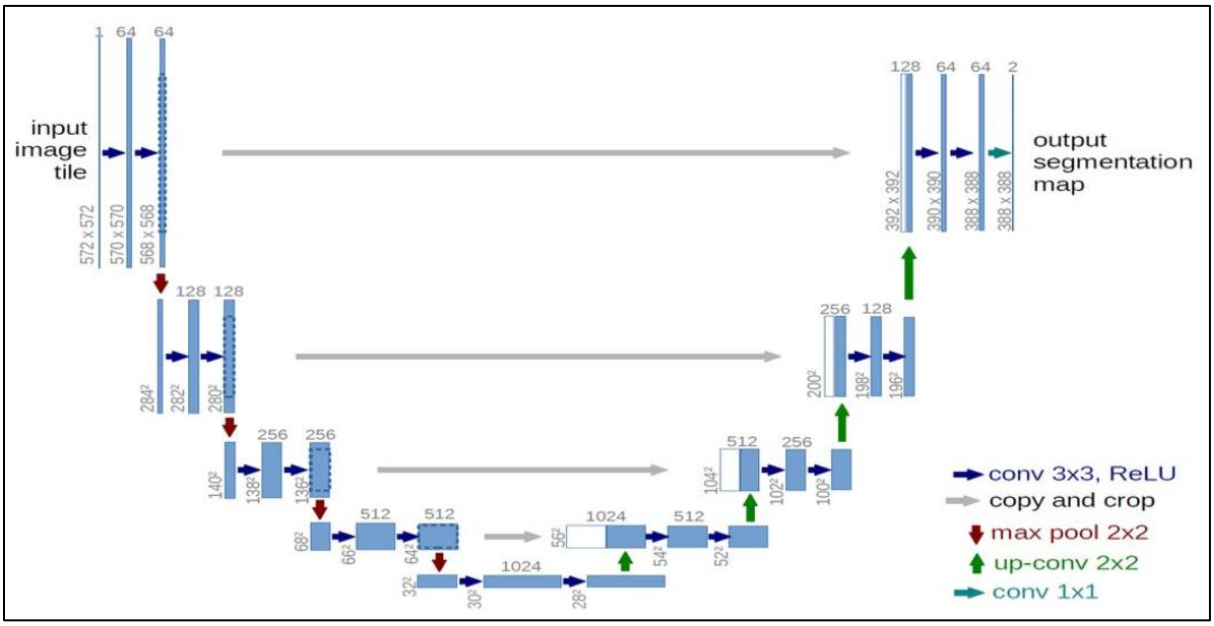


Figure 3. U-Net Segmentation [8]

The encoder network consists of four encoder blocks. Each block consists of two convolutional layers with a kernel size of 3*3 with valid padding, then a ReLU activation function. This is sent into a maximum pooling layer having a kernel size of 2*2. The max pooling layer reduces the spatial dimensions by half, thereby lowering the computational cost of training the model.

The bottleneck layer is between the encoder and decoder networks. This is the bottommost layer, as seen in the model above. It comprises of two convolutional layers, followed by ReLU. The bottleneck produces the final feature map representation

3.2.5 CNN for Image Classification

After segmentation, a convolutional neural network (CNN) is used to categorise the segmented images into categories indicating Alzheimer's disease presence or absence. CNNs are well-suited for image data because they can extract hierarchical features and conduct classification using learnt representations. Training the CNN on segmented images allows the model to focus on the most relevant characteristics discovered by U-Net, enhancing classification accuracy and resilience. Figure 4 shows the architecture of CNN used.

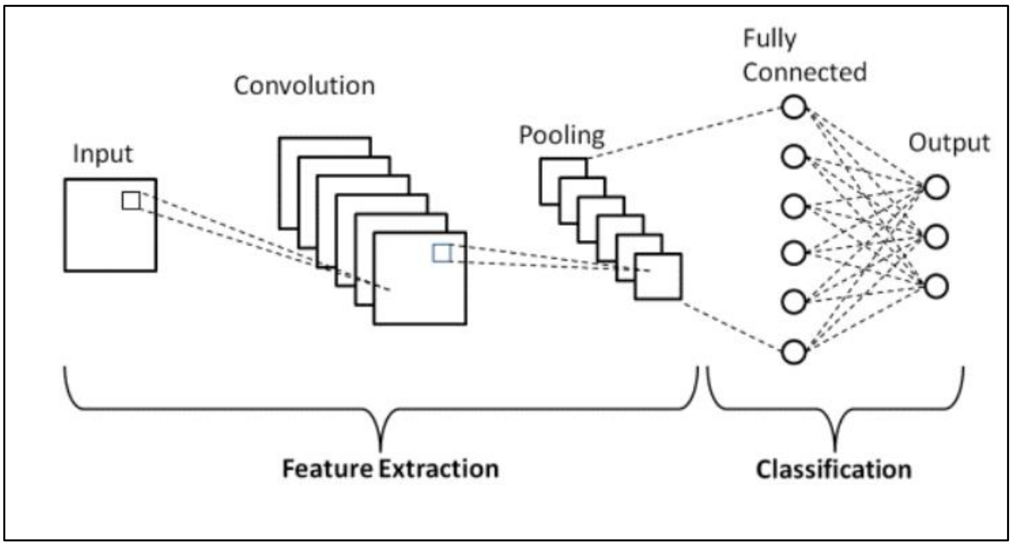


Figure 4. CNN classification [9]

- Integration of U-Net and CNN

The integration of U-Net and CNN in a unified architecture requires initial U-Net training to provide accurate segmentation masks. These masks are subsequently used to crop or emphasise ROIs in the original images, which are input into the CNN. This phased technique enables targeted learning and classification using the most clinically important characteristics derived from the images.

- Evaluation Metrices

The model's performance is measured using measures such as the Dice coefficient and Intersection over Union (IoU) for segmentation accuracy, as well as accuracy, precision, recall, and the F1-score for classification effectiveness [10].

4. Results

The collected ADNI MRI dataset is divided in 80:20 ratio after pre-processing and the model are implemented. Figure 5 shows the dataset used.

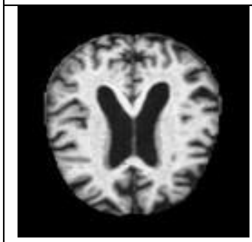
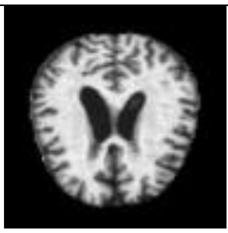
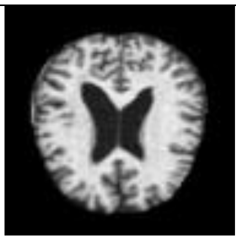
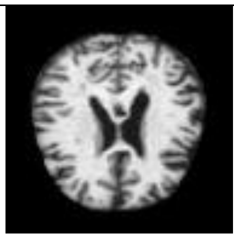
Mild	Moderate	Non-Demented	Very Mild demented
			

Figure 5. ADNI Dataset

The Figure 6 shows the results after image Pre-processing.

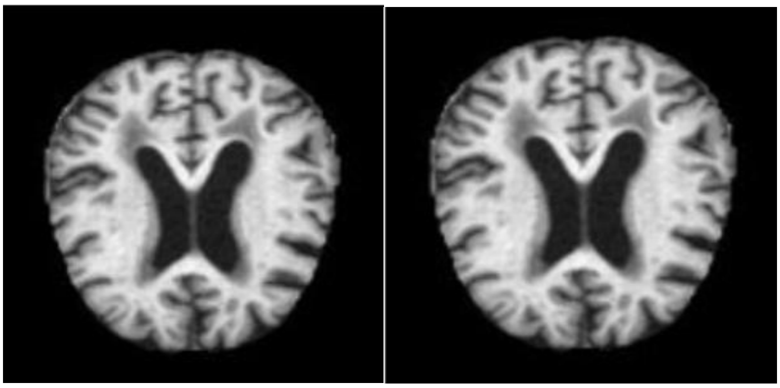


Figure 6. Original and Normalized Image

Figure 7 shows the results obtained after implementing Histogram Equalization.

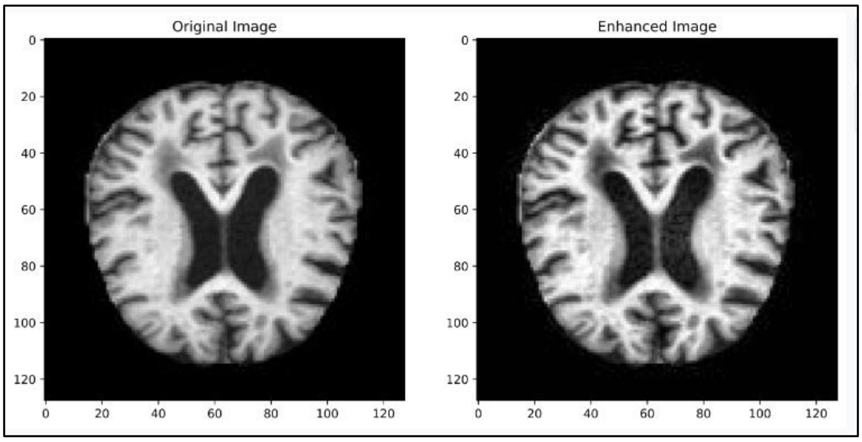


Figure 7. Image after Pre-processing

The Figure 8 shows the results obtained after segmentation.

Figure 8. Segmented Image

Dice co-efficient :0.83

Intersection over Union :0.79

Figure 9 depicts the Confusion Matrix after the integration of U-Net and CNN in the ADNI dataset.

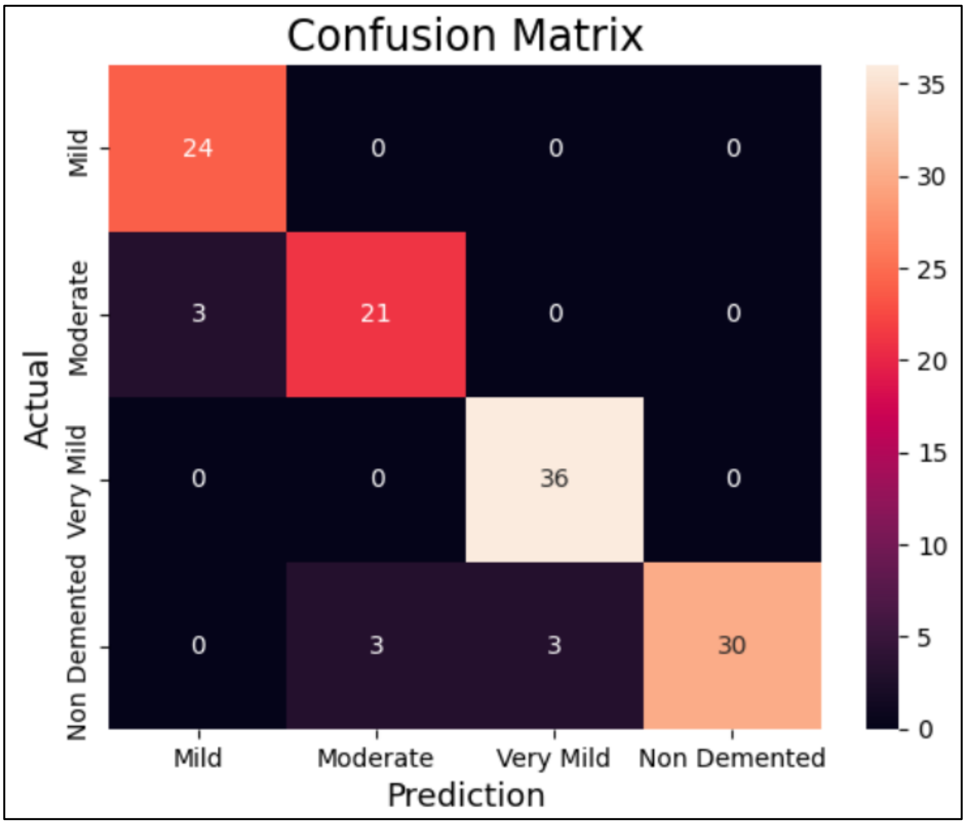


Figure 9. Confusion Matrix

	precision	recall	f1-score	support
Mild	0.89	1.00	0.94	24
Moderate	0.88	0.88	0.88	24
Very Mild	0.92	1.00	0.96	36
Non-Demented	1.00	0.83	0.91	36
accuracy			0.93	120
macro avg	0.92	0.93	0.92	120
weighted avg	0.93	0.93	0.92	120

Figure 10. Performance Matrices of Proposed Model

On the above analysis, the integration of model with U-Net and CNN model achieves a good accuracy rate of 93% using ADNI dataset as shown in Figure 10.

5. Conclusion

In this research study, U-Net and CNNs are integrated for segmentation and classification, this approach has the potential to identify Alzheimer's disease diagnostics, providing a powerful tool for radiologists and neurologists. This model approach is particularly appropriate for activities that need both the prediction and target, such as medical diagnosis using imaging data. The model is trained with the ADNI dataset and has undergone the preprocessing stage of image normalization and adaptive contrast enhancement. Using U-Net and CNN the model achieves an accuracy rate of 93%. In the future, the model can be trained with a very- large dataset.

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