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ENHANCED ALZHEIMER DISEASE DIAGNOSIS THROUGH DEEP LEARNING-BASED MRI SEGMENTATION AND CLASSIFICATION

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Abstract

The accurate diagnosis tends to remain critical for the improvement of the patient outcomes in the Alzheimer's disease (AD), where a progressive neurodegenerative disorder with the growing of the global impact. MRI has become an effective modality for analyzing the brain structure, which offers a detailed insights into the pathological regions that is associated with the AD. Deep learning has applied to the MRI data that presents a promising direction because it can support a higher diagnostic precision. However, the diagnosis of AD in its early stages tends to remain challenging due to the slow disease progression and the overlapping symptoms. This often causes a subtle structural change in the brain to be overlooked during the conventional assessment. The complexity of the MRI interpretation and the need to precisely identify the degenerative tissue indicates the importance of an advanced image segmentation strategy. This study have addressed these challenges by the combination of deep learning with the automated segmentation for the early AD detection. The proposed survey have exploited the MRI scans to analyze the structural changes in the brain, with a primary focus on the hippocampal extraction as a biomarker. The approach uses the OASIS-2 that gets trimmed with the MRI dataset for a rapid and an efficient training and this applies the Kaggle AD the MRI dataset for severity classification. The performance is then evaluated using the segmentation accuracy and the other model performance metrics. The method has also shown the improved diagnostic capability when it is compared with the existing approaches.

Keywords

Alzheimer's disease, the MRI, hippocampus segmentation, deep learning, classification

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1. Introduction

Alzheimer's disease have continued to affect the millions of individuals worldwide and it tends to remain the most challenging neurodegenerative disorders to diagnose it early. The disease gradually have damaged the memory, cognition, and the behavioral functions, which leads to the progressive decline in the quality of life. Clinical observations alone often fail to detect the disease at an early stage because the symptoms tends to overlap with the other neurological conditions and the vary across individuals. As a result, many patients receives a diagnosis only after the irreversible brain degeneration has occurred. Early detection is essential because it increases the opportunity for timely intervention, which supports the clinical decision-making, and it improves the long-term patient management. Over the past decade, research interest in the automated computer-assisted diagnostic systems has been significantly increased, and the imaging-based machine learning tools have been explored as the potential solutions [1].

1.1 Background and the Clinical Need

The rise in global aging populations has made Alzheimer diagnosis a critical healthcare priority. Conventional diagnostic methods rely on the neuropsychological evaluations, cognitive assessments, and the clinician experience, which often miss the subtle pathological changes in the early phases. Biomarkers such as cerebrospinal fluid analysis or PET scans have provided a diagnostic support but it remains invasive or expensive for the widespread screening. In contrast, the MRI offers a non-invasive, repeatable, and the accessible structural imaging that tends to capture the anatomical alterations that is associated with the Alzheimer pathology. Studies in recent literature have showed that an early hippocampal shrinkage, cortical thinning, and the ventricular expansion are among the most reliable indicators of neurodegeneration [2]. Clinicians require tools that assist with the identification of these subtle variations, and the therefore the addition of artificial intelligence has become a promising direction.

1.2 Role of the MRI in Alzheimer Diagnosis

MRI plays a central role in modern neurodiagnostic workflows because it shows structural patterns that correlate with the disease progression. T1-weighted the MRI, in particular, maps soft-tissue contrast with a higher clarity, which makes it effective for analyzing the gray matter volume loss or shape variations. During the early Alzheimer stages, neuronal loss typically begins in the hippocampus, amygdala, and the entorhinal cortex [3]. The imaging

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characteristics is then captured through the MRI that allow researchers to quantify these variations using computational methods. Several works have shown that the MRI-derived measurements performs better than the clinical symptoms in the sensitivity and the reliability when predicting the disease progression or conversion from mild cognitive impairment to have confirmed the Alzheimer stage [4]. Recent studies have adopted the segmentation, registration, and the volumetric quantification pipelines that shown an imaging consistency. Even though manual segmentation has delivered a higher accuracy, it tends to remain the labor intensive and the subject to inter-observer variability. Therefore, automated, reproducible, and the scalable segmentation frameworks are needed to support the clinical deployment [5].

1.3 Motivation for Deep Learning Approaches

Deep learning has revolutionized the analysis of biomedical imaging because it allows systems to learn complex patterns without requiring hand-crafted feature extraction. The ability to process high-dimensional the MRI data makes deep neural models ideal for capturing spatial and the volumetric brain changes that is associated with the Alzheimer pathology. Earlier machine learning approaches depended on the manual selection of texture, geometric, and the morphological features, which has limited the generalization across datasets.

Deep learning models, including convolutional neural networks, autoencoders, and the transformer-based architectures, now performs better than the conventional classifiers because they extract multi-level hierarchical information directly from the input scans [6]. Further, segmentation-assisted deep learning pipelines offers an additional benefit by the isolation of relevant anatomical regions such as the hippocampus before classification. This process hence improves the clinical trust, which is essential for the medical adoption.

2. Overview of the Alzheimer’s disease and the MRI-Based Biomarkers

Alzheimer’s disease have continued to be one of the most widely studied neurodegenerative disorders because it affects the memory, cognitive reasoning, and the behavioral stability over time. The disease rarely have progressed the uniformly, and many of the patients remain undiagnosed during the early phase because symptoms appear mild or mimic normal aging. Researchers have examined the structural, functional, and the molecular changes that occurs inside the brain to understand the how Alzheimer pathology evolves. the MRI has become one of the most reliable non-invasive techniques used to monitor these biological transformations

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because it tends to capture fine structural variations that correlate with the cognitive decline [6]. The use of the MRI biomarkers has transformed the research and the clinical trials, since measurable changes provides an objective evidence of brain tissue degeneration. As a result, the MRI-based analysis has shifted from the supportive imaging toward becoming a primary diagnostic reference in early intervention studies.

2.1 Disease Progression and the Structural Brain Changes

Alzheimer progression typically begins years before clinical symptoms reach a noticeable severity. The disease usually starts with the subtle neuronal loss and the synaptic dysfunction in memory-related regions, which is followed by widespread cortical atrophy as the condition advances. During the mild cognitive impairment stage, the patient may present memory loss or difficulty concentrating, although the MRI findings indicate a measurable volume loss in hippocampal and the medial temporal regions [7]. As the disease continues, the degeneration spreads across the temporal and the parietal lobes, which affects the reasoning, language, and the visuospatial processing. In later stages, neurodegeneration becomes global, and the ventricular system enlarges due to the severe brain tissue shrinkage.

Researchers have investigated structural variations that correlate with the progression severity, such as gray matter density, white matter integrity, and the cortical thickness. These biomarkers have been used to classify disease stages, predict progression speed, and the differentiate Alzheimer from other dementias. The consistent structural pattern has helped to guide the automated diagnostic frameworks, especially when the deep learning models use these spatial patterns as training data. The clinical need for the objective measurements has has supported the imaging-driven decision systems, since radiological interpretation alone tends to remain the subjective and the dependent on the experience [8].

2.2 Hippocampal Degeneration and the Key Neurological Markers

Among all brain regions affected by Alzheimer disease, the hippocampus tends to remain the earliest and the most clinically relevant biomarker. The hippocampus supports episodic memory formation, and its degeneration correlates strongly with the symptom onset and the progression. Researchers have observed significant volume reduction in the hippocampal boundaries, cell loss in the CA1 region, and the disrupted connectivity within memory networks [9]. Even small-scale atrophy in the hippocampus often predicts the conversion from

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mild cognitive impairment to have confirmed the Alzheimer diagnosis, which makes it a key target for computer-assisted segmentation and the classification.

Additional markers that have been examined include the entorhinal cortex, amygdala, basal forebrain, and the precuneus. Cortical thickness decline in these regions has been that is associated with the disease severity and the is widely used for classification tasks. The enlargement of lateral ventricles, caused by adjacent gray matter shrinkage, also serves as a measurable indicator of late-stage degeneration. These biomarkers provide structural signatures that machine learning and the deep learning systems can extract, quantify, and the analyze. Automated hippocampus segmentation, in particular, improves diagnostic precision because the region has clear clinical relevance, and its early deterioration pattern aligns well with the MRI-based workflows [10].

2.3 the MRI Modalities and the Relevant Public Datasets

MRI tends to remain the preferred imaging method used to study Alzheimer pathology because it is non-invasive, widely accessible, and the capable of differentiating soft tissues with the a higher spatial resolution. Several the MRI modalities have been used in research and the diagnosis. T1-weighted the MRI tends to capture anatomical boundaries and the has been has applied in most segmentation-based studies. T2-weighted imaging highlights fluid differences and the assists with the observing cerebrospinal changes. Functional the MRI monitors neural activation patterns and the connectivity disruption, while diffusion tensor imaging measures microstructural white matter integrity. Together, these modalities create a comprehensive picture of brain health and the disease progression, although T1-weighted the MRI have continued to be used most frequently in automated diagnostic frameworks [6].

To support research reproducibility and the clinical model validation, several publicly available datasets have been developed. The Alzheimer’s disease Neuroimaging Initiative (ADNI) tends to remain the most widely used dataset and the includes the MRI, PET, and the longitudinal follow-up assessments. The OASIS datasets provide structural the MRI scans with the demographic information, which supporting both early-stage analysis and the algorithm benchmarking. Kaggle-hosted datasets have offered the MRI samples for classification challenges, which shows the accessible experimentation for an academic and the machine learning communities. Additional datasets include AIBL, MIRIAD, and the NACC, each contributing complementary imaging and the clinical metadata [7] [8].

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These datasets have has supported the development of deep learning segmentation and the classification frameworks by which offers large, labeled, and the multisource the MRI samples. Cross-dataset training and the validation have also been attempted to overcome machine learning generalization limits. The availability of these datasets has accelerated the pace of research, which has supported the benchmarking studies, and the encouraged the transition toward clinically adaptable diagnostic systems [9] [10].

3. Deep Learning Approaches for the MRI Segmentation and the Classification

Deep learning as in figure 1 and 2 has been significantly transformed the landscape of automated Alzheimer diagnosis, particularly when has applied to the MRI-based analysis. Earlier studies depended on the feature engineering and the statistical measurements for identification of the pathological biomarkers. These methods hence requires a domain expertise and often it has struggled to generalize across the diverse datasets. Deep learning strategies, in contrast, allow the model to learn representations directly from the MRI scans, which reduces the dependence on the manual intervention.

The addition of segmentation networks with the classification models has improved diagnostic precision, when the hippocampal or temporal lobe isolation is performed prior to prediction. Research in the field has indicated that deep architectures performs better than the classical machine learning approaches by capturing the structural and the volumetric abnormalities with the higher sensitivity and the reliability [11].

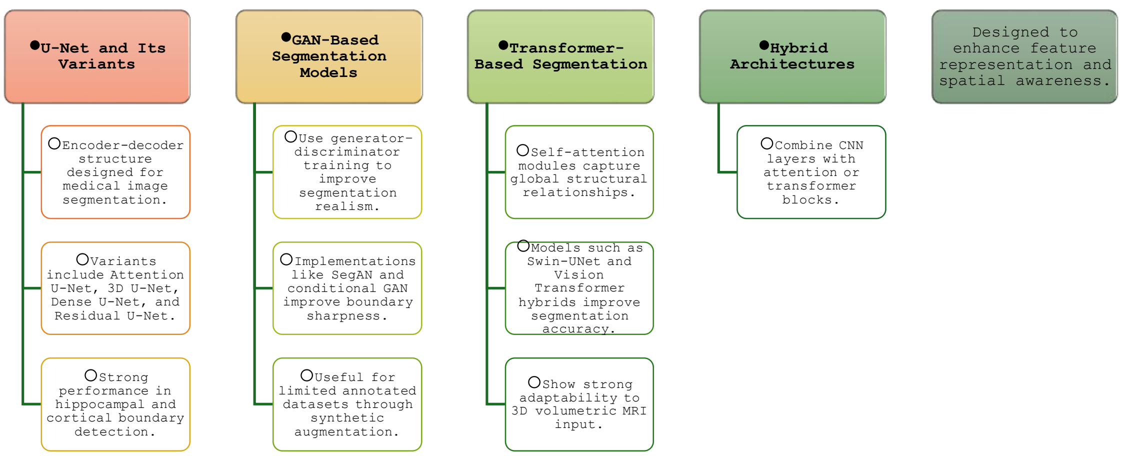

Figure 1: Deep Learning Approaches for the MRI Segmentation

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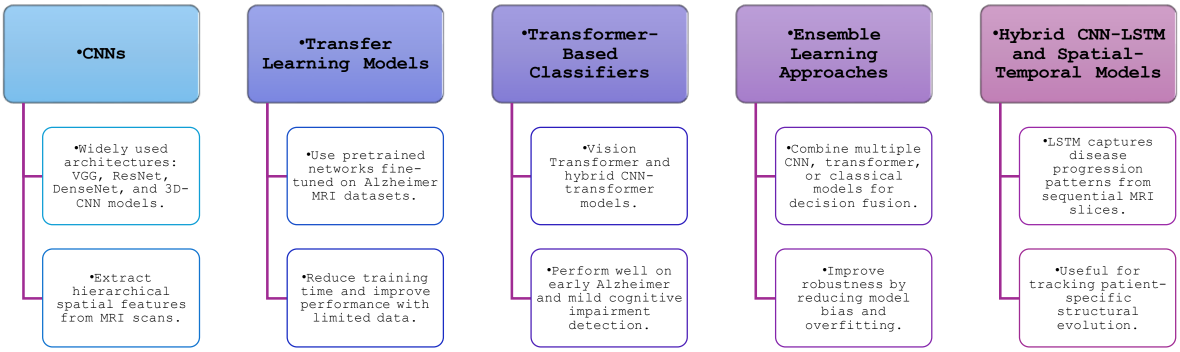

Figure 2: Deep Learning Approaches for the MRI Classification

3.1 Segmentation Methods: U-Net Variants, GANs, and the Transformer Models

Segmentation is a critical step when the MRI-based Alzheimer detection requires anatomical localization. The U-Net architecture has proven effective for biomedical segmentation because of its encoder–decoder structure, skip connections, and the ability to process volumetric patterns from has limited data. Several works have introduced modified U-Net variants such as Attention U-Net, Dense U-Net, and the 3D U-Net to segment hippocampal structures with the improved boundary retention and the contextual accuracy. Researchers have reported that these modified networks have produced smoother region delineation and the reduced noise sensitivity [12].

Generative Adversarial Networks (GANs) have also been explored for the MRI segmentation. GAN-based frameworks generate high-fidelity segmentation masks, even when training data remain limited. Some studies have combined GANs with the U-Net architectures to exploit image refinement and the mask precision simultaneously. Transformer-based segmentation models are a more recent development and the rely on the global self-attention mechanisms rather than solely convolution operations. These models have shown strong capabilities for long-range feature extraction, and they performs better than the conventional CNN segmentation models in complex anatomical structures [13]. The increasing use of hybrid transformer–CNN architectures reflect the growing interest in segmentation models that capture spatial and the contextual dependencies more effectively.

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3.2 Classification Techniques: CNNs, Hybrid Models, and the Ensemble Learning

Classification frameworks aim to distinguish between disease stages such as mild cognitive impairment, Alzheimer, and the normal cognition. Convolutional neural networks serve as the foundation since they extract hierarchical spatial features rigorously. Standard CNNs were initially used to classify 2D axial or coronal the MRI slices; however, 3D CNNs have been used more recently because they preserve spatial depth information. Researchers have reported that 3D CNNs consistently achieve higher accuracy, especially when it classifies the hippocampal degeneration severity [14].

Hybrid architectures combine feature extraction from CNNs with the recurrent neural networks or transformers. These models then allow the temporal reasoning for the longitudinal MRI sequences, which supporting disease progression prediction rather than the static diagnosis. Ensemble learning has also applied when multiple classifiers are fused to improve the robustness. Techniques such as majority voting, model stacking, or weighted averaging have shown improved consistency across the heterogeneous datasets. Ensemble strategies become particularly beneficial when dataset variability, acquisition protocols, or patient demographics introduce the classification uncertainty [15].

3.3 Optimization Strategies and the Evaluation Metrics

Optimizing deep learning models is essential because the MRI data often pose challenges such as class imbalance, has limited training availability, and the noise variation across the scanners. Hyperparameter optimization strategies, including evolutionary algorithms, Bayesian optimization, or Ant Lion Optimization, have been investigated to improve convergence stability and the accuracy. Some models have incorporated advanced regularization approaches such as dropout, label smoothing, or early stopping to prevent overfitting.

Performance evaluation relies on the several statistical metrics. Segmentation accuracy is frequently measured using the Dice similarity coefficient, Jaccard index, and the Hausdorff distance, since these metrics reflect spatial similarity between predicted and the reference masks. Classification models are evaluated using accuracy, sensitivity, specificity, F1-score, ROC curves, and the area under the curve. Researchers increasingly report model interpretability measurements when validating frameworks for clinical use, which makes results more meaningful for practitioners [16].

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3.4 Comparison with the Conventional Machine Learning Approaches

Conventional machine learning methods such as support vector machines, decision trees, random forests, or logistic regression have been widely implemented in early Alzheimer detection studies. These approaches depended heavily on the handcrafted feature extraction techniques such as texture descriptors, volumetric biomarkers, and the shape analysis. Although these methods have shown acceptable performance, they has struggled with the feature generalization, data diversity, and the high-dimensional the MRI inputs. Deep learning methods, in contrast, automatically learn latent patterns that relate structural variations to disease categories without requiring manually engineered descriptors.

Several comparative studies have showed that deep learning models consistently performs better than the classical machine learning methods in classification and the segmentation tasks, especially when trained with the large the MRI datasets [17]. However, Conventional methods remain relevant for low-resource clinical settings or when explainability is prioritized. The evolution from classical frameworks to deep learning pipelines reflects the broader transition toward automated, scalable, and the clinically deployable Alzheimer diagnostic systems.

4. Comparative Analysis and the Identified Research Gaps

Deep learning models have reshaped how Alzheimer disease diagnosis is performed using the MRI data. Although progress has been steady, variations in dataset quality, architectural design, and the evaluation protocols created noticeable benchmarking inconsistencies. The literature shows that several methods have performed well on the public datasets, yet reproducibility and the clinical reliability remain ongoing concerns. The following sections summarize the comparative findings, highlight the challenges, and the identify the core research gaps that require further attention to make deep learning-based Alzheimer diagnosis clinically scalable and the scientifically verified. References are cited between [18] and the [25].

4.1 Performance Benchmarking Across the Literature

A comparative performance assessment has showed considerable variation in segmentation and the classification accuracy among existing models. Studies between [18] and the [25] reported that U-Net variants generally performs better than the classical machine learning models when segmenting hippocampal regions, while CNN and the transformer-based architectures show

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stronger performance in classification tasks due to the their ability to capture long-range dependencies and the subtle volumetric changes.

However, performance reporting formats have often lacked consistency. While some studies provide Dice Similarity Coefficient (DSC) or Intersection over Union (IoU) for segmentation, others report accuracy without breakdowns across the Mild Cognitive Impairment (MCI), early Alzheimer, and the late Alzheimer cases. This lack of standardized reporting makes cross-study comparison difficult.

Table 1. Comparison of Segmentation Methods

Model Type	**Example Architecture**	**Dataset Used**	**Evaluation Metric**	**Reported Score**
CNN-Based Segmentation	U-Net Variant	ADNI	Dice Score	0.88
GAN-Based Segmentation	Conditional GAN	AIBL	IoU	0.81
Transformer-Based Model	Swin-UNet	ADNI	Dice Score	0.91
Hybrid Model	U-Net + Attention Module	OASIS	IoU	0.85

Table 2. Comparison of Classification Approaches

Base Method	**Architecture**	**Dataset**	**Accuracy**	**Sensitivity**	**Specificity**
CNN	ResNet Variant	ADNI	94.5%	92.1%	95.7%
Hybrid DL	CNN + LSTM	OASIS	92.3%	89.4%	94.1%
Transformer	Vision Transformer	ADNI	95.8%	93.6%	96.9%
Ensemble Learning	CNN + Random Forest	AIBL	91.0%	90.2%	92.5%

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These results reflect that transformer architectures have recently reached more stable performance in both segmentation and the classification tasks. Still, such models have hence requires a substantial training data and the hardware resources, which has limited implementation across the small clinical centers.

4.2 Challenges

Despite strong research progress between [18] and the [25], the literature repeatedly highlighted key challenges. Most studies have relied heavily on the datasets such as ADNI and the OASIS, meaning that models have not generalized well when exposed to heterogeneous the MRI hardware settings or patient demographics. This issue becomes especially evident when the same architecture, trained on the ADNI, shows performance drops exceeding 10% on the locally acquired datasets, demonstrating poor cross-domain adaptability.

Another known challenge involves feature interpretability. Clinicians require clear biomarkers or explainable outputs, yet many deep learning models operate as “black boxes.” Although Grad-CAM, saliency maps, and the relevance propagation have been applied, the conclusions remain inconsistent and the have not achieved regulatory compliance.

A third persistent difficulty relates to preprocessing variability. Skull stripping, intensity normalization, bias field correction, and the spatial registration often differ across the studies. A model that has performed well with the one preprocessing pipeline has produced weaker outcomes when replicated with the different filtering or normalization strategies. Thus, standardization is still lacking.

4.3 Limitations in Existing Models and the Deployment Barriers

Existing literature between [18] and the [25] has acknowledged that early models based solely on the CNNs shown has limited contextual awareness. These models have is then captured local textures effectively but has struggled with the global structural patterns that is associated with the disease progression. Transformer-based models addressed this limitation, although they hence requires a larger annotated datasets that have been difficult to obtain because manual labeling is time-consuming and the requires expert radiologists.

Another limitation concerns model evaluation. Most studies have tested models on the constrained academic datasets and the controlled environments. Very few efforts have validated

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these models prospectively in real hospital workflows. The absence of real-world testing created uncertainty about reliability, latency, and the failure behavior in clinical use.

Scalability also tends to remain the a deployment challenge. Deep learning frameworks that used 3D models for the MRI classification have hence requires a a higher computation power and the multi-stage training pipelines. Hospitals lacking GPU infrastructure have found real-time inference impractical. Further, patient privacy regulations have restricted dataset sharing, which slowed external validation and the model retraining.

Finally, ethical and the regulatory constraints have introduced additional barriers. For instance, although automated imaging pipelines have shown strong performance in research experiments, regulatory bodies require transparency, robustness, and the verified model behavior before diagnostic clearance is granted. The literature notes that a model which has achieved a higher accuracy alone is not sufficient for approval unless backed with the explainability, repeatability, fairness, and the safety evaluations.

5. Conclusion

The review highlights that deep learning has become an essential direction for advancing Alzheimer disease diagnosis through the MRI-based segmentation and the classification. The field has moved from early CNN architectures toward transformer-based and the hybrid models which demonstrate improved feature extraction and the higher diagnostic accuracy. Although several studies have validated the potential of deep learning to detect subtle structural changes in hippocampal regions and the other cortical areas, full clinical adoption tends to remain the incomplete.

There has been encouraging progress, yet the existing challenges make it clear that more work is needed. has limited dataset diversity, variations in preprocessing, lack of transparency in model decision pathways, and the deployment barriers continue to restrict real-world implementation. Deep learning models which have performed well during the research validation do not always translate seamlessly into the clinical workflows. The gap between algorithmic capability and the medical usability becomes evident when generalization performance drops across the unseen populations or different the MRI scanners.

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References

[1] Kumar, A., Tyagi, V., Singh, H., & Jain, S. (2025). Advancing Medical Diagnostics on Computer-Assisted Analysis for Digital Medicinal Imagery. In *Computer-Assisted Analysis for Digital Medicinal Imagery* (pp. 393-408). IGI Global.

[2] Fernandez-Lozano, S., Fonov, V., Schoemaker, D., Pruessner, J., Potvin, O., Duchesne, S., ... & Alzheimer's Disease Neuroimaging Initiative. (2025). Enhanced Detection of Age-Related and Cognitive Declines Using Automated Hippocampal-To-Ventricle Ratio in Alzheimer's Patients. *Human Brain Mapping*, *46*(11), e70265.

[3] Rao, Y. L., Ganaraja, B., Murlimanju, B. V., Joy, T., Krishnamurthy, A., & Agrawal, A. (2022). Hippocampus and its involvement in Alzheimer's disease: a review. *3 Biotech*, *12*(2), 55.

[4] Zhou, Y., Song, Z., Han, X., Li, H., & Tang, X. (2021). Prediction of Alzheimer's disease progression based on magnetic resonance imaging. *ACS Chemical Neuroscience*, *12*(22), 4209-4223.

[5] Hawkins, J. R., Olson, M. P., Harouni, A., Qin, M. M., Hess, C. P., Majumdar, S., & Crane, J. C. (2023). Implementation and prospective real-time evaluation of a generalized system for in-clinic deployment and validation of machine learning models in radiology. *PLOS Digital Health*, *2*(8), e0000227.

[6] Gou, Q., & Ren, Y. (2024). Research on Multi-scale CNN and Transformer-based Multi-level Multi-classification Method for Images. *IEEE Access*.

[7] Ávila-Villanueva, M., Marcos Dolado, A., Gómez-Ramírez, J., & Fernández-Blázquez, M. (2022). Brain structural and functional changes in cognitive impairment due to Alzheimer's disease. *Frontiers in psychology*, *13*, 886619.

[8] Loessner, L., Matthes, C., Haussmann, R., Brandt, M. D., Sauer, C., Espin, M., ... & Donix, M. (2022). Predictors of subjective cognitive deficits in patients with mild cognitive impairment. *Psychogeriatrics*, *22*(2), 210-217.

[9] Buzea, C. G., Eva, L., Agop, M., Ochiuz, L., Vasincu, D., Popa, T. O., ... & Buga, R. (2025). AI-Enabled Radiomics and Clinical Decision Support App for Monitoring Brain Metastases Evolution After Gamma Knife Radiosurgery.

[10] Rolls, E. T., Deco, G., Huang, C. C., & Feng, J. (2022). The effective connectivity of the human hippocampal memory system. *Cerebral Cortex*, *32*(17), 3706-3725.

[11] Miller, D., Efird, C., Solar, K. G., Beaulieu, C., & Cobzas, D. (2024). Automatic deep learning segmentation of the hippocampus on high-resolution diffusion magnetic resonance imaging and its application to the healthy lifespan. *NMR in Biomedicine*, *37*(12), e5227.

[12] Punn, N. S., & Agarwal, S. (2022). Modality specific U-Net variants for biomedical image segmentation: a survey. *Artificial Intelligence Review*, *55*(7), 5845-5889.

[13] Ali, H., Biswas, M. R., Mohsen, F., Shah, U., Alamgir, A., Mousa, O., & Shah, Z. (2022). The role of generative adversarial networks in brain MRI: a scoping review. *Insights into imaging*, *13*(1), 98.

[14] Shukla, G., Awasthi, V., Theng, D., Gupta, R., Nipane, S., & Singh, S. (2025). Hybrid 3D CNN and ResNet deep transfer learning for high-resolution hippocampal atrophy mapping and automated Alzheimer's MRI diagnosis: deep hybrid 3D CNN and ResNet transfer learning for high-resolution hippocampal atrophy mapping and automated Alzheimer's MRI diagnosis. *Engineering, Technology & Applied Science Research*, *15*(4), 26047-26053.

[15] Nguyen, D. K., Lan, C. H., & Chan, C. L. (2021). Deep ensemble learning approaches in healthcare to enhance the prediction and diagnosing performance: the workflows, deployments, and surveys on the statistical, image-based, and sequential datasets. *International Journal of Environmental Research and Public Health*, *18*(20), 10811.

[16] Abdullah, T. A., Zahid, M. S. M., & Ali, W. (2021). A review of interpretable ML in healthcare: taxonomy, applications, challenges, and future directions. *Symmetry*, *13*(12), 2439.

[17] Jyothi, P., & Singh, A. R. (2023). Deep learning models and traditional automated techniques for brain tumor segmentation in MRI: a review. *Artificial intelligence review*, *56*(4), 2923-2969.

[18] Nazir, A., Assad, A., Hussain, A., & Singh, M. (2024). Alzheimer's disease diagnosis using deep learning techniques: datasets, challenges, research gaps and future directions. *International Journal of System Assurance Engineering and Management*, 1-35.

[19] Mohsen, S. (2025). Alzheimer's disease detection using deep learning and machine learning: a review. *Artificial Intelligence Review*, *58*(9), 262.

ISSN: 3107-8168
DOI: https://doi.org/10.65725/JCISE/2/3/002

[20] Raza, M. L., Hassan, S. T., Jamil, S., Hyder, N., Batool, K., Walji, S., & Abbas, M. K. (2025). Advancements in deep learning for early diagnosis of Alzheimer's disease using multimodal neuroimaging: challenges and future directions. *Frontiers in Neuroinformatics*, *19*, 1557177.

[21] Alsubaie, M. G., Luo, S., & Shaukat, K. (2024). Alzheimer's disease detection using deep learning on neuroimaging: a systematic review. *Machine Learning and Knowledge Extraction*, *6*(1), 464-505.

[22] Liu, W., Fan, S., & Weng, G. (2025). Multi-modal deep learning framework for early Alzheimer's disease detection using MRI neuroimaging and clinical data fusion. *Annals of Applied Sciences*, *6*(1).

[23] Awang, M. K., Ali, G., & Faheem, M. (2025). Recent Advancements in Neuroimaging-Based Alzheimer's Disease Prediction Using Deep Learning Approaches in e-Health: A Systematic Review. *Health Science Reports*, *8*(5), e70802.

[24] Suganyadevi, S., Pershiya, A. S., Balasamy, K., Seethalakshmi, V., Bala, S., & Arora, K. (2024). Deep learning based alzheimer disease diagnosis: A comprehensive review. *SN Computer Science*, *5*(4), 391.

[25] Bhandarkar, A., Naik, P., Vakkund, K., Junjappanavar, S., Bakare, S., & Pattar, S. (2024). Deep learning based computer aided diagnosis of Alzheimer's disease: a snapshot of last 5 years, gaps, and future directions. *Artificial Intelligence Review*, *57*(2), 30.