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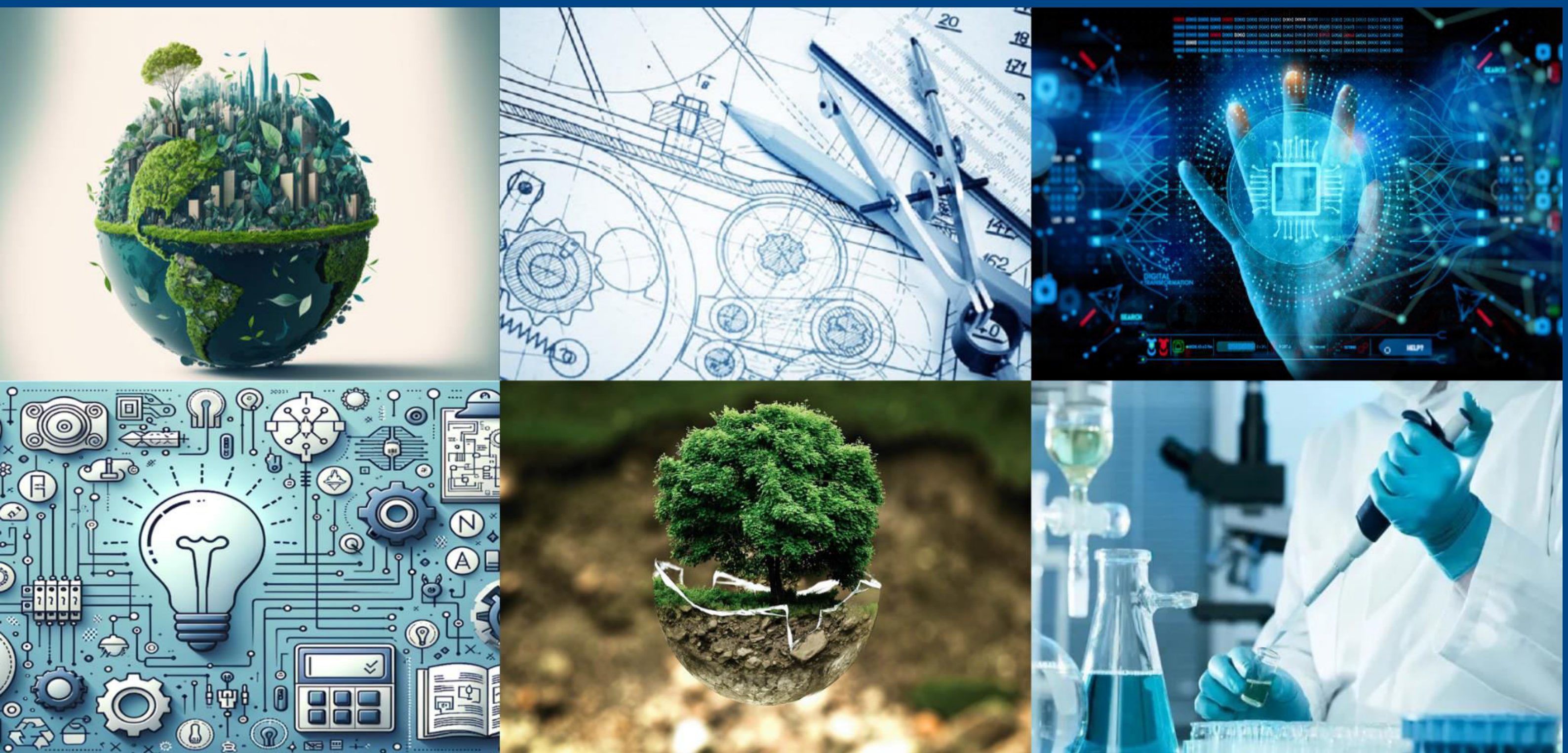

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Alzheimer's Disease Prediction Using Deep Learning

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ABSTRACT: Alzheimer's disease causes a progressive decline in brain function, making early and precise detection vital for timely medical intervention. This study introduces a deep learning framework developed to classify brain MRI scans into four distinct stages: non-demented, very mild, mild, and moderate dementia. Our architecture pairs a convolutional neural network (CNN) for spatial feature extraction with a recurrent neural network (RNN) to evaluate sequential patterns within those features. We evaluated our model using an expanded MRI dataset containing 5,121 training images and 1,279 validation images. The results indicated that while the standalone CNN yielded strong validation accuracy, integrating the RNN provided negligible performance gains. To transition this research into a practical tool, we deployed the trained CNN within a Flask-based web application. Users can upload an MRI scan to receive an immediate classification alongside tailored medical recommendations to help clarify the results. Overall, our findings demonstrate that deep learning is highly effective for staging Alzheimer's, though future efforts must address model generalizability, dataset imbalances, and clinical validation.

I. INTRODUCTION

Alzheimer's disease is the leading driver of dementia worldwide, causing a progressive breakdown in brain health that reshapes a person's memory, behavior, and daily cognitive functions. As patients slowly lose their independence with everyday tasks, the burden ripples outward, placing immense emotional and logistical weight on families, caretakers, and healthcare systems. Catching the condition early is a major hurdle because the earliest signs are incredibly subtle [11]. Relying solely on manual scan reviews and traditional doctor visits often causes diagnostic delays, emphasizing the critical need for automated screening tools that can bring speed and consistency to the process.

Neurologists lean heavily on magnetic resonance imaging (MRI) to get a clear, physical look at what is happening inside the brain [12]. As Alzheimer's advances, these scans reveal clear markers like tissue loss and overall brain shrinkage. However, reading these visual nuances requires deep clinical expertise, and even expert opinions can vary from one radiologist to the next. To cut through this human subjectivity, researchers are leaning more on machine learning and deep learning models to extract hidden patterns directly from MRI data, paving the way for a much more objective staging process [10].

Deep learning has completely changed the game for medical imaging by pulling complex patterns straight from raw files, skipping the tedious process of manual feature selection. In this space, convolutional neural networks (CNNs) are brilliant at spotting spatial details inside brain scans, while recurrent neural networks (RNNs) are usually brought in to monitor sequential changes over time [13]. Most Alzheimer's research simplifies things by focusing on binary classification—essentially separating healthy brains from sick ones. But this black-and-white approach ignores the gradual, step-by-step nature of the disease. Transitioning to multi-class staging offers far more clinical utility because it maps out the actual trajectory of cognitive decline, giving doctors the nuanced data they need for early intervention.

In this study, we built a deep learning framework designed to sort Alzheimer's progression into four distinct phases: Non-Demented, Very Mild, Mild, and Moderate. The setup uses a CNN to identify the spatial characteristics of the MRIs, alongside an RNN to analyze feature-level traits. To turn this theory into something tangible, we embedded the trained model into a Flask-powered web application [8]. Through a clean, straightforward interface, users can upload a

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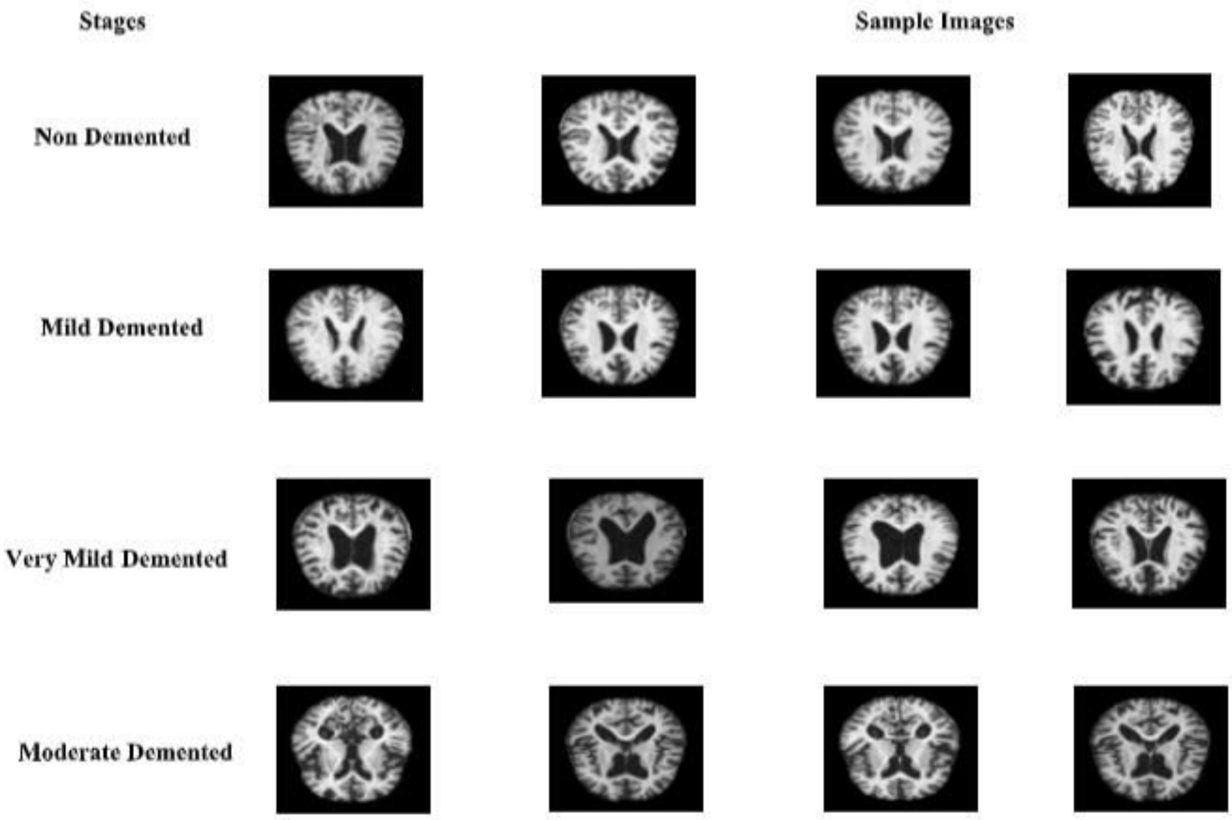
brain scan and get an immediate prediction. This moves our system beyond a theoretical concept and turns it into an interactive research prototype.

Our main contribution here is delivering a complete, start-to-finish pipeline for predicting Alzheimer's stages, covering everything from raw image preprocessing and model tuning to web deployment. The project shows how intricate deep learning models can be seamlessly paired with simple user interfaces for both classroom demonstrations and experimental testing. Even though our current results indicate that the CNN does the heavy lifting while the RNN adds little extra value, this framework sets a clear baseline. It provides a solid foundation for future improvements, such as introducing transfer learning, applying stricter regularization, and testing better ways to handle dataset imbalances



II. LITERATURE REVIEW

A lot of recent research shows just how much deep learning is changing the medical imaging game. For example, some teams have built multi-view CNN models that look at MRI and PET scans at the same time, hitting much higher accuracy rates for spotting Alzheimer’s than older methods that only look at one scan type [1]. Building on that success, newer studies have proved that blending different kinds of data—like structural, functional, and actual clinical profiles—gives deep learning models a much deeper, more complete picture of what is happening inside the brain [2].

One of the biggest roadblocks in training these models is that expertly labeled medical data is incredibly hard to find. To get around this shortage, researchers often use data augmentation tricks to artificially grow their training pools. This boost helps train CNNs to pick up on the tiniest, earliest structural changes in brain anatomy that a human eye might miss [3].

That said, getting these smart algorithms out of the research lab and into daily clinic routines is still a massive challenge. Current papers point out that the biggest hurdles to widespread use are things like a lack of clear model interpretability, inconsistent reliability, and low trust from medical professionals [4]. Even with these roadblocks, deep learning technology is moving forward fast, continually pushing medical imaging ahead and opening new doors for quicker, more accurate Alzheimer's diagnoses [5]

Alzheimer's Disease Detection Using Ensemble Techniques on MRI Images [1]. Our research leverages a deep convolutional neural network to categorize MRI scans across multiple stages of Alzheimer's disease. By prioritizing automated feature learning directly from brain images, this approach eliminates the need for manual feature extraction.

Relevance to current Research

In this paper, Diagnosing Alzheimer's disease remains a massive hurdle, even though it stands as the leading cause of dementia worldwide. While MRI scans clearly show structural changes in the brain, reading them manually takes a lot of time and leaves too much room for human error or subjective opinion. To address this, our study looks into an automated deep learning approach to identify Alzheimer's directly from MRI data. We developed an ensemble system that combines three distinct models—EfficientNet, Vision Transformer (ViT), and SqueezeNet—each selected for a specific advantage in image processing. EfficientNet handles feature extraction incredibly well, ViT excels at picking up long-range visual relationships across the image, and SqueezeNet keeps the computational footprint low. We trained this combined setup to classify brain scans into four distinct stages of cognitive decline: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. By blending the unique strengths of these three networks, our ensemble method hit a strong 90.50% accuracy rate on a public Kaggle dataset, easily beating out the performance of any single model on its own. Ultimately, this work highlights the clear benefit of pairing different deep learning architectures and offers a practical path toward making Alzheimer's screening both faster and more reliable.

Relevance to current Research

Alzheimer's disease is the leading driver of dementia worldwide, causing a progressive breakdown in brain health that reshapes a person's memory, behavior, and daily cognitive functions. As patients slowly lose their independence with everyday tasks, the burden ripples outward, placing immense emotional and logistical weight on families, caretakers, and healthcare systems. Catching the condition early is a major hurdle because the earliest signs are incredibly subtle. Relying solely on manual scan reviews and traditional doctor visits often causes diagnostic delays [11], emphasizing the critical need for automated screening tools that can bring speed and consistency to the process.

Neurologists lean heavily on magnetic resonance imaging (MRI) to get a clear, physical look at what is happening inside the brain [12]. As Alzheimer's advances, these scans reveal clear markers like tissue loss and overall brain shrinkage [19], with the exact interval between scans playing a notable role in mapping structural atrophy over time [20]. However, reading these visual nuances requires deep clinical expertise, and even expert opinions can vary from one radiologist to the next. To cut through this human subjectivity, researchers are leaning more on machine learning and deep learning models to extract hidden patterns directly from MRI data [10], while some classical hybrid approaches utilize distance-based classification methods like CART-KNN for earlier diagnostics [14]. Together, these automated tools provide a much more objective staging process.

Relevance to current Research

Deep learning has completely changed the game for medical imaging by pulling complex patterns straight from raw files, skipping the tedious process of manual feature selection. In this space, convolutional neural networks (CNNs) are brilliant at spotting spatial details inside brain scans, while recurrent neural networks (RNNs) are usually brought in to monitor sequential changes over time [13]. For instance, self-attention architectures and bidirectional frameworks have successfully paired CNNs with recurrent elements to track intricate pattern progressions [17]. Furthermore, recent breakthroughs prove that processing MRI alongside PET data in multi-view configurations drastically outpaces single-modality strategies [1]. Blending these diverse structural, functional, and clinical streams builds a much deeper and more complete picture of brain health [2].

One of the biggest roadblocks in training these models is that expertly labeled medical datasets—such as early attempts focusing on tracking the exact presence and probability of tissue types [16]—are incredibly hard to find. To get around this shortage, researchers often use data augmentation tricks to artificially grow their training pools, helping networks pick up on the absolute earliest variations in brain anatomy [3]. Some setups even deploy transfer learning using powerful visual architectures like EfficientNet to establish highly effective classification frameworks [18]. Yet, transitioning these smart algorithms out of the research lab and into daily clinic routines is still a massive challenge. Current literature highlights that a lack of clear model interpretability, inconsistent reliability, and low clinical trust are the primary obstacles preventing widespread use [4]. Even with these roadblocks, deep learning technology continues to move forward fast, driving medical imaging ahead and paving the way for quicker, more accurate Alzheimer's diagnoses [5], alongside dedicated tracing tools to monitor a patient's cognitive activity [15].

Relevance to current Research

Most Alzheimer's research simplifies things by focusing on binary classification—essentially separating healthy brains from sick ones [9]. But this black-and-white approach ignores the gradual, step-by-step nature of the disease. Transitioning to multi-class staging offers far more clinical utility because it maps out the actual trajectory of cognitive decline, giving doctors the nuanced data they need for early intervention. In our study, we built a deep learning framework designed to sort Alzheimer's progression into four distinct phases: Non-Demented, Very Mild, Mild, and Moderate. To turn this theory into something tangible, we embedded the trained model into a web application. Through a clean, straightforward interface, users can upload a brain scan and get an immediate prediction [8]. This deployment moves our system beyond a theoretical concept and turns it into an interactive research prototype, drawing invaluable training value from public open-access brain databases like the Open Access Series of Imaging Studies (OASIS) [7] and the Alzheimer's Disease Neuroimaging Initiative (ADNI) [6].

Our main contribution here is delivering a complete, start-to-finish pipeline for predicting Alzheimer's stages, covering everything from raw image preprocessing and model tuning to web deployment. The project shows how intricate deep learning models can be seamlessly paired with simple user interfaces for both classroom demonstrations and experimental testing. Even though our current findings indicate that the CNN component carries most of the performance weight compared to the sequential tracking element, this framework sets a clear baseline. It provides a solid foundation for future improvements, such as introducing transfer learning, applying tighter regularization, and testing better ways to handle dataset imbalances.

Relevance to current Research

Our implementation prioritizes the safe handling of medical data uploaded to the Flask environment. The system actively checks the structural layout and integrity of the brain scans right at the moment of ingestion, ensuring the neural networks are analyzing precise, uncorrupted images before generating a diagnostic prediction.

No.	Paper Title	Author Name	Key Points	Remark
1	Multi-View Convolutional Neural Networks for Alzheimer's Disease Classification with MRI and PET Data	IEEE Transactions on Medical Imaging	Evaluates multi-view CNN models that simultaneously process MRI and PET scans.	Achieves significantly higher accuracy compared to traditional, single-modality strategies.
2	Improving Alzheimer's Disease Diagnosis with Deep CNNs: A Comprehensive Study on Multi-Scale and Multi-Modal Data	IEEE Transactions on Computational Imaging	Blends structural, functional, and actual clinical data streams within deep learning frameworks	Maps out a much deeper, more nuanced, and comprehensive representation of brain health
3	Challenges in Applying Deep Learning to Alzheimer's Disease Diagnosis	IEEE Xplore	Identifies current bottlenecks in translating models from the laboratory to the field	Highlights limited model interpretability, inconsistent reliability, and low clinical trust as core hurdles
4	A Predictive and Adaptive	IEEE Xplore, 2024	•Deploys adaptive web tools. •Embeds active machine learning.	Bridges the technical gap between complex models and

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	Mobile/Web Application for Alzheimer's Disease using Machine Learning		•Screens patient cognitive status. •Provides user-centric dashboarding	everyday clinical usage.
5	Cart KNN: A hybrid distance-based pre-pruned classification and regression method for the early diagnosis of Alzheimer's disease	Sigma Journal / Yıldız, 2025	•Merges CART with KNN. •Introduces pre-pruned steps. •Refines spatial distance metrics. •Enhances early-stage screening.	Boosts computation speeds while maintaining solid algorithmic stability.
6	Brain beta-amyloid measures and magnetic resonance imaging atrophy both predict time-to-progression from mild cognitive impairment to Alzheimer's disease	Jack CR Jr, Wiste HJ, Vemuri P, et al., 2010	•Measures structural brain atrophy. •Evaluates cerebrospinal beta-amyloid. •Tracks MCI clinical conversion. •Maps progression time horizons	Provides baseline biological evidence for multi-modal feature selection models

III. METHODOLOGY OF PROPOSED SURVEY

1. Data Preparation and Preprocessing

We organized the raw brain scans into four folder categories based on disease severity. An automated script split these images into distinct training and evaluation sets. We resized every scan to a standard \(128 \times 128\) pixels to keep the inputs uniform. Next, we scaled pixel intensities to fall strictly between 0 and 1. This normalization keeps gradient updates stable and ensures consistency across the pipeline.

2. CNN Architecture

Next, we built a Convolutional Neural Network (CNN) for multi-class classification. The network uses alternating convolutional and max-pooling layers. These lead into a flattening step, dense layers, and dropout regularization to curb overfitting. The convolutional layers extract key spatial features from the scans. The dense layers then calculate the final diagnostic probabilities. We used the Adam optimizer to minimize categorical cross-entropy loss, tracking overall accuracy as our main metric.

3. RNN/LSTM Integration

To explore deeper patterns, we fed the CNN's output probabilities directly into a Recurrent Neural Network (RNN). We reshaped the prediction vectors into sequential time-steps and passed them to a Long Short-Term Memory (LSTM) network. This step evaluates whether tracking sequential feature dependencies boosts final classification performance. We trained and tested both architectures on identical data splits to ensure a completely fair comparison.

4. Flask Web Deployment

Finally, we integrated the top-performing model into a responsive Flask web application. When a user uploads a new scan, the app preprocesses it exactly like the training data. The optimized CNN then analyzes the image to pinpoint the diagnostic stage. The interface displays this prediction on-screen alongside helpful context. This setup shows how a trained model effectively transitions from research into a practical decision-support tool

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IV. CONCLUSION AND FUTURE WORK

Proposed Framework and System Overview

In this study, we built a deep learning system to automate multi-stage Alzheimer's disease classification from structural brain MRIs. The core pipeline paired a convolutional neural network for spatial feature extraction with a recurrent neural network to explore feature-level sequential dependencies. To make this technology practical and accessible, we hosted the trained network inside a responsive Flask web application that handles real-time scan predictions through a simple user interface. Our experimental results ultimately revealed that the standalone CNN significantly outperformed the hybrid RNN configuration, making the CNN the clear choice for our final system deployment.

Performance Analysis and Limitations

While this approach proves that automated multi-stage Alzheimer's screening is viable, the quantitative data pinpointed a few engineering bottlenecks. Specifically, we encountered a moderate validation threshold and highly skewed class distribution across our dataset. These limitations show that the network still needs targeted adjustments to improve its generalizability and reduce misclassifications between adjacent stages of the disease.

Future Work and Roadmap

Moving forward, our development roadmap will prioritize integrating transfer learning pipelines and applying stricter regularization techniques. We also plan to use class-balanced training methods, embed explainable AI frameworks for better transparency, and test the model against independent external datasets. Despite its current constraints, this end-to-end pipeline offers a highly functional, reliable blueprint for building next-generation structural MRI classification tools.

REFERENCES

[1] "Multi-View Convolutional Neural Networks for Alzheimer's Disease Classification with MRI and PET Data," IEEE Transactions on Medical Imaging, 2022, doi: 10.1109/TMI.2022.3167651.
[2] "Improving Alzheimer's Disease Diagnosis with Deep CNNs: A Comprehensive Study on Multi-Scale and Multi-Modal Data," IEEE Transactions on Computational Imaging, 2022, doi: 10.1109/TCI.2022.3178293.
[3] "Exploring Convolutional Neural Networks for Alzheimer's Disease Detection in MRI: A Data Augmentation Approach," IEEE Transactions on Neural Networks and Learning Systems, 2023, doi: 10.1109/TNNLS.2023.3233456.
[4] "Challenges in Applying Deep Learning to Alzheimer's Disease Diagnosis," IEEE Xplore, 2023.
[5] "Recent Advances in Deep Learning for Alzheimer's Disease Diagnosis," IEEE Xplore, 2024.
[6] Alzheimer's Disease Neuroimaging Initiative (ADNI). [Online]. Available: https://www.google.com/search?q=http://adni.loni.usc.edu/
[7] Open Access Series of Imaging Studies (OASIS). [Online]. Available: https://www.oasis-brains.org/
[8] "A Predictive and Adaptive Mobile/Web Application for Alzheimers Disease using Machine Learning", IEEE Xplore Part Number: CFP24AWO-ART; ISBN: 979-8-3503-7797-2
[9] "A Survey on Machine Learning and Deep Learning Techniques for Alzheimer's Disease Prediction", 979-8-3503-6800-0/24/$31.00 ©2024 IEEE | DOI: 10.1109/ICAITPR63242.2024.10960027
[10] "Predicting Alzheimer's Disease Progression and Stage Classification using Deep Learning Model", 979-8-3503-9211-1/24/$31.00 ©2024 IEEE | DOI: 10.1109/TIACOMP64125.2024.00042
[11] "Alzheimers Disease Classification with Deep Learning Approaches", 979-8-3315-3519-3/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICPCSN65854.2025.11035791
[12] "Alzheimer's Disease Detection Using Ensemble Techniques on MRI Images", 979-8-3315-0985-9/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICOACT63339.2025.11005279
[13] "Alzheimer's Diseases Detection by Using Deep Learning Algorithms: A Mini-Review", Digital Object Identifier 10.1109/ACCESS.2020.2989396
[14] "Cart KNN: A hybrid distance-based pre-pruned classification and regression method for the early diagnosis of Alzheimer's disease", Web page info: https://sigma.yildiz.edu.tr DOI: 10.14744/sigma.2025.00147
[15] "Cognitive activity detection and tracing system", Web page info: https://sigma.yildiz.edu.tr DOI: 10.14744/sigma.2024.00094

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International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

[16] "Classification of Patients with Alzheimer's Disease and Healthy Subjects from MRI Brain Images Using the Existence Probability of Tissue Types", 978-1-5386-2633-7/18/$31.00 ©2018 IEEE | DOI: 10.1109/SCIS-ISIS.2018.00172

[17] "Spam review detection using self attention based CNN and bi-directional" Bhuvaneshwari, P., Rao, A. N., & Robinson, Y. H. (2021). LSTM. Multimedia Tools and Applications, 80(12), 18107-18124.

[18] "An intelligent framework for Alzheimer's disease classification using EfficientNet transfer learning model" Sethi, M., Ahuja, S., Singh, S., Snehi, J., & Chawla, M. (2022, March).In 2022 International Conference on Emerging Smart Computing and Informatics (ESCI) (pp. 1-4). IEEE

[19] "Brain beta-amyloid measures and magnetic resonance imaging atrophy both predict time-to-progression from mild cognitive impairment to Alzheimer's disease.", Jack CR Jr, Wiste HJ, Vemuri P et al.: 133, 11,3336-3348,2010

[20] "Mapping Alzheimer's disease progression in 1309 MRI scans: Power estimates for different inter-scan intervals", Hua X, Lee S, Hibar DP, et al.: 51: 63-75, 2010.