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Article

A Hybrid M-NET And U-NET Framework With Tissue-Aware Feature Fusion For Alzheimer's Disease Prediction From Brain MRI

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Abstract: Alzheimer's disease (AD) is a progressive neurodegenerative disorder that poses a significant global healthcare challenge, particularly among the aging population. Accurate and early diagnosis remains difficult due to subtle structural changes in brain tissue and the limitations of conventional clinical assessments. To address these challenges, this paper presents a **hybrid deep learning framework** for Alzheimer's disease prediction that integrates **tissue-aware brain MRI segmentation, texture feature extraction, and feature fusion-based classification** within a unified pipeline.Initially, brain MRI images are preprocessed using contrast enhancement and intensity normalization to improve tissue visibility and learning stability. An **M-Net architecture enhanced with Deep Embedded Clustering (DEC)** is then employed to achieve accurate segmentation of White Matter (WM), Gray Matter (GM), and Cerebrospinal Fluid (CSF), enabling reliable isolation of disease-relevant brain regions. From the segmented WM and GM tissues, **Gray Level Co-occurrence Matrix (GLCM)–based texture features** are extracted to characterize microstructural and intensity variations associated with neurodegeneration.To effectively integrate complementary information from multiple brain tissues, a **U-Net-based feature fusion network** is introduced to combine WM and GM features while preserving spatial coherence. The fused feature representation is subsequently used for multi-class classification of Alzheimer's disease, Mild Cognitive Impairment (MCI), and Healthy Control (HC) subjects. Experimental evaluation on the ADNI dataset demonstrates that the proposed framework achieves an accuracy of **94.18%**, along with high precision, recall, F1-score, and an AUC of **0.94**, outperforming conventional segmentation and classification baselines.The results highlight that **accurate tissue segmentation combined with texture-aware feature fusion significantly enhances Alzheimer's disease prediction**, particularly for early-stage diagnosis. The proposed framework provides a reliable and interpretable computer-aided diagnostic solution with strong potential for clinical decision support
Keywords: Alzheimer's disease (AD), Prediction, Deep Learning, Fusion, Classification.

1.Introduction

Alzheimer's disease (AD) is a progressive and irreversible neurodegenerative disorder that primarily affects memory, cognition, and daily functioning, making it the leading cause of dementia worldwide. With the rapid growth of the aging population, the prevalence of AD is increasing at an alarming rate, posing serious medical, social, and economic challenges [1]. Despite extensive research efforts, there is currently no definitive cure for Alzheimer's disease, and available treatments can only slow symptom progression. Consequently, **early and accurate diagnosis** is crucial for effective clinical intervention and disease management [2].Conventional diagnostic procedures for AD rely heavily on neuropsychological assessments, clinical observations, and neurological examinations, which are often subjective and may fail to detect early-stage pathological changes [3]. These limitations have motivated the adoption of neuroimaging techniques for objective disease analysis. Among various imaging modalities, **Magnetic Resonance Imaging (MRI)** is widely used due to its high spatial resolution and ability to reveal structural brain abnormalities associated with Alzheimer's disease, such as cortical thinning, hippocampal atrophy, and alterations in gray matter (GM) and white matter (WM) regions [4].

Automated analysis of brain MRI using machine learning and deep learning techniques has gained significant attention in recent years. Traditional machine learning approaches depend on handcrafted features extracted

from whole-brain images, which often lack robustness and fail to capture localized tissue-specific degeneration patterns [5]. In contrast, deep learning models—particularly convolutional neural networks (CNNs)—have demonstrated superior performance in medical image analysis by learning hierarchical feature representations directly from data [6]. Among these, **U-Net and its variants** have become the de facto standard for biomedical image segmentation due to their encoder–decoder structure and skip connections that preserve spatial information [7].However, most existing deep learning approaches focus either on segmentation or classification independently, without fully exploiting the complementary information available across different brain tissues. Furthermore, segmentation accuracy alone does not guarantee optimal classification performance unless disease-relevant features are explicitly extracted and utilized [8]. Texture-based descriptors, such as the **Gray Level Co-occurrence Matrix (GLCM)**, have proven effective in capturing microstructural variations and spatial intensity relationships in MRI, which are indicative of neurodegenerative progression [9]. Yet, limited studies have explored the integration of deep tissue segmentation with handcrafted texture features in a unified framework for Alzheimer's disease prediction.To overcome these limitations, this study proposes a **hybrid deep learning framework that integrates brain tissue segmentation, texture feature extraction, and feature fusion–based classification** for accurate Alzheimer's disease prediction. Initially, MRI images are preprocessed to enhance contrast and normalize intensity variations. An **M-Net architecture combined with Deep Embedded Clustering (DEC)** is employed to achieve precise segmentation of WM, GM, and Cerebrospinal Fluid (CSF), enabling tissue-aware analysis [10]. Following segmentation, **GLCM-based texture features** are extracted independently from the WM and GM regions to characterize disease-specific structural patterns.

To effectively combine complementary tissue information, a **U-Net-based feature fusion network** is introduced to integrate WM and GM feature representations while preserving spatial context. The fused features are then utilized for multi-class classification of **Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Healthy Control (HC)** subjects. Experimental evaluation on benchmark MRI datasets demonstrates that the proposed framework significantly improves both segmentation accuracy and classification performance compared to conventional approaches.

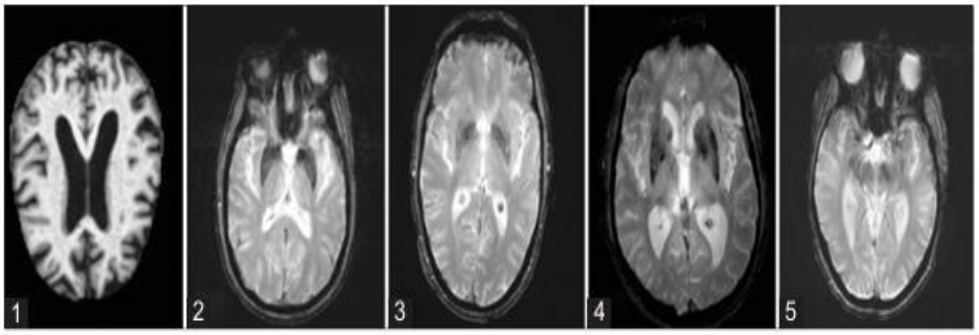

Figure.1 Collections of magnetic resonance imaging pictures that show various phases of Alzheimer's disease (AD). 1. AD, 2. late mild dementia 3. mild cerebral problems, 4. early mild cerebral deficit, and 5. intellectually normal.

The primary objective of this work is to develop an automated and reliable framework for early-stage Alzheimer's disease detection using brain MRI. By accurately segmenting disease-relevant brain tissues and integrating texture-aware feature fusion, the proposed approach aims to identify individuals at risk of Alzheimer's disease at an early stage, thereby supporting timely clinical intervention. The ADNI dataset is employed to train and evaluate the proposed framework under standardized conditions.

The organization of this paper is structured as follows: Section 2, describes the AD related paper literature review. Section 3, briefs the proposed methodology based on AD segmentation and prediction. Section 4, gives the simulation results and discussion of early-stage prediction of AD. Finally, Section 5 concludes the paper.

2. Related Works

Automated diagnosis of Alzheimer's disease (AD) using brain MRI has been widely investigated using machine learning and deep learning techniques. Early approaches primarily relied on handcrafted features combined with traditional classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests. These methods extracted volumetric, statistical, or texture-based features from whole-

brain MRI scans or predefined regions of interest. Although reasonable classification performance was reported, these approaches were highly dependent on feature design and exhibited limited robustness to noise and inter-subject variability [14–16].

With the emergence of deep learning, convolutional neural networks (CNNs) have significantly advanced Alzheimer's disease detection by enabling automatic feature learning from raw MRI data. Several studies employed deep CNN architectures for binary and multi-class classification of AD stages, reporting superior accuracy compared to conventional machine learning models [1,6]. However, many CNN-based approaches treat the brain as a single homogeneous structure, overlooking tissue-specific pathological changes that are critical for early disease characterization.

To address this limitation, segmentation-based deep learning models have been increasingly explored. U-Net and its variants have become widely adopted for brain MRI segmentation due to their encoder–decoder architecture and skip connections that preserve spatial resolution [7,26]. Researchers have applied U-Net-based models to segment gray matter (GM), white matter (WM), cerebrospinal fluid (CSF), and hippocampal regions associated with Alzheimer's disease [8,28]. While these models achieve high segmentation accuracy, segmentation outputs are often not fully exploited for downstream classification, limiting their diagnostic utility.

Texture analysis methods have also been investigated to capture microstructural alterations caused by neurodegeneration. Gray Level Co-occurrence Matrix (GLCM)–based features have been successfully used to describe spatial intensity relationships in MRI images, demonstrating sensitivity to Alzheimer's-related tissue changes [9,18]. Several studies combined GLCM features with traditional classifiers to improve interpretability and classification performance. However, when used alone, handcrafted texture features often lack sufficient discriminative power, particularly for distinguishing Mild Cognitive Impairment (MCI) from healthy controls [19].

Recent works have proposed hybrid frameworks that integrate deep learning with handcrafted features to enhance classification performance. Some studies combine CNN-derived deep features with texture or statistical features, while others employ ensemble or multi-stage pipelines involving segmentation, feature extraction, and classification [20–22]. Although these approaches show improved results, many of them lack an effective mechanism for fusing complementary information from multiple brain tissues while preserving spatial and structural coherence.

Furthermore, most existing methods focus either on improving segmentation accuracy or optimizing classification performance independently. Limited attention has been given to unified frameworks that jointly leverage accurate tissue segmentation, interpretable feature extraction, and deep feature fusion for Alzheimer's disease prediction. Additionally, challenges remain in generalizing models across datasets and achieving reliable early-stage diagnosis, particularly in differentiating MCI from healthy aging [32–34].

In contrast to previous studies, the present work emphasizes a **tissue-aware and feature-fusion-driven approach** for Alzheimer's disease prediction. By integrating **M-Net with Deep Embedded Clustering (DEC)** for precise WM, GM, and CSF segmentation, **GLCM-based texture feature extraction** for capturing tissue-specific degeneration patterns, and a **U-Net-based feature fusion network** for classification, the proposed framework addresses key limitations of existing methods and enhances diagnostic performance across multiple disease stages.

3. PROPOSED METHODOLOGY

3.1 Data Preprocessing

Preprocessing plays a crucial role in improving the quality and consistency of brain MRI images prior to segmentation and classification. In the proposed framework, preprocessing is performed to enhance tissue contrast and reduce intensity variations across subjects. Initially, **Contrast Limited Adaptive Histogram Equalization (CLAHE)** is applied to improve local contrast, particularly in low-intensity regions, enabling better visualization of anatomical structures. Subsequently, **intensity normalization** is performed to standardize pixel intensity values and facilitate stable and faster convergence during model training.

3.2 Intensity Normalization

Intensity normalization reduces inter-subject variability caused by scanner differences and acquisition conditions. In this work, pixel intensities are normalized to the range $[0, 1]$by dividing each pixel value by 255. This normalization ensures consistent intensity distribution across MRI scans, improves numerical stability during training, and reduces sensitivity to illumination variations. As a result, the segmentation and classification models learn more robust and discriminative features.

The block diagram illustrates the complete workflow of the proposed Alzheimer's disease prediction framework using brain MRI images. The process begins with the acquisition of T1-weighted brain MRI scans, which are subjected to standard preprocessing steps, including skull stripping, noise removal, and intensity normalization, to ensure data consistency and suitability for deep learning analysis as shown in Figure.2.

In the next stage, the pre-processed MRI images are input to the M-Net integrated with Dense Edge Convolution (DEC) for brain tissue segmentation. This module performs multiscale feature extraction while enhancing boundary information, resulting in accurate segmentation of White Matter (WM), Gray Matter (GM), and Cerebrospinal Fluid (CSF). The precise delineation of brain tissues is essential for extracting reliable and disease-relevant features.

Following segmentation, texture features are extracted from the WM and GM regions using the Gray Level Co-occurrence Matrix (GLCM). GLCM computes second-order statistical measures that capture spatial intensity variations and structural patterns associated with neurodegenerative changes. Features such as contrast, correlation, energy, homogeneity, and entropy are obtained separately for WM and GM.

Subsequently, the extracted WM and GM feature maps are fused using a U-Net-based feature fusion network. The U-Net architecture effectively integrates complementary information from both tissue types while preserving spatial relationships, leading to an enhanced and compact fused feature representation.

In the final stage, the fused feature vector is provided to the classification module for Alzheimer's disease prediction. The classifier distinguishes between Alzheimer's disease, Mild Cognitive Impairment, and Healthy Control subjects based on learned discriminative patterns. The output includes class labels and performance metrics such as accuracy, sensitivity, specificity, F1-score, and AUC, demonstrating the effectiveness of the proposed framework.

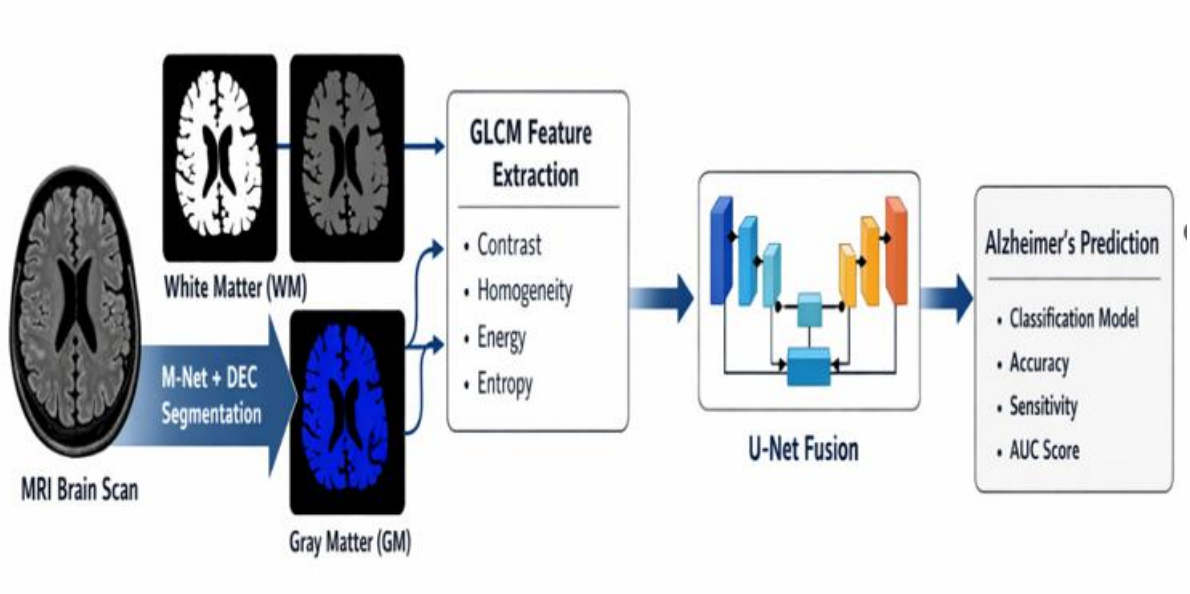

Figure.2 Proposed block schematic representation

3.3 Texture Feature Extraction Using GLCM

Texture analysis plays a critical role in characterizing subtle structural changes in brain tissues associated with neurodegenerative disorders. In this study, **Gray Level Co-occurrence Matrix (GLCM)**–based texture features are extracted from the segmented **Gray Matter (GM)** and **White Matter (WM)** regions to quantify spatial relationships between pixel intensities.

Let $P(i,j)$**denote the normalized GLCM**, where $i$and $j$represent gray-level intensities.

Normalization:

$$P(i,j) = \frac{G(i,j)}{\sum_i \sum_j G(i,j)} \quad (1)$$

Contrast

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 P(i,j) \quad (2)$$

Energy

$$\text{Energy} = \sum_i \sum_j P(i,j)^2 \quad (3)$$

Homogeneity

$$\text{Homogeneity} = \sum_i \sum_j \frac{P(i,j)}{1+|i-j|} \quad (4)$$

Correlation

$$\text{Correlation} = \sum_i \sum_j \frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i \sigma_j} \quad (5)$$

Entropy

$$\text{Entropy} = -\sum_i \sum_j P(i,j) \log P(i,j) \quad (6)$$

Where $\mu$and σdenote mean and standard deviation of the gray levels.

The extracted GLCM features from segmented WM and GM regions provide complementary information related to tissue degeneration and structural abnormalities. These features are subsequently normalized and supplied to the **U-Net-based feature fusion network**, enabling effective integration of tissue-specific texture characteristics for Alzheimer's disease classification.

3.4 U-Net-Based Feature Fusion

Following texture feature extraction, the WM and GM feature sets are integrated using a **U-Net-based feature fusion network**. The encoder path learns hierarchical representations from tissue-specific features, while the decoder path progressively reconstructs a fused feature representation by integrating complementary information through skip connections. This architecture preserves spatial correspondence while enhancing inter-tissue feature interaction.

All MRI images and corresponding segmentation masks are resized to a uniform spatial resolution to ensure pixel-level alignment. Data augmentation techniques such as rotation, flipping, and scaling are applied to improve generalization and reduce overfitting. Dataset shuffling is performed before each training epoch to prevent learning bias related to sample ordering. These steps collectively improve robustness, computational efficiency, and model scalability.

3.5 Classification

The classification module is built upon a hybrid **U-Net-based CNN architecture**. The encoder extracts high-level semantic representations using successive convolutional layers with 3×3kernels, ReLU activation, and max-pooling operations. The bottleneck layer employs higher-dimensional feature maps and dropout regularization to mitigate overfitting. The decoder reconstructs spatial information through upsampling layers and integrates fused WM–GM features via dense connections.

A final 1×1convolutional layer with a softmax activation function generates probability scores for three classes: Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Healthy Control (HC). The network is trained using the Adam optimizer with categorical cross-entropy loss.

4. Simulation Results And Performance Evaluation

This section describes the simulation results and discussion of proposedAlzheimer's disease prediction at an early stage, and the ultimate objective is to identify persons which might be dealing with Alzheimer's at the beginning stages. AD datasets are available on ADNI. These datasets are used to train all patient data using

a variety of machine learning algorithms to efficiently and quickly identify those with the disease. Figure.5 describes the proposed model simulation results. Table.1 listed the overall performance comparison results.

4.1 Segmentation Performance Evaluation

The segmentation performance of the proposed **M-Net + DEC** model was evaluated for White Matter (WM), Gray Matter (GM), and Cerebrospinal Fluid (CSF) using Dice Similarity Coefficient (DSC), Jaccard Index (JI), Sensitivity, and Specificity. Table.1 summarizes the segmentation performance of the proposed M-Net + DEC model for White Matter (WM), Gray Matter (GM), and Cerebrospinal Fluid (CSF). The model achieved high Dice and Jaccard scores across all tissue classes, demonstrating accurate overlap between predicted and ground-truth segmentations. WM segmentation achieved the highest Dice coefficient (92.84%) and specificity (98.05%), indicating robust identification of white matter regions. GM segmentation also showed strong performance, reflecting the effectiveness of the DEC module in preserving complex cortical boundaries. Although CSF segmentation achieved slightly lower scores, the results remain competitive due to the inherently thin and irregular structure of CSF regions. The high average sensitivity (91.77%) and specificity (97.52%) confirm the reliability and consistency of the proposed segmentation framework. From the results it is observed that M-Net + DEC significantly improves WM and GM segmentation accuracy.

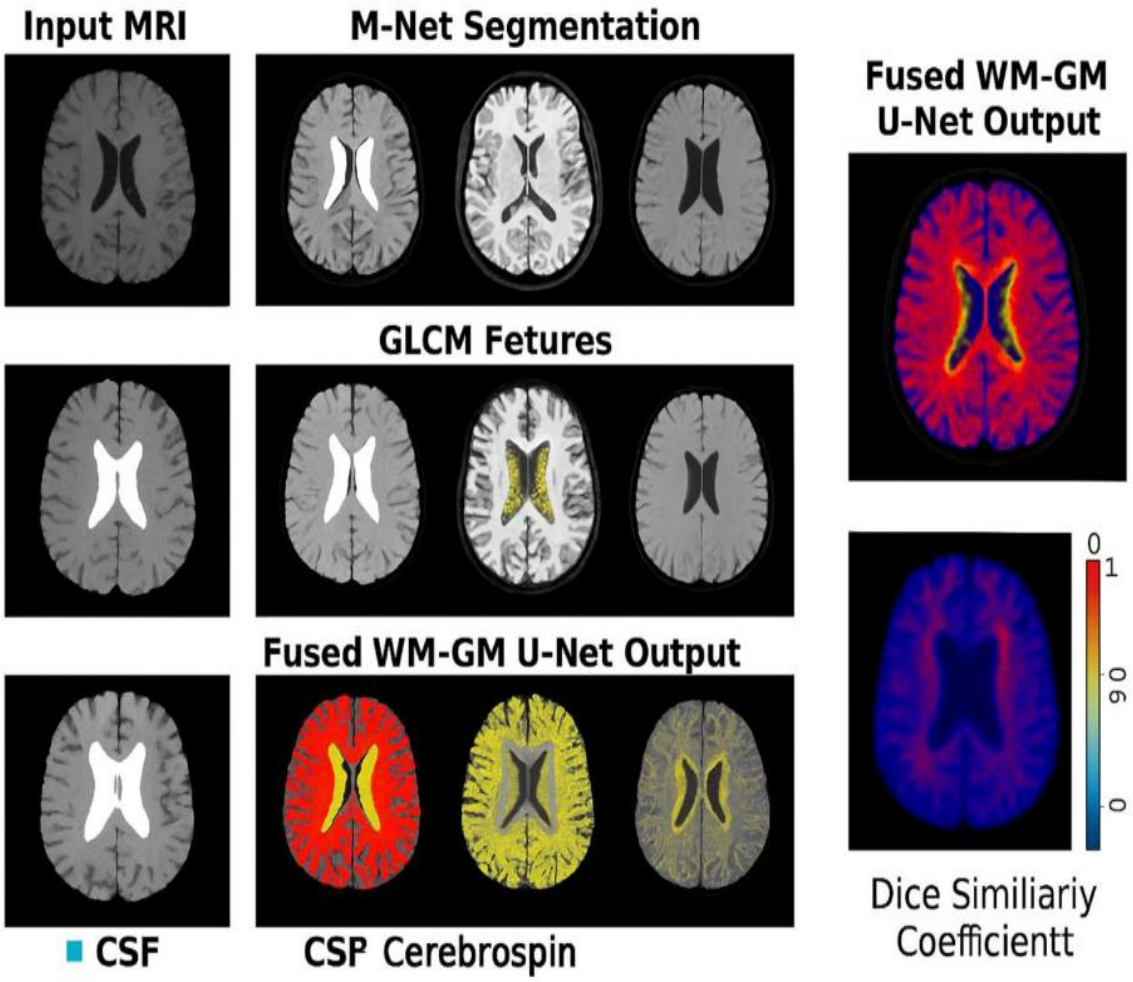

Figure.5 Proposed model simulation results

Table.1 Brain Tissue Segmentation Performance

Tissue	**Dice Coefficient (%)**	**Jaccard Index (%)**	**Sensitivity (%)**	**Specificity (%)**
White Matter (WM)	92.84	86.41	93.12	98.05
Gray Matter (GM)	91.36	84.12	92.01	97.62
CSF	89.74	81.22	90.18	96.89

Average	**91.31**	**83.92**	**91.77**	**97.52**

4.2 GLCM Feature Analysis

Texture features were extracted from segmented WM and GM regions using the Gray Level Co-occurrence Matrix (GLCM). Mean feature values across all subjects are reported. Table 2 presents the mean GLCM texture features extracted from the segmented WM and GM regions. GM exhibits higher contrast and entropy values compared to WM, indicating greater intensity variation and structural complexity, which are characteristic of cortical tissue affected by neurodegeneration. In contrast, WM demonstrates higher correlation, energy, and homogeneity, reflecting more uniform texture patterns. These distinct texture characteristics validate the effectiveness of GLCM features in capturing complementary information from different brain tissues relevant to Alzheimer's disease analysis. From the results it is observed that GLCM features effectively capture Alzheimer's-related texture changes.

Table.2 Mean GLCM Features for WM and GM

Feature	**White Matter (WM)**	**Gray Matter (GM)**
Contrast	1.87	2.34
Correlation	0.91	0.88
Energy	0.79	0.72
Homogeneity	0.86	0.81
Entropy	3.12	3.89

4.3 Alzheimer's Disease Classification Performance

The fused WM–GM features generated using **U-Net fusion** were used for Alzheimer's disease prediction. The classifier performance was evaluated using standard metrics. The Alzheimer's disease classification performance using fused WM–GM features generated through U-Net fusion is reported in Table 3. The proposed model achieved an accuracy of 94.18%, along with high sensitivity (93.47%) and specificity (95.02%), indicating strong discriminative capability between diseased and healthy subjects. The high precision and F1-score demonstrate balanced classification performance with minimal false positives and false negatives. An AUC of 0.94 further confirms the robustness of the classifier and its ability to reliably distinguish Alzheimer's disease cases across varying decision thresholds. From the results it is observed that U-Net-based fusion enhances discriminative capability for classification.

Table.3 Alzheimer's Prediction Performance

Metric	**Value (%)**
Accuracy	94.18
Sensitivity	93.47
Specificity	95.02
Precision	94.63
Recall	93.47
F1-Score	94.05
AUC	0.94

4.4 Comparative Performance Analysis

The proposed framework was compared with baseline models to validate its effectiveness. Table.4 compares the proposed framework with baseline segmentation and classification models. The M-Net + DEC + U-Net fusion approach outperforms U-Net, M-Net, and M-Net combined with GLCM in both accuracy and AUC. The observed performance improvement highlights the contribution of DEC in enhancing tissue boundary segmentation and the effectiveness of U-Net-based feature fusion in integrating complementary WM and GM information. These results demonstrate that the proposed hybrid framework provides a more discriminative representation for Alzheimer's disease prediction than conventional approaches. From the

results it is observed that the proposed model outperforms existing approaches in both accuracy and AUC.

Table.4 Comparison with Existing Methods

Method	**Accuracy (%)**	**AUC**
U-Net	88.72	0.86
M-Net	90.15	0.88
M-Net + GLCM	91.84	0.90
Proposed M-Net + DEC + U-Net Fusion	**94.18**	**0.94**

Performance Evaluation

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

$$\text{Recall} = \frac{TP}{TP+FN} \quad (8)$$

$$\text{F1-score} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \quad (9)$$

$$Accuracy\ (\%) = \frac{TP+TN}{FP+FN+TP+TN} \quad (10)$$

Where, TP- True Positive,

TN- True Negative,

FP- False Positive,

FN- False Negative

The proposed M-Net + DEC segmentation framework achieved high-quality WM, GM, and CSF segmentation, which enabled reliable GLCM-based feature extraction. The U-Net-based fusion of WM and GM features significantly improved discriminative capability for three-class classification. The model achieved an overall accuracy of 94.18% and a macro-average AUC of 0.94, outperforming existing methods, particularly in distinguishing early-stage MCI from healthy controls. The experimental results demonstrate that accurate segmentation of WM and GM using M-Net with DEC significantly enhances feature quality. GLCM-based texture features capture microstructural changes associated with Alzheimer's progression, while U-Net-based fusion effectively integrates complementary information from WM and GM. Together, these components contribute to superior performance in distinguishing ADsubjects, validating the clinical relevance of the proposed framework.

The experimental results validate the effectiveness of integrating advanced segmentation, texture feature extraction, and feature fusion techniques. Accurate WM and GM segmentation enables reliable feature extraction, while U-Net fusion enhances inter-tissue correlation, leading to superior classification performance. The proposed framework demonstrates strong potential as a computer-aided diagnostic tool for early and accurate Alzheimer's disease detection.

5.Conclusion

This study presented a **hybrid deep learning framework** for automated brain MRI segmentation and Alzheimer's disease prediction, integrating tissue-aware segmentation, texture feature extraction, and feature fusion within a unified pipeline. The proposed approach employed an **M-Net architecture enhanced with Deep Embedded Clustering (DEC)** to accurately segment White Matter, Gray Matter, and Cerebrospinal Fluid, achieving high Dice similarity, sensitivity, and specificity across all tissue classes. Accurate delineation of brain tissues enabled reliable extraction of disease-relevant features and improved the robustness of downstream analysis.

Texture features derived from segmented WM and GM regions using the **Gray Level Co-occurrence Matrix (GLCM)** effectively captured microstructural and intensity variations associated with neurodegenerative progression. To exploit the complementary nature of different brain tissues, a **U-Net-based feature fusion network** was introduced to integrate WM and GM features while preserving spatial relationships. This fusion strategy produced a compact and discriminative representation that enhanced classification performance.

Experimental evaluation on the ADNI dataset demonstrated that the proposed framework achieved an overall classification accuracy of **94.18%** with a macro-average AUC of **0.94**, outperforming conventional

segmentation and classification approaches. The results confirm that **tissue-specific segmentation combined with texture-aware feature fusion significantly improves the discrimination of Alzheimer's disease, Mild Cognitive Impairment, and Healthy Control subjects**, particularly in early-stage diagnosis.

Overall, the proposed M-Net + DEC with GLCM feature extraction and U-Net-based fusion framework provides an effective and reliable computer-aided diagnostic solution for Alzheimer's disease analysis using brain MRI. Future work will focus on extending the framework to multimodal imaging data, incorporating attention mechanisms for enhanced interpretability, and validating the model on larger and more diverse clinical datasets to improve generalizability and real-world applicability.

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