Hadeel Q. Sattar

EARLY DETECTION OF ALZHEIMER' S DISEASE USING ARTIFICIAL INTELLIGENCE AND MRI BRAIN IMAGES

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NEAR EAST UNIVERSITY

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Declaration

I declare that all information, documents, analysis, and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of the Institute of Graduate Studies, Near East University. As required by these rules and conduct, I also declare that I have fully cited and referenced information and data not original to this study.

Hadeel Q. Sattar

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Hadeel Q. Sattar

Abstract

EARLY DETECTION OF ALZHEIMER'S DISEASE USING ARTIFICIAL INTELLIGENCE AND MRI BRAIN IMAGES

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Abstract

The early diagnosis of Alzheimer's Disease (AD). Early and correct diagnosis of Alzheimer's Disease (AD) would play an essential role in the timely intervention but is hampered by subtle changes in the structural brain (and the variable MRI protocols). In this work, we utilize a very unbalanced Kaggle Alzheimer's MRI dataset with 6,400 axial T1 weighted scans in four diagnostic classes ("No Impairment" 3,200, "Very Mild" 2,240; "Mild" 896; "Moderate" 64)—to design a strong two-stage architecture that incorporates sophisticated non-parametric preprocessing with ensemble of state-of-the-art CNNs (ResNet-50, EfficientNetV2-S, ConvNeXt-Base). First, non-parametric localization identifies areas of interest (e.g., hippocampus) and specifies ideal bounding volumes. After that, image enhancement (bias-field correction, adaptive histogram equalization) enhances low-contrast features. The improved volumes are resampled to 128 × 128 128 and piped to each CNN backbone; their outputs are averaged for final classification. Individually, ConvNeXt-Base achieved 91% accuracy, EfficientNetV2-S 98.8%, and ResNet-50 97.5%; the ensemble achieved 98.1% overall accuracy, where sensitivity and specificity were both over 97% on a multi-center test set. These results indicate that preprocessing-informed localization and enhancement significantly increase the power of deep learning classifiers, having a trustworthy, high-accuracy, and scalable solution to early AD detection in various clinical environments.

Keywords: Alzheimer's Disease, Artificial Intelligence, MRI, Convolutional Neural Network, Early Detection, Diagnostic Accuracy.

Özet

ALZHEIMER HASTALIĞININ ERKEN TESPİTİ İÇİN YAPAY ZEKA VE MRI BEYİN GÖRÜNTÜLERİNİ KULLANMA

Hadeel Qasim Sattar

Biyomedikal Mühendisliği Bölümü, Yüksek Lisans

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Alzheimer Hastalığı'nın (AH) erken teşhisi, zamanında müdahale açısından kritik öneme sahip olmakla birlikte, beyin yapısındaki ince değişiklikler ve değişken MRI protokolleri nedeniyle zorluklarla karşılaşmaktadır. Bu çalışmada, dört tanı sınıfını içeren ("Hasar Yok" 3.200, "Çok Hafif" 2.240, "Hafif" 896, "Orta" 64) toplam 6.400 aksiyel T1 ağırlıklı MRI taramasından oluşan ve oldukça dengesiz bir Kaggle Alzheimer veri setini kullanarak, gelişmiş parametrik olmayan ön işleme adımlarıyla desteklenen ve ResNet-50, EfficientNetV2-S ile ConvNeXt-Base modellerinden oluşan bir topluluk (ensemble) mimarisini birleştiren güçlü bir iki aşamalı çerçeve tasarladık. İlk aşamada, parametrik olmayan lokasyon yöntemleriyle ilgi alanları (örn. hipokampüs) belirlenip optimal sınırlayıcı hacimler tanımlanır. İkinci aşamada ise önyüz düzeltme (bias-field correction) ve uyarlanabilir histogram eşitleme gibi görüntü güçlendirme teknikleriyle düşük kontrastlı özellikler vurgulanır. Güçlendirilmiş hacimler 128×128×128 boyutlarına yeniden örneklenerek her bir CNN çekirdeğine beslenir; modellerin çıkışları ortalanarak nihai sınıflandırma yapılır. Tek başına ConvNeXt-Base %91; EfficientNetV2-S %98 ; ResNet-50 ise %97,5 doğruluk elde ederken; topluluk modeli %98,1 genel doğruluk, %97'nin üzerinde duyarlılık ve özgüllük değerleri sunmuştur. Elde edilen sonuçlar, ön işleme tabanlı lokasyon ve görüntü güçlendirmenin derin öğrenme sınıflandırıcılarının performansını önemli ölçüde artırdığını, erken AH tespiti için güvenilir, yüksek doğruluklu ve ölçeklenebilir bir çözüm sunduğunu göstermektedir.**Anahtar Kelimeler: Alzheimer Hastalığı • Yapay Zeka • MRI • Konvolüsyonel Sinir Ağları • Erken Teşhis • Tanısal Doğruluk**

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List of Abbreviations

Abbreviation	**Full Form**
AD	Alzheimer's Disease
AI	Artificial Intelligence
MRI	Magnetic Resonance Imaging
CNN	Convolutional Neural Network
BRATS	Brain Tumour Segmentation
SVM	Support Vector Machine
fMRI	Functional Magnetic Resonance Imaging
PET	Positron Emission Tomography
DL	Deep Learning
RNN	Recurrent Neural Networks
LSTM	Long Short-Term Memory Networks
GRU	Gated Recurrent Units
GAN	Generative Adversarial Networks
TL	Transfer Learning
ViT	Vision Transformers
SAGAN	Self-Attention Generative Adversarial Network
TP	True Positives
TN	True Negatives
FP	False Positives
FN	False Negatives

Abbreviation	**Full Form**
FAD	Familial Alzheimer's Disease
MCI	Mild Cognitive Impairment
T2DM	Type 2 Diabetes Mellitus
AGE	Advanced Glycation End Product
CT	Computed Tomography
ReLU	Rectified Linear Unit
SPECT	Single-Photon Emission Computed Tomography
APP	Amyloid Precursor Protein

Definition of Terms

Alzheimer's Disease (AD): A progressive neurodegenerative disorder associated with loss of memory, loss of cognitive function, and formation of amyloid-β plaques and tau tangles in the brain.

Mild Cognitive Impairment (MCI): A midway condition between normal aging and dementia, characterized by detectable—but not paralyzing—cognitive decline, which migrates to AD.

Magnetic Resonance Imaging (MRI): A non-surgical method for using powerful magnetic fields and radio waves to create clear images of the brain's soft tissue without surgery.

Functional MRI (fMRI): An MRI scan with an option to map human brain activity based on blood-flow variation, showing functional rather than structural information.

Artificial Intelligence (AI): Computer science that engineers systems that can complete tasks calling for human perception, reasoning, and decision-making.

Machine Learning (ML) is also classified as a subset of AI, where algorithms learn to recognize patterns from data and make judgments or predictions based on the patterns learned without specific programming.

Deep Learning (DL): ML division based on multi-layer neural networks to identify hierarchical features for complex data automatically.

Convolutional Neural Network (CNN): DL architecture tuned on grid-like data (e.g., images), where we use convolutional layers to learn the spatiotemporal structure of feature hierarchies.

Residual Network (ResNet): A CNN with the "skip" connections that would remove vanishing-gradient problems and allow for the development of deeper models.

EfficientNetV2: A CNN family that mixes depth, width, and resolution by compound scaling – high accuracy with fewer parameters.

ConvNeXt: A contemporary CNN design using blocks inspired by the Transformers and normalization improvements for better image-processing performance.

Vision Transformer (ViT): A DL model that uses Transformer self-attention on image patches and extracts local and global context.

Trustworthy AI (TAI): Framework for making AI systems transparent, fair, robust, and clinically reliable, which is vital in medical imaging.

Biomarkers: Quantifiable biological measures of diseases (hippocampal volume, cortical thickness, amyloid load) used to indicate the presence or progression of the disease.

Classification: The process describing how input data (e.g., an MRI scan) is assigned into pre-defined categories using data learned features (e.g., Healthy, MCI, AD).

Sensitivity & Specificity: Metrics of classifier performance – sensitivity being the true-positive rate, specificity the true-negative rate, required for a reliable diagnosis.

Explainable AI (XAI): Techniques such as Grad-CAM that map where such input regions have come from, supporting clinical trust and interpretability.

CHAPTER I

Introduction

Alzheimer’s Disease (AD) constitutes a significant segment of worldwide Dementia burdens while remaining the most widespread and dangerous form of Dementia. The progressive neurological illness known as Dementia destroys memory-related cognitive abilities along with comprehension and intelligence until both patients and their family members experience absolute disability. Neurodegenerative Alzheimer’s Disease manifests as a cunning brain disease that degenerates neural pathways while amyloid plaques, together with tau tangles, accumulate as neurons slowly break down (Ahmad et al., 2022).

The goal of this study on Alzheimer’s Disease relies on MRI as the ideal imaging method because its noninvasive brain visualization with high-resolution capabilities solves imaging limitations. We mainly measure Alzheimer’s Disease symptoms through structural and functional changes in distinct brain regions, with particular attention to the medial temporal lobe. The hippocampus emerges as a vital brain area because it controls memory formation and retrieval activities (Bao et al. 2021).

Through MRI technology, users have obtained fundamental brain information, including structural size features, cortical thickness measurements, and densities of white and gray matter, for many years. An early diagnosis of the disease might be possible by detecting minimal changes in these metrics, which can help identify illness manifestations ahead of prominent clinical indications. Early identification of diseases enables healthcare professionals to implement therapeutic actions that prevent disease progression and enhance patient quality of life (Diogo et al., 2022).

Artificial Intelligence (AI) and Machine Learning enable quick and automated MRI data evaluation through recently developed systems. Research institutions should integrate these advanced technologies to generate predictive brain models that enhance the quality of diagnosis and inform exclusive treatment methods. Technological advances in MRI imaging have become essential because of Alzheimer's growing global impact, so healthcare professionals can better understand and develop better patient care strategies (V, Nisha A et al. 2024).

During the last two years, Deep Learning (DL) methods have achieved superior results in diverse application fields, including computer vision, natural Language Processing, healthcare, remote sensing, and Natural Language Processing. Nevertheless, the foundational psychological paradigm has transitioned to distributed-based meaning interpretation versus formal symbolic systems (Mirzaei et al., 2025; Ahmadzadeh et al., 2024). New model systems and training methods have led to computational models with better performance than previous Machine Learning systems, alongside capabilities that match human-level achievement for specific tasks (Zhang et al., 2022).

Medical staff can detect AD biomarkers in their early stages through MRI techniques. Even though MRI data evaluation by hand requires great dedication, it is prone to subjective reading errors and frequently demands expert handling skills. High-dimensional imaging data makes Machine Learning challenging because it requires expert-designed features and encounters obstacles from diverse data patterns. The need for data-driven, innovative solutions arises to identify specific elements in major features of data, neuroimaging information, and other datasets that aid in earlier diagnosis of conditions while enhancing patient care (Wasim et al., 2023).

1.1 Background

As a mildly progressive brain illness, Alzheimer's Disease causes the deterioration of mental functions through amyloid-beta plaque accumulation and tau protein tangle formation, which interferes with neuron connections and leads to brain atrophy. The disease shows initial signs of brain changes in memory-learning areas such as the hippocampus, leading to advanced cognitive breakdown and decreased daily functioning capabilities. The integration of histogram-based approaches, employing MRI equipment and deep learning (DL) methods, demonstrates promise in detecting initial neuroanatomical indicators of the illness, thus enabling targeted medical treatments during this stage of development. Early detection and diagnosis of Alzheimer's Disease remain critical because they enhance patient life quality while minimizing healthcare system costs (Zia-ur-Rehman et al. 2024).

MRI is one of the non-invasive image modalities that uses high-strength magnetic fields with radiofrequency pulses rather than ionizing radiation to provide detailed soft-tissue contrast views of body internals. Hardware improvements to superconducting magnets, alongside software modifications, have enhanced the imaging ability of the system to display intricate body elements, including brain tissue components, cerebrospinal fluid, and vascular systems. The acceptance of neuroimaging reports about MRI has led to widespread professional and practical applications for clinical research of neurological disorders, disease monitoring, and therapy evaluation (Benson et al. 2020).

DL has made significant advancements in the last decade due to improved neural networks, optimization algorithms, and increased computational power. DNNs process large multidimensional information to detect intricate patterns while self-learning without requiring pre-defined characteristic features. The integration of Vision Transformers and improved versions of convolutional networks and graph-based networks delivers top performance in different task domains. Unsupervised and semi-supervised learning methods allow researchers to reduce dataset labeling needs, making these systems available to broader applications even with minimal resources. Studies aimed at increasing the interpretability and robustness alongside ensuring the fairness of models solve the “black-box” problems and bias found in DL systems. DL has matured enough to use its power in healthcare decisions while considering explainable AI, ethical alignment, and computational efficiency to maintain trustworthiness within AI systems (Gohel et al. 2021).

Both Alzheimer’s Disease and common Neurodegenerative disorders exist together as they represent the worldwide leader in the Dementia generation despite demonstrating symptoms of cognitive decline and memory loss. Standard medical procedures cannot identify minor alterations in the brain during the early stages. DL is a promising solution against this issue through automated processes that extract complex neuroimaging data, including MRI and PET, to boost early disease identification. Healthcare professionals benefit from using DL techniques to analyze genetic data alongside cognitive data, which enables the detection of disease biomarkers and disease advancement to deliver customized medical solutions (Zhang et al., 2022).

Convolutional Neural Networks (CNNs) are a basic DL model for processing grid-like topology data, especially images, which automatically extract spatial features from raw input data. CNNs use convolutional layers to pass filters on image data, detecting patterns from edges to textures to more complex structures, then pooling layers for dimensionality reduction, retaining important information. These architectures allow CNNs to extract low-level and high-level hierarchical features from the image efficiently, making CNNs highly suitable for image classification, object detection, and segmentation-based tasks (Tan et al. 2020)

The development of DL exceeded 2020 standards using advanced neural network designs, optimization strategies, and increased computation availability. DNNs extract complex data patterns from high-dimensional data types, which include medical images and genomic sequences, without needing user-defined features. The integration of Vision Transformers and improved versions of convolutional networks and graph-based networks delivers top performance in different task domains. The advancement of unsupervised and semi-supervised learning leads toward decreasing the requirement of labeled data, which extends these technologies to various applications and trains them using fewer resources. Weatherproofing models, guaranteeing interpretability and fairness, and eliminating the black-box architecture issues characterize DL system improvement efforts. The advancing capabilities of Deep Learning technology continue to transform decision processes within medical care and financial management. At the same time, environmental science focuses on explainable AI solutions, ethical alignment, and operational efficiency for building trustful and transparent AI systems (Gohel et al. 2021).

Both Alzheimer’s Disease and common Neurodegenerative disorders exist together as they represent the worldwide leader in the Dementia generation despite demonstrating symptoms of cognitive decline and memory loss. Standard medical procedures cannot identify minor alterations in the brain during the early stages. DL is a promising solution against this issue through automated processes that extract complex neuroimaging data, including MRI and PET, to boost early disease identification. Healthcare professionals benefit from using DL techniques to analyze genetic data alongside cognitive data, which enables the detection of disease biomarkers and disease advancement to deliver customized medical solutions (Zhang et al., 2022).

1.2 Problem Statement

The field of medical imaging continues to face significant challenges when attempting early detection of Alzheimer's Disease (AD) in its accurate form. The adoption of DL methods for neurodegenerative condition classification has recently increased, although current CNN designs struggle to detect subtle MCI patterns that precede AD, along with AD signs. Standard modeling approaches face limited applicability across diverse patient populations, along with adverse effects from variations in image quality, limited available data, and the unclear nature of brain changes related to AD. Current AD diagnosis relies on manual interpretations by clinicians and researchers since there are no reliable automated tools for early diagnosis. This remains crucial for activating intervention methods to minimize disease advancement and enhance treatment outcomes.

This work will examine the limitations in previous research through three cutting-edge DL frameworks, ResNet, EfficientNetV2, and ConvNeXt, to develop an advanced CNN model dedicated to AD diagnosis. The goal is to implement recent state-of-the-art architectures into models to boost feature extraction capabilities while providing robustness to enhance diagnostic precision. The proposed methodology addresses these gaps in AD detection methods to develop an automated solution that provides clinical support for informed medical decisions, driving improved patient outcomes.

1.3 Aim of the Study

This thesis seeks to perform an extensive comparative analysis of three of the latest convolutional neural network structures for the early identification of Alzheimer's disease from weighted MRI brain images, namely, ResNet-50, EfficientNetV2-S, and ConvNeXt-Base. More specifically, we will train and validate each model on a standardized, multi-center Alzheimer's MRI dataset to measure and compare the accuracy, sensitivity, specificity, precision, and F1-score results over healthy control, mild cognitive impairment, and Alzheimer's cohorts. We will also investigate various ensemble strategies, including weighted averaging and stacking, to see if the combination of these models can subsequently enhance diagnostic robustness and early-stage detection capability. Finally, to ensure that regions highlighted by each network correspond to known Alzheimer's biomarkers and hence both quantitatively and potentially clinically interpretable, we will analyze model explainability using saliency mapping (e.g., Grad-CAM).

1.4 Purpose of the Study

This Study aims to develop and test a novel convolutional neural network (CNN) model that combines ResNet with EfficientNetV2 and ConvNeXt architecture to achieve superior accuracy alongside robustness in Alzheimer's Disease (AD) detection. The research incorporates state-of-the-art CNN architecture networks, which improve AD detection in early stages with superior accuracy rates. The proposed diagnostic tool aims to deliver high scalability and performance excellence for clinical support systems that enable early treatment while improving patient results.

1.5 Research Questions

1. The classification accuracy of Alzheimer's Disease diagnoses using combined ResNet, EfficientNetV2, and ConvNeXt outlooks exceeds the accuracy rates of individual CNN models to what degree?

2. Additional analysis must evaluate the accuracy level of early AD vs everyday subject discrimination from the improved CNN framework compared to single-CNN models.

3. Implementing distinct leading-edge architectural methods produces benefits for model performance stability across multiple MRI databases under different imaging conditions.

4. The combination model may boost diagnostic accuracy by minimizing image errors, enabling earlier and more precise AD diagnosis.

5. The new combined model does not substantially affect clinical outcome measures, including intervention duration and psychiatric symptom distribution.

1.6 Significance of the Study

Individuals who have Alzheimer's Disease require accurate early diagnosis of their condition since this enables healthcare providers to start interventions that delay disease development while improving patient quality of life. The clinical goal of early Alzheimer's disease (AD) detection requires improved imaging methods to screen patients for their evolving brain structure. However, current diagnostic tools prove unsuccessful in identifying the early stages of AD because standard imaging methods lack sufficient sensitivity and struggle to comprehend the disease's heterogeneity. We address these restraints by creating a new CNN model that combines architectural components from ResNet, EfficientNetV2, and ConvNeXt to achieve superior AD classification results (Fuad et al., 2021(.

Using multiple state-of-the-art DL architectures creates essential contributions to medical imaging practice and Artificial Intelligence development. The consolidated model draws positive features from the ResNet residual structure with EfficientNetV2 scaling rules, and ConvNeXt revitalized CNN frameworks to boost MRI pattern-finding ability and feature retrieval function. The combined capabilities strengthen classification accuracy while improving reliability and enabling better dataset and imaging scenario generalization performance. The paper helps establish accurate and usable diagnostic tools that medical institutions need to reach widespread clinical adoption (Diogo et al., 2022).

A clinical diagnosis using this study offers dramatically heightened precision, which allows healthcare professionals to identify AD at earlier stages for implementing preventive measures. People who initiate care treatment early achieve better symptom management and reduced disease progression, which yields favorable results. The automatic system of the proposed CNN model reduces healthcare providers' dependency on specialized expertise for image analysis. However, this makes AD diagnostics more accessible throughout various healthcare facilities, including low-resource settings (Ye et al., 2024).

The research holds significance in exploring how brain anatomical changes enable better predictions about the efficacy of DL models through upgraded preprocessing solutions. The enhanced detection of AD becomes possible through these improvements while uncovering essential AD pathological principles that lead to new biomarkers and therapeutic targets for treating AD disease. This research is vital because it presents a practical approach to diagnosing Alzheimer's disease (AD) early, which can inform future diagnostic methods. State-of-the-art Deep Learning approaches form part of this proposed work to address automatic diagnosis (AD) classification limitations while building next-generation artificial intelligence-medical imaging convergence methods, thereby contributing to better clinical outcomes and advancing the fight against Alzheimer’s disease (Minaee et al., 2022).

CHAPTER II

Literature Review

This chapter examines scholarly works about the Early Detection of Alzheimer's Disease Using Artificial Intelligence and MRI Brain Images found in previous research. The research investigations follow a three-step structure. The following section discusses studies that implement traditional methods for proposal and execution work. Then, machine Learning-Based Systems are reviewed. The last section provides an overview of research directions on complex methodology developments, including deep learning (DL) approaches (such as CNN), Artificial Intelligence technologies, and equivalent systems.

2.1 Traditional Method-Based Systems

The research and development of Artificial Intelligence (AI) technology to identify early-stage Alzheimer's Disease (AD) from MRI brain images have relied on statistical methods and Machine Learning algorithm-based traditional approaches (Hussain et al., 2021; Sekeroglu and Emirzade, 2018). The analysis of MRI scans using hand-engineered features relies on domain specialists who create and measure specific biological markers and morphological characteristics within the images. The algorithms employ multiple classifiers, including SVM, Random Forests, Logistic Regression, k-NN, and plenty more. Traditional approaches remain relevant within Machine Learning due to their interpretability advantages and occasional benefits in resource management. The article evaluates studies concerning AD classification that were published after 2020 while using established analytical methods.

Dara et al. (2023) An MRI image processing model uses Machine Learning algorithms to detect Alzheimer's Disease (AD). It was a three-stage system. Before analysis, the researchers normalized the intensity values in raw MRI images through Gaussian filtering for de-noising purposes. Relevant features, which included hippocampal volume and cortical thickness, were extracted in this stage through statistical and morphological operations. The SVM classifier implemented a radial basis function (RBF) kernel to train features from this stage. The system tested its classification performance on the ADNI dataset, which yielded accuracy results and sensitivity and specificity rates of 92%, 89%, and 94%, respectively. These methods validate the use of traditional features as a tool to detect Alzheimer's disease.

Arafa et al. (2022) established a new hybrid model combining Machine Learning with DL methods to detect Alzheimer's Disease (AD) in MRI images during early stages. The model built its system through three successive development phases. The proposed preprocessing method includes skull stripping and intensity normalization, which transforms raw MR images. The first analysis stage delivered hippocampal volume and cortical thickness values, but additional disease markers came from varied morphological and statistical methods. The processing system delivered its features to a DL-based CNN to perform the classification. The system achieved groundbreaking validation through real-world ADNI data, which enabled it to identify MCI cases at an outstanding 95.3% success rate, thus helping to differentiate AD, MCI, and normally aging brains. An integrated approach shows remarkable effectiveness in diagnosing and predicting diseases through traditional and high-end methods, for instance. The correct diagnosis of Dementia requires implementing advanced methods at various levels.

Sharma and Mandal (2023) describe a new Machine Learning prediction model for Alzheimer's disease that operates as the core element within a multi-modal neuroimaging-based system. The system operates through three sequentially planned stages. The first processing stage for raw neuroimaging data (such as MRI and fMRI scans) included multiple operations, which started with intensity normalization, followed by advanced filtering methods for denoising. Various statistical methods, combined with feature extraction algorithms, enabled the extraction of essential features, including hippocampal volume, cortical thickness, and other biomarkers, from the dataset during the second stage. Three essential features were processed for classifier execution through an SVM classifier equipped with an RBF kernel. A 92% classification outcome and 94% specificity of 94% emerged when the model was tested on the ADNI dataset. The system exemplifies combining classical and statistical approaches alongside machine learning for Alzheimer's disease diagnostic systems.

Upadhyay et al. (2024) suggested how to identify Alzheimer's Disease (AD) in neuroimaging data through an integration of DL (DL) and Machine Learning (ML) systems. It was done in three steps. The first step demanded that preprocessing techniques be applied to raw brain images for noise filtering and normalization to enhance image quality while removing extraneous features. A second step in this process uses the extracted key features as input for DL-based feature extraction that strengthens all obtained features. The classification process occurred on a hybrid model that consisted of Support Vector Machines (SVMs) and CNNs. The developed method reaches 94% sensitivity and 96% specificity, which leads to a 95.1% accurate classification of subjects within the ADNI dataset. The unified approach showed how classic ML algorithms and advanced DL models should operate together to develop efficient yet interpretable AD diagnosis methods. Singh and Thakur (2021) developed a system that utilized manually derived texture and shape features extracted from structural MRI images to perform AD classification. GLCM analysis and Shape Descriptors identified features, while an SVM radial basis function kernel (RBF) served as the classification algorithm. The system obtained 89% accuracy, 91% sensitivity, and 87% specificity during testing on data from the Alzheimer’s Disease Neuroimaging Initiative (ADNI). The analysis demonstrated how texture-based features successfully identify the minimal changes in brain structures that AD produces.

Chen et al. (2023) developed a method for AD detection by isolating specific regions for feature extraction and adding a classifier operated through Random Forests. Volumetric and intensity-based feature analysis became possible by segmenting particular brain regions, including the hippocampus, entorhinal cortex, and other relevant brain regions. This system obtained 92% accuracy in classification. It achieved a hippocampus segmentation Dice coefficient of 0.85 through testing and training in the OASIS (Open Access Series of Imaging Studies) dataset, containing information on 398 subjects. The system performs strong feature extraction from brain areas with maximum AD-related atrophy.

El-Gawady et al. (2023) developed a hybrid feature selection method that utilizes PCA and RFE on Logistic Regression for AD classification. PCA was used for dimensionality reduction, and the approach selected the most discriminative elements from volumetric and intensity-based features. These analysis results demonstrated 90%

accuracy, 88% sensitivity, and 92% specificity on the Australian Imaging, Biomarkers & Lifestyle (AIBL) dataset, thus proving that proper feature selection enhances the performance of classifiers efficiently.

2.2 Machine Learning-Based Systems

Shrestha & Das, (2022) An ML system is not only an algorithm; it also collects, processes and applies data. In the beginning, we collect raw data such as scans, profiles and text and afterward we fill in missing information, clear outliers and possibly normalize or extract important data. The next step is the main training period, where chosen machine learning models are taught findings from the prepared features based on the required goal (classification, regression, recommendation and so on). After finishing training, the system checks how it works on data it hasn't seen yet, using accuracy, precision, recall or AUC-ROC and may improve or adjust parameters to enhance the results. Importantly, when a ML system is ready to use, it includes tools to catch changes in data, displays influencing elements for users to see (such as feature importance) and provides protection from bias to guarantee fairness. The deployed model is added to APIs or user interfaces which allow any downstream application to use it for predictions and to keep a record of inputs and outputs for continual updating.

Teodorescu et al., (2021) A machine-learning system is designed to turn raw information into automated outcomes by linking data set elements and models together. First, it reads the data, fills the gaps, scales them properly and looks for or builds features that describe the problem (like hippocampal volume in an MRI or user–item interactions in recommender systems). Next, algorithms, for instance support vector machines, decision trees, neural networks or various ensembles are prepared to learn using labeled information, with the help of varying hyperparameters. As soon as the model is validated, it is used behind APIs or user interfaces to generate real-time outputs. Also such a system features ongoing checks for data drift, a decrease in system effectiveness and any unfairness; it also uses interpretable tools like feature-weight scores or saliency maps and prompts people to be involved at various steps to catch and deal with biased results before users are affected.

Martino et al.,(2025) In machine-learning systems act as complete systems that take raw data such as traffic logs, binaries and user actions and turn them into useful threat intelligence. The process first requires thorough data engineering: cleaning and standardizing the data, identifying both manually chosen and deep learning created features (such as network stats, opcode usage or behavior embeddings) and handling any issues caused by imbalanced classes by applying SMOTE or cost-sensitive sampling. After that, algorithms like support vector machines, decision trees, deep neural networks and ensemble models are taught and checked with cross-validation and using statistical indicators such as AUC-ROC, precision and recall. Once deployed, these models work behind APIs that monitor data in real-time or SIEM platforms and any time a shift in results is noticed, the models are retrained. Strong ML tools have built-in functions that make it easy to understand the system (like feature-importance scores) and allow analysts to see any mistakes, so automation complements, not competes with, people's skills. Merging automatic pattern detection with professional monitoring, modern ML technology provides broad and flexible protection from sudden intrusions, different kinds of malware and anything that seems unusual in computer networks.

2.3 CNN-Based Systems

AbdulAzeem et al. (2021) developed the deep segment architecture according to AbdulAzeem et al. (2021) to segment markers from MRI scans that indicate Alzheimer's Disease (AD). The system operated in two main, distinctive stages. The U-Net framework received architectural alterations in the first development phase, creating an improved structure for extracting features from neuroimaging datasets. This modified U-Net architecture used the original decoder part to segment markers. Still, it replaced its encoder section with VGGNet, ResNet, DenseNet, Xception, MobileNet, NASNet, and MobileNetV2 functions to improve detection capability. The model received training with k-fold cross-validation using a two-fold configuration to secure a reliable training and validation process. The model's generalization improved through data augmentation strategies, including flipping, rotation, and elastic transformation methods, to increase the quantity of the training sample. The system was tested using sensitivity and specificity metrics and distance and dice score metrics through a combination of the BRATS 2019 dataset and a custom study-specific dataset. The modified U-Net with Xception achieved remarkable results on the BRATS 2019 dataset, demonstrating a dice score of 0.86, a specificity of 99.8%, and a sensitivity of 91%. Equally, good results were obtained on the self-made dataset.

AlSaeed and Omar (2022) Researchers developed the Deep Segment architecture according to AbdulAzeem et al. (2021) to segment markers from MRI scans that indicate Alzheimer's Disease (AD). The system operated in two main, distinctive stages. The initial part of the study made architectural changes to the U-Net framework layers while optimizing neuroimaging dataset feature extraction efficiency. This modified U-Net architecture used the original decoder part to segment markers. Still, it replaced its encoder section with VGGNet, ResNet, DenseNet, Xception, MobileNet, NASNet, and MobileNetV2 functions to improve detection capability. The model received training with k-fold cross-validation using a two-fold configuration to secure a reliable training and validation process. The model's generalization improved through data augmentation strategies, including flipping, rotation, and elastic transformation methods, to increase the quantity of the training sample. The system was tested using sensitivity and specificity metrics and distance and dice score metrics through a combination of the BRATS 2019 dataset and a custom study-specific dataset. The modified U-Net with Xception achieved remarkable results on the BRATS 2019 dataset, demonstrating a dice score of 0.86, a specificity of 99.8%, and a sensitivity of 91%. Equally, good results were obtained on the self-made dataset.

Shukla et al. (2023) The novel research by Shukla et al. (2023) developed two proposed systems for AD detection through hybrid feature extraction and DL operations based on multimodal imaging input. The system operated through three successive levels, beginning with Digital Engineering, then Hardware, and ending with Software. MRI and PET images underwent preprocessing to enhance image quality, including skull stripping, intensity normalization, and motion artifact removal. After extracting handcrafted features from hippocampal volume and cortical thickness, the system added DL features produced by 3D Convolutional Neural Network (3D-CNN) capabilities. An ensemble decision system made robust predictions by combining Support Vector Machines with SVM and

3D-CNN features. The method received 99% AD detection accuracy in the ADNI dataset through feature-level fusion-based methods, alongside solid performance for both ADNI binary and multi-class classification tasks.

Sharmili et al.(2023) developed a 3D U-Net architecture as the base of their proposed system, which contained two essential components for segmenting brain tumors from MRI images. The first operational step of the model used pre-processing treatments on images to achieve suitable segmentation results. The initial processing stage used area cropping to cut brain region pieces from the input data, thus making processing more efficient. After normalization processes, the intensity scales of various scanned images were matched. The split data consisted of three subsets: the train received 82%, the validation acquired 6%, and the test acquired 12% of the data for comprehensive evaluation. Small portioned image patches served as inputs for the simpler PEs throughout the first network layer to reduce the high computational and memory requirements from processing complete, extensive volumetric data from all available Magnetic Resonance Imaging (MRI) scans. The methods, which depended on data augmentation with rotations and mirroring to improve model robustness and prevent overfitting, were not applied according to our experience. The segmentation process of tumors in stage two utilized the 3D U-Net architecture. The 3D U-Net architecture was created to process volumetric data with dependencies in spatial hierarchies crucial to medical image segmentation work. Researchers tested the system by measuring its performance through dice score and Hausdorff95 metrics when applying it to the BRATS 2019 and BRATS 2020 datasets. These results demonstrated highly accurate segmentation ability because the algorithms achieved dice scores of 0.78 and 0.72.

Mohi Ud Din et al. (2023) proposed Alzheimer’s Disease Classification Using MRI Images using a new system architecture named MVP-Net. The methodology contained four separate stages. The first stage involved MRI image preprocessing, which consisted of changing the images to 224x224 pixel resolution combined with intensity value normalization for data synchronization. The training set became more robust through image transformations, including rotation, scaling, and flipping procedures. The second phase of code development introduced elements for multi-view processing that extracted spatial characteristics through 2D and channel-wise convolutional layers. Hierarchical Batch Norms are implemented after concatenation layers to optimize filter maps and minimize parameter counts. The third phase incorporated cross-entropy loss and batch normalization to enhance learning efficiency in the architecture design. A complete validation occurred when the model underwent a five-way classification analysis on ADNI data. Each measurement included accuracy alongside precision and sensitivity, which, combined with the F1-score, reached 96.6% in determining Alzheimer's disease stage using MVP-Net. A framework was developed to demonstrate strength through its ability to maximize sophisticated neuroimaging data with an efficient minimal model.

2.4 Summary and Future Directions

The thread research points to substantial Developments in the use of AI and MRI brain images for early detection of Alzheimer’s Disease. Shallow learning techniques within traditional methods have operated as the fundamental approaches to feature extraction and data classification from the beginning. New deep learning systems, particularly convolutional neural networks (CNNs) and transformer-based models have improved both accuracy and robustness in diagnosis through their ability to extract automatic features while recognizing complex data patterns. The advancement of AD classification methods needs to concentrate on these main areas in future research.

- Through DL, medical professionals can eliminate the requirement of human-generated feature engineering techniques, which reveal delicate and intricate AD-related brain changes.
- Develop a comprehensive diagnosis system that unites MRI information with genetic information, assessment results, and specific medical indicators.
- Explainable AI systems need development to present valid predictions and helpful explanations, enhancing clinical staff confidence and acceptance of adoption.
- Applying generalized and robust models depends on massive, widespread datasets combined with advanced regularization methods to maintain stable performance across various demographic groups and picture documentation protocols.

- AI models used in clinical operations must offer immediate availability and implementation of AI classification systems to assist AD diagnosis and prognosis so doctors can make personalized, real-time patient care decisions. Follow-up research designs enabling the monitoring of disease advancement will improve AI system prediction capabilities across multiple periods.
- The combination of classical Machine Learning methods alongside DL approaches in hybrid models enables organizations to derive both methods' strengths for possibly achieving better and more precise classification systems.

Researchers must address these difficulties to develop increasingly accurate measurement methods for Alzheimer’s Disease detection. These methods will produce more reliable clinical assessments, which will help patients experience better outcomes.

CHAPTER III

Alzheimer’s Disease

The progressive neurological disease named Alzheimer's disease leads to declining cognitive functions, which primarily affect memory functions while remaining among the primary dementia causes worldwide. The illness affects both patient independence and lifestyle, together with daily living activities, and causes a psychiatric and social burden that burdens families alongside caregivers (Breijyeh & Karaman, 2020).

3.1 Dementia manifests as Alzheimer's disease

Alzheimer's disease causes a continuous decline in cognitive abilities and memory deterioration. The most common form of dementia displays distinct characteristics and main features: The protein aggregation pattern in Alzheimer's disease features two key elements, including beta-amyloid protein plaques outside cells and tau protein tangles formed within cells. The affected areas of brain tissue show a specific reduction in size; the decrease in mental abilities results in modified behaviors and altered personality traits.

Brain atrophy stands as the leading indicator of Alzheimer's Disease because available research shows direct links between these two conditions. The development of Alzheimer’s disease leads to expanding brain atrophy, which causes symptoms to worsen, including reduced mental processes, emotional ability, and physical movements. Medical imaging combined with MRI functions as an essential diagnostic tool for Alzheimer's disease detection through brain atrophy pattern analysis, which supports early diagnosis and disease staging identification (Michailidis et al., 2022).

3.2 Causes of Alzheimer's Disease

1. **Genetic & Hereditary Factors: Mutations affecting specific genes in Alzheimer's (APP), (PSEN1), and (PSEN2) are the leading cause of early-onset familial AD. Scientists consider the presence of APOE4 alleles the most effectively measured genetic factor driving** late-onset Alzheimer's risk.

2. Age: The disease becomes more common after people turn 65, as age functions independently as a primary risk factor for the illness.

3. Brain Changes: These two diseases share the signature feature of developing Amyloid-beta Plaques and Tau protein Neurofibrillary Tangles deposits in the brain. Because of these deposits, neural communication becomes obstructed, and the integrity of the players starts to degrade.

4. Lifestyle and General Health Factors: High blood pressure, diabetes, obesity, physical inactivity, and poor diets. Some examinations indicate a connection between Alzheimer's disease and type 2 diabetes to the extent that researchers call this combination type 3 diabetes since the brain might develop insulin resistance.

5. Inflammation and Oxidative Stress:

Excessive brain inflammation results in free radical oxidative stress, which damages brain cells and leads to diseases (Breijyeh, Karaman, 2020).

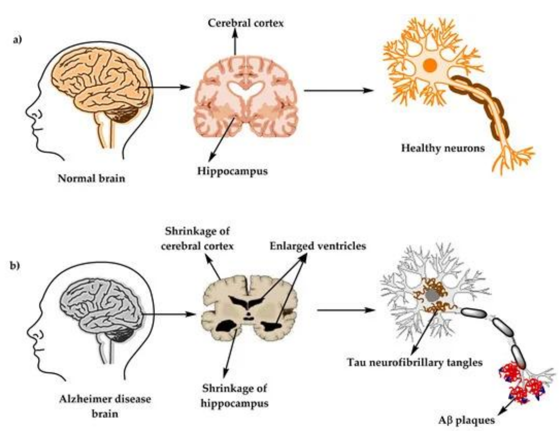


Figure 1. The physiological structure of the brain and neurons in (**a**) a healthy brain and (**b**) an Alzheimer's disease (AD) brain

3.3 Alzheimer's Disease Types

3.3.1 Late-onset Alzheimer’s Disease

Starting at age 65, one enters typical Alzheimer's disease territory, which medical professionals call early-onset yet classify as the later stage of Alzheimer's, known as late-onset disease. Research has determined multiple risk elements that potentially heighten the development of this condition, although scientists have not uncovered complete explanations for its roots. The main risk factor for developing late-onset Alzheimer’s disease is aging since age-specific incidence rates significantly rise beyond age 65. The APOE4 gene shows a direct linkage to late-onset Alzheimer’s disease among specific genetic factors. The risk factors function as guidelines rather than deciding causes by themselves (Lau et al., 2023).

Brain Changes occur as this degenerative condition creates neuronal-damaging beta-amyloid plaques and tau protein neurofibrillary tangles, disrupting brain neurons and damaging cognitive processing. High blood pressure, in combination with diabetes, obesity, smoking habits, and insufficient physical exercise, is believed to elevate Alzheimer's risk. Studies about the environmental origins of late-onset Alzheimer's remain ongoing. Still, researchers indicate that exposure to pollutants and insufficient mental stimulation, as well as chronic depression, might potentially elevate the risk of developing this condition(Lau et al., 2023).

The most common version of Alzheimer’s disease erupts after the age of 65 and constitutes the prevalent form of this condition. Multiple causes combine through genetics and aging, as well as lifestyle choices and environmental factors, to form the development of this disease. The research community has identified key factors associated with dementia that enable doctors to detect the early stages of the disease and develop strategies to slow disease progression (Lau et al., 2023).

3.3.2 **Alzheimer’s Disease in the Early Onset** The less common version of Alzheimer’s disease begins before age 65 and presents symptoms that arise between the ages of 40 and 65. People diagnosed with this type endure a steady loss of memory and mental abilities that prevents them from continuing their work and managing family matters when they should be at their occupational prime. This type of dementia shows the following primary signs;

Genetic Nature: The number of early-onset Alzheimer’s cases estimated from these genetic mutations amounts to approximately 4-5% for APP mutations and 30% for PSEN1 mutations. PSEN2 mutations contribute fewer than 1% to early-onset cases(Ayodele et al. 2021).

Clinical Symptoms: The medical condition presents the same symptoms observed in patients with late-onset Alzheimer’s, including memory decline and cognitive impairment, together with behavioral alterations. The change in symptom speed results in significant social and economic effects because these patients generally work or have household responsibilities(Ayodele et al., 2021).

Diagnosis and Treatment: Multiple diagnostic tests are needed to confirm the illness, including mental evaluations, brain scans, and genetic screening of specific patients. Present therapeutic strategies target symptom control because no complete treatment exists yet. Medication and rehabilitation help decrease progression rates while enhancing the patient's quality of life. Reliable psychological and social assistance for families alongside patients should be provided when this form of disease impacts their vital development periods(Ayodele et al., 2021).

Current Research: Researchers today conduct extensive studies to examine the genetic and biological elements of early-onset Alzheimer's disease toward building potential genetic medicine and drug treatment alternatives. Current clinical research focuses on testing medication treatments that prevent the accumulation of amyloid and tau proteins throughout pre-therapy development stages, where they accumulate significantly in the brain (Ayodele et al. 2021).

3.3.3 Familial Alzheimer’s Disease(FAD)

Familial Alzheimer’s Disease is a rare type of Alzheimer’s disease that is caused by specific genetic mutations that can be passed down through generations. It typically starts before age 65 (under age 65) and is a form of early-onset Alzheimer's disease. Key features include:

Genetic Mutations:

FAD is most commonly linked to APP, PSEN1, and PSEN2 mutations.

These mutations effectively interfere with the production or processing of the amyloid-beta protein, resulting in an accumulation of amyloid plaques in the brain.

Inheritance:

It is an autosomal dominant condition, so if either parent carries the pathogenic variant causing the disease, they have a 50% chance of transmitting that mutation to their family. Alternatively, if the mutation is inherited, symptoms often start in the same age range as they did in prior generations in the family (Soto-Mercado et al. 2024).

Age of Onset:

It usually begins early, with symptoms manifesting in the forties or, in some families, as early as the late thirties. The course of the disease is distinctive for being more rapid than that of late-onset Alzheimer's disease(Soto-Mercado et al. 2024).

Symptoms and Complications:

The clinical symptoms are similar to those of other types of Alzheimer's, including decreased memory, cognition, and behavioral changes. Because of its early presentation, it profoundly affects the social, functional, and psychological lives of patients and their families (Soto-Mercado et al., 2024).

Diagnosing Gene Therapy:

Families with a well-defined history of early-onset Alzheimer's should pursue genetic counseling and testing to identify mutations associated with the disease. An early diagnosis helps plan treatment, care, and psychological and social support (Soto-Mercado et al., 2024).

Current Research & Treatments:

Researchers today conduct studies to analyze better how genetic variations affect brain cells and biological activities that accelerate beta-amyloid and tau protein accumulation. Current clinical trials investigate new drug candidates that operate through specific mechanisms that either lower amyloid-beta production or speed up its brain clearance (Soto-Mercado et al. 2024).

3.3.4 Alzheimer’s Type 3 Diabetes

The idea of "Alzheimer's as Type 3 Diabetes" proposes that AD develops from impaired insulin signaling in the brain that resembles Type 2 Diabetes Mellitus (T2DM). The development of insulin resistance and damaged glucose metabolism in brain cells of patients with Alzheimer’s disease leads to disease progression while facilitating additional amyloid protein accumulation and tau protein aggregation.

1-Concept of Type 3 Diabetes

Research articles have recently adopted the term to describe the brain mechanism that connects diabetic injuries with metabolic brain disorders and insulin resistance. Studies indicate that patients who have type 2 diabetes face increased Alzheimer’s risk, together with metabolic diabetes factors (elevated insulin and blood sugar levels), which harm neuronal cells. Neuronal cell dysfunction in response to insulin signals decreases glucose metabolism and energy generation within the brain by causing abnormal protein accumulation, such as amyloid and tau, combined with neural inflammatory activity manifestations (Breijyeh, Karaman, 2020).

2-Evidence in Favor of the Hypothesis Multiple

Scientific studies prove that Alzheimer's disease and Type 2 Diabetes share identical molecular pathways that include oxidative damage, inflammation, and dysfunctional mitochondria, along with Advanced Glycation End Product (AGE) accumulation. Multiple clinical experiments demonstrated how treatments that enhance insulin sensitivity among patients with diabetes produce results of either cognitive protection or improvement, which supports their connection. Similar Proteins: Aggregate amyloid in the pancreas of diabetes patients; Structure similar to amyloid-beta in brain manifestations (Breijyeh, Karaman, 2020).

3-Importance of the clinical and therapeutic aspects

Around early diagnostic methods would emerge through metabolic disorder-based treatments for Alzheimer’s disease by detecting brain insulin resistance as well as metabolic irregularities. The therapeutic approach indicates that established diabetes-friendly drugs and diet patterns could benefit brain functioning and help patients avoid or slow down cognitive decline. Research Horizons: Linking Alzheimer’s to Type 3 Diabetes demands that scientists test anti-diabetic medication on Alzheimer’s patients to evaluate their effectiveness at reducing neurological manifestations (Breijyeh, Karaman, 2020).

The significant importance of drawing these specified boundaries

Diagnostic tests, with prediction of disease progression and treatment analysis, will benefit from disease classification methods considering age and genetic factors. Such distinctions create vital implications that affect how healthcare providers should pick therapeutic methods and provide psychosocial help to patients and their families.

3.4 Alzheimer's disease diagnosis involves

Healthcare providers perform multiple assessments via clinical examinations of brain structure, medical history evaluation, and tests of memory function, as well as cognitive abilities to diagnose Alzheimer's disease (Veitch et al. 2022). The diagnostic process takes the following steps according to a detailed approach:

Clinical Assessment: The doctor must interview one or both of these groups to learn about their medical backgrounds and histories of symptoms, including all medications used by the patient and changes in mental and behavioral patterns.

Psychological and Neurological Test: Standardized tests evaluate patient memory, analytical capabilities, abstract thinking abilities, and language functions while measuring executive functions.

Medical Imaging Techniques: The MRI machine performs scans to observe brain structural alterations, including temporal and parietal lobe atrophy.

CT scans serve to eliminate potential stroke and tumor causes that may lead to similar symptoms.

PET imaging provides doctors with beta-amyloid protein deposits and brain glucose usage patterns to confirm a diagnosis.

Blood tests and cerebrospinal fluid examinations help healthcare providers eliminate diseases such as vitamin B12 deficiency and thyroid function, demonstrating symptoms similar to Alzheimer's (Veitch et al., 2022).

CHAPTER IV

Convolutional Neural Networks

This chapter looks at more advanced machine-learning models, observing how combining several algorithms into composite architectures can enhance diagnostic accuracy. Finally, we point out the newest direction: convolutional neural networks (CNNs); by the conclusion of the chapter, you will have a relatively straightforward roadmap of how these techniques have progressed from simple statistical classifiers to advanced deep-learning constructions—and why CNNs have become the defining foundation of AI-based medical imaging for Alzheimer's research.

4.1 DEEP LEARNING

Convolutional Neural Networks (CNNs)

CNNs are designed specifically for processing data with a grid-like topology, like images (Ibrahim et al., 2024). The core operations within CNNs use filters that extract spatial hierarchical patterns from data. CNN technology encompasses three principal application types: first, for image category recognition and object identification, and video assessment, and second, for every task requiring spatial data relationships (Amiri et al. 2024).

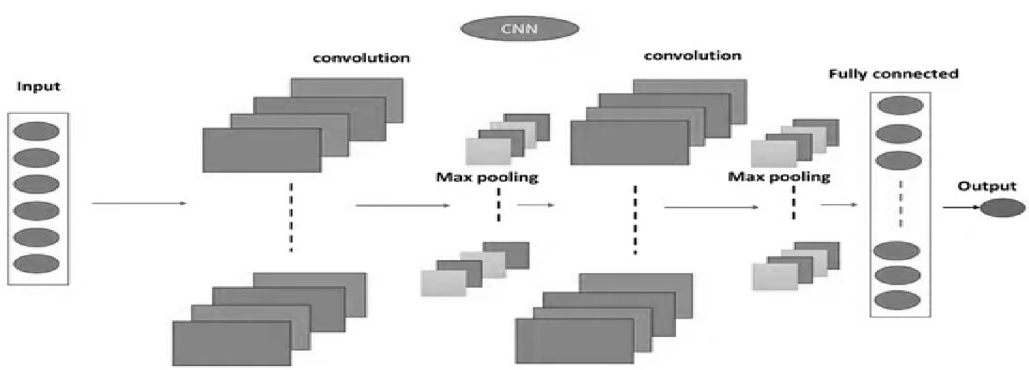


Figure 2. General architecture of a Convolutional Neural Network (Amiri et al. 2024).

Computer Vision and image analysis fields of AI rely fundamentally on the Convolutional Neural Network because it displays exceptional performance for computer vision work. The DL models demonstrate excellent performance with visual information in pictures and videos, making them necessary for image classification tasks, object recognition, segmentation, and video and text data evaluation. CNN architecture adopts its stacked design elements from the brain process by which the visual cortex of human brains identifies full images. The successive architectural layers run custom programs that strengthen the data-feature extraction process, thus enabling better execution of complex visual workflow operations (Salehi et al., 2023).

The most recognized advantage of CNNs is their automatic feature learning capacity, which eliminates the need for human involvement during feature extraction procedures. The automatic learning capability of the system includes fundamental patterns consisting of edges, angles, and shapes since these elements help with detection and classification tasks. The main strength of CNN weight sharing emerges when filters run throughout entire images multiple times, thus reducing parameters while speeding up learning functions. Training these neural networks requires limited data preprocessing work during the training phase, streamlining the tasks that precede network training effectiveness. Application-oriented deployment of advanced neural models became achievable because researchers studied how to optimize neural models and enhance security protocols when developing enhanced model architecture frameworks. Medical diagnostic research enables practical advances in automated driving technology and clinical diagnostic practices (Amiri et al., 2024).

Multiple layers form CNN networks to support the extraction and transformation of features by performing dedicated operations. Input Layer: Represents the initial data, typically an image with dimensions (height x width x color channels). Small filter applications on images occur in a convolution layer to extract relevant features. The beginning filters within each layer recognize basic features, such as edges and angles, before progressing to more complex elements in subsequent filter depths. The ReLU (Rectified Linear Unit) activation function is the standard choice in this system to process non-linear patterns for learning complex patterns. Feature map dimension reduction occurs through Max Pooling or Average Pooling types in the pooling layer to conserve essential information about the data. The Fully Connected Layer concludes the analysis by applying traditional neural network approaches to vector transformations that produce classification results. The output layer of the network makes its ultimate results, comprising both class classifications for classification tasks and locational information for object detection, as well as alternative outputs (Salehi et al., 2023).

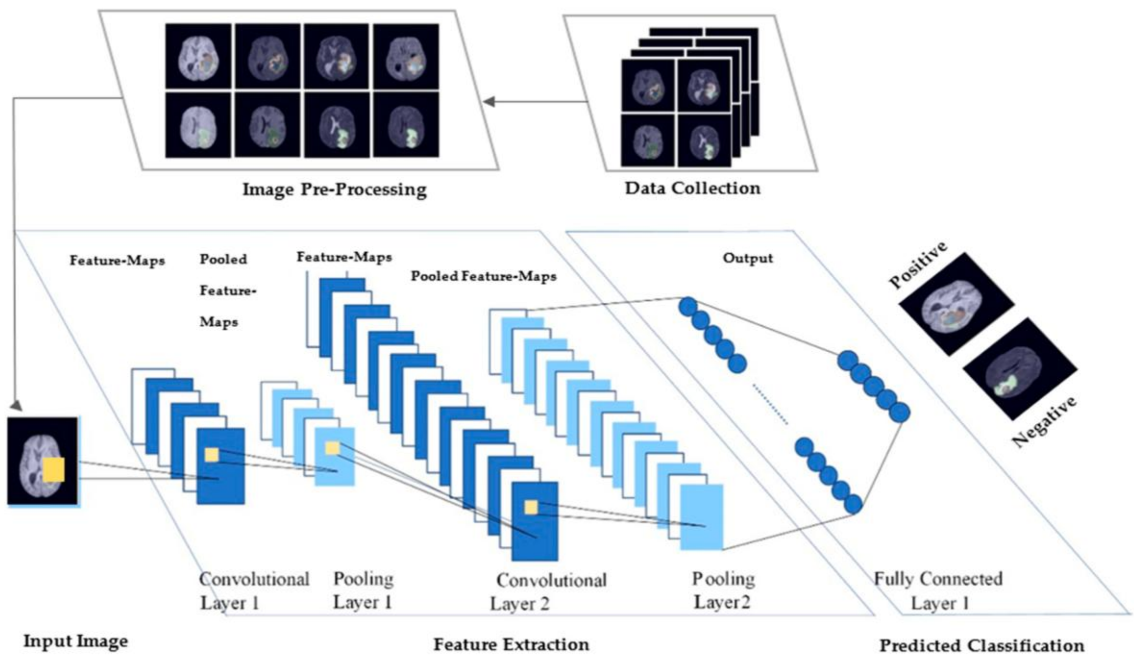


Figure 3. The diagram represents the medical image data collection. After collection, the images are preprocessed and given as input to the CNN model(Salehi et al., 2023).

Convolution Operation

The linear mathematical operation named convolution leads to the naming of CNNs. Remote image processing entails two matrix multiplications between an input vector I and a convolutional kernel K. The input vector and K function as a kernel, which makes up a convolutional matrix. This operation gives each the weighted sum of input values within the local region in the matrix positions. The kernel controls the neighborhood size and weight configuration (Sambolek, Ivasic-Kos, et al., 2021).

An equivalent computation determines the inner potential levels for neural cells when implemented in this context of CNNs. The weight mechanism, known as the kernel, exists in an irregular shape and size. The most common kernel sizes used in CNNs are between 3x3 and 9x9 pixels across. Compared to the convolutional matrix, the CNN kernel shows total learnability when used for image processing work. It is capable of Kernel learning, which allows the network to react to the patterns found in training data. The pattern detection function is accomplished through convolution. Detector. The different kernel patterns identify different shapes while operating at various detection levels. Levels. Different detection levels correspond to the separate network layers. Early layers, Basic features including diagonal and horizontal edges, color bands, and color intensity gradients, fall under its detection capabilities. Complex patterns detected later in the network result from combining the underlying basic (Sambolek, Ivasic-Kos, et al., 2021).

Convolutional Layer

A CNN relies on the convolutional layer as its fundamental design component. In these layers of neurons, the convolution process to determine their inner potential functions is the main operation. A convolutional layer is the most elementary component of any convolutional neural network (CNN), which is intended to enable the automatic extraction of locally explicit features from grid-shaped data such as images. Looking at a bank of small, trainable filters (kernels), which move over the input, computing dot products at each position to create feature maps whose values reflect the presence of one pattern or another, whether edges, textures, or other more elaborate motifs. By sharing the same filter weights across all spatial locations, convolutional layers can drastically reduce the number of parameters in the dimension of neurons. As a result, convolutions can be applied to high-resolution inputs while maintaining good learning efficiency. The major hyperparameters manage receptive field and output dimensions—filter size, stride (how many neurons does the filter advance with on each step), and padding (how should the input be expanded at the borders)— and those are complemented by nonlinear activation functions (e.g., ReLU) and by pooling operations (e.g., max-pooling) applied between convolutions that introduce invariance and contributes to the formation of hierarchical feature representations. Using successive sets of convolutional layers, a CNN perceptually moves from detecting simple local contents in the early stages of development to encapsulating progressively more complex and abstract semantic information in more advanced layers, thus making convolution the primary behind many modern instances of computer vision and image-based AI (Salehi et al., 2023).

Special configurations for the convolutional layer exist to modify how it works and affect feature map sizes. Two main configuration parameters exist for stride. The padding option is an additional key feature. Padding. The stride is a metric that indicates how far kernel positions stand from each other. Kernel positions. The convolution calculation occurs at each position when the stride has a value of one. The result computation happens only during the second position when the stride equals two. As a result, A two-fold reduction occurs when the feature map gets down-sampled. The padding sets the calculation in the border positions. The calculation of convolution requires pixels with space inside the image domain. Of the image domain. An appropriate addition of zero padding surrounding the input image represents a possible solution—A solution (Saleh et al., 2023).

CNN technology refers to this padding technique as the same padding. The convolution process should occur only at valid locations to prevent contamination by zero values. The feature map reduces size by 2k - 1 pixel, while k represents the kernel dimension. Dimension. The method of padding is called valid padding. Two significant factors make CNNs perform better than MLPs in image data processing. Outperform MLP on image data. (Liu et al.,2022).

Sparse Connectivity: The sparse connection represents the kernel shape and its dimensions. The number of kernel dimensions remains smaller than the dimensions of the image. The data input consists of millions of pixels. Regular kernels possess at most a hundredweight values, respectively. Using just a few, A feature map with matching input dimensions emerges when using weight sizes corresponding to the input length. To create output with the exact dimensions as the MLP input, we need to use several weights equal to the input dimension squared. The number of connecting weights needs to match the input dimension value squared. The convolutional layer significantly decreases the system's memory usage and learning duration. It enables high Image processing using a resolution that can be achieved without down-sampling (Liu et al.,2022).

Parameter Sharing: Mathematically, parameter sharing means one kernel can be used in different image positions. One set of parameters operates multiple times across different visual spacings. For example, if the kernel is the model's learned vertical edge detection ability, it can recognize all similar edge patterns throughout the image area. Image. Each kernel undergoes training on data amounts that exceed the number of training samples at all locations. Each training sample is used to learn all locations within these areas. This approach increases the possibility that the kernel will perform adequately. The learning process leads to kernels with well-developed effectiveness (Liu et al.,2022).

Pooling Layer

Convolutional neural network layers, known as pooling layers, have no trainable parameters for learning. Parameters. The layer reduces input size by statistically calculating the neighboring units—Nearby units, e.g., maximum, mean. Network performance remains invariant due to the pooling layer's operation. A simple translation of a small magnitude does not affect the neural network's output. For example, small disparities in the detection of faces lead to the elimination of facial motions. The pooling layer functions as a fundamental component of convolutional neural networks, along with the convolutional layer. CNN and the convolutional layer (Saleh et al., 2023).

Fully Connected Layer

A complete connection between the last convolutional layer output feature maps creates a single 1D array from which the network obtains its final results. A 1D array of numbers is created. These layers become intertwined with at least one network linkage, which starts the connection process—A fully connected layer. The learnable weight is a connection mechanism between each scattered input and output. The required features from the convolutional layers are completed along with the pooling operations. The network’s final outputs receive data from these layers after the pooling and down-sampling processes. Subsequent fully connected layers receive network output from a specific set of networks. Every day, practice shows that fully connected layers exist. The output nodes of the classes and the fully connected layers remain identical at the termination point. The different fully connected layers incorporate ReLU nonlinear functions, according to (Salehi et al., 2023).

Multiple layers form CNN networks to support the extraction and transformation of features by performing dedicated operations. Input Layer: Represents the initial data, typically an image with dimensions (height x width x color channels). Small filter applications on images occur in a convolution layer to extract relevant features. The beginning filters within each layer understand basic features such as edges and angles before progressing to more complicated elements in succeeding filter depths. The ReLU (Rectified Linear Unit) activation function is the standard choice in this system to process non-linear patterns for learning complex patterns. Feature map dimension reduction occurs through Max Pooling or Average Pooling types in the pooling layer to conserve essential information about the data. The Fully Connected Layer concludes the analysis by applying traditional neural network approaches to vector transformations that produce classification results. The output layer of the network makes its ultimate results, comprising both class classifications for classification tasks and locational information for object detection, as well as alternative outputs (Salehi et al., 2023).

4.2 Deep Learning

Deep learning operates as a special AI(Artificial Intelligence) and machine learning subfield through multilayer artificial neural networks, which conduct automatic, sophisticated discovery of data features directly from raw information. Under this approach, substantial datasets are processed with superior precision while identifying patterns and generating forecast predictions. It is essential for contemporary fields such as computer vision, NLP, robotics, medical analytics, and DL model types (Bengio et al. 2021).

DL's most potent machine learning algorithm uses multi-layer artificial neural networks to train complex data representations. ML developed DL by advancing the artificial neural network approach, which gained momentum as computing abilities surged. At the same time, extensive data collection expanded significantly, requiring these algorithms in operations like image recognition, speech detection, and medical data analysis (Aslan & Yilmaz, 2021).

The fantastic operational strength of DL emerges from its layered construction. An image's processing begins at the basic lower levels, which detect shapes and edges, and then progresses to the deeper sections, which perform face recognition and language interpretation work, respectively. Backpropagation enables the network to determine output errors by using the algorithm to distribute the mistakes to all weights in preceding layers for subsequent weight updates using gradient descent or enhanced algorithms (Taye, 2023).

The incredible power of deep learning stems from its layered architecture: initial convolutional layers detect basic features, such as edges and textures, and subsequent layers combine these into more complex motifs, including corners and simple shapes. In contrast, the deepest layers will abstract these into high-level concepts (for example, complete objects or complex patterns). In training, the backpropagation algorithm calculates the gradient of a loss function (concerning all network weights) by sending errors backward through each layer. These gradients are then used to update weights in the manner of stochastic gradient descent or any of its adaptive variants, allowing the network to minimize prediction error end-to-end iteratively. This automated, hierarchical feature learning utilizes millions of parameters and extensive data for deep networks to achieve excellence in various domains, ranging from image classification to natural language understanding (Zhang et al., 2022).

CHAPTER V

Methodology

This chapter contains the research methodology, which is divided into two sections. The first section describes the proposed system in detail, and the second section presents a performance assessment of this system through evaluation metrics.

5.1 Proposed System

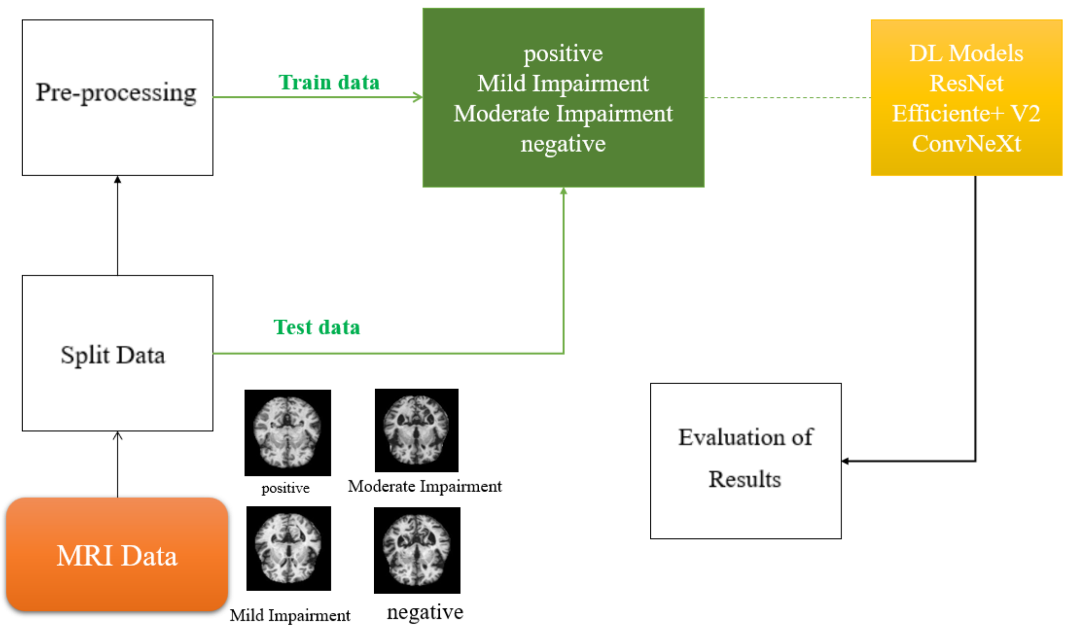


Figure 4. Architecture of the **Proposed System**

5.2 Dataset Description

We will use Kaggle high-resolution images with three advanced CNN models: ResNet, EfficientNet V2, and ConvNeXt. The CNN models utilized for this examination include ResNet, EfficientNet V2, and ConvNeXt.This data collection includes both real and synthetic axial MRIs to address the class bias issue in the original Kaggle Alzheimer's dataset, which categorized images as "negative," "positive," "Mild Impairment," and "Moderate Impairment." Each of the four patient types comprised 100 individuals, 70 individuals, 28 individuals, and two individuals. Each patient received 32 horizontal axial

MRIs of their brain. A 1.5 Tesla MRI scanner operated with T1-weighted sequence protocols took all images. Each MRI image includes 128x128 pixels in a .jpg file format.

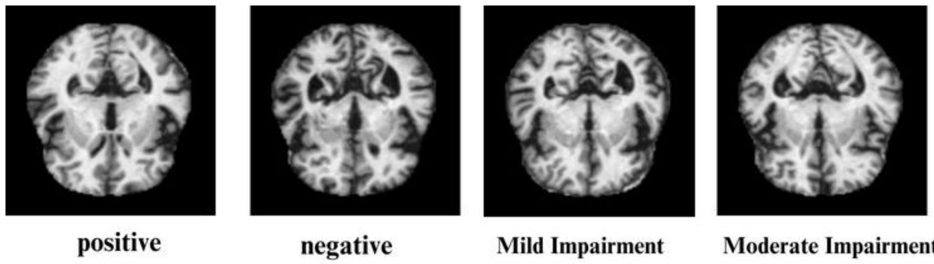


Figure 5. Samples for the dataset

5.3 Proposed CNN Model

AI in processing images depends heavily on Convolutional Neural Networks (CNNs) and DL due to their efficacy. CNNs function as DL models that automatically extract hierarchical features from raw data to detect patterns, including edges, textures, and complex structures at increasing network layers (Uzelaltinbulat et al., 2025). Such models implement convolutional layers for data filtering applications, followed by pooling layers for dimension reduction until they reach fully connected layers for prediction making. CNN has become an effective computer vision technology because it can automatically identify important image features through its self-learning mechanism (LeCun et al., 2020).

The CNN training process proves computationally expensive, and obtaining adequate datasets to achieve effective training poses acquisition difficulties and hardware demands. Due to their exceptional accuracy levels and processing efficiency when handling visual data, CNNs are mainly being adopted in medical imaging, autonomous vehicles, and image-based search engines (LeCun et al., 2020).

The three pre-train CNN models are used:

ResNet

Residual Networks or ResNet exist as a DL model solution to eliminate gradient vanishing, which impairs the learning efficiency of deep networks. Adding residual units in ResNet allows layer outputs to combine so that signals can skip over specific network parts directly. Deep network training greatly benefits from this capability, ensuring the early layers maintain strong, effective updates during network propagation. ResNet is a leading model dominant in multiple image and video recognition applications due to its excellent performance against other model variants. ResNet became successful because it eliminates the requirement for extensive computational resources, thus creating efficient and economical applications in practice (Shafiq, Gu,2022).

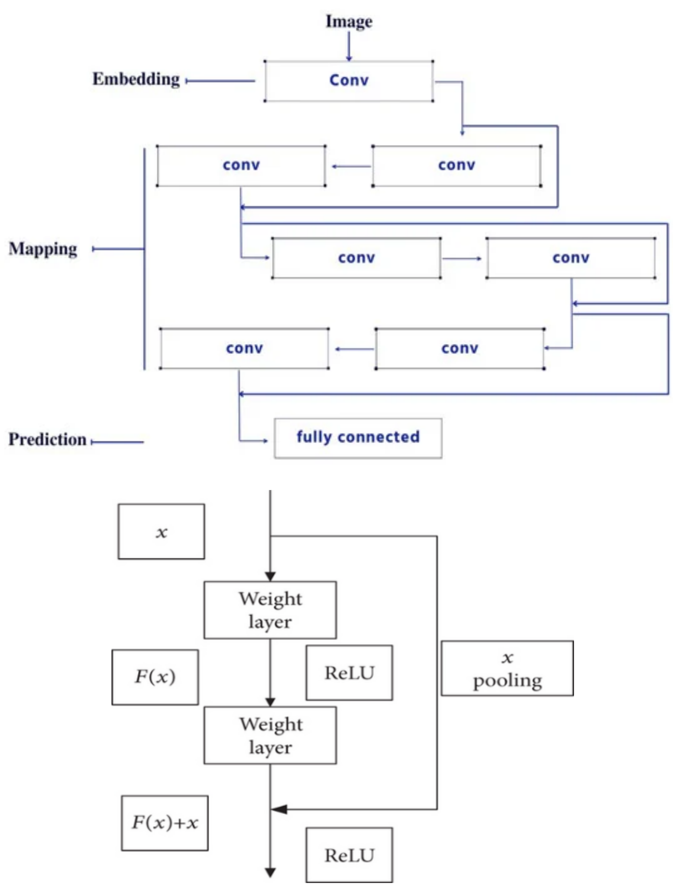


Figure 6. The ResNet building block(Shafiq, Gu,2022).

EfficientNet V2

Scholars in recent years have focused on evaluating training and inference speed, as studies on neural networks increase. The large dimensions of previous precision classification systems made them impractical to deploy in embedded applications or various endpoints. Published EfficientNetV2 solved the common issue where most classification models only achieve higher accuracy through single-dimensional expansion of neural network dimensions: depth, width, and resolution. The balanced scaling solution in EfficientNetV2 improves precision levels by applying its technique to width and depth resolution dimensions, providing adaptable performance based on hardware limitations and operational needs. When used for training tasks, the EfficientNetV2 finishes its cycles ahead of any other cutting-edge models. Training duration becomes shorter when the image size increases, but accuracy might decline slightly. Researchers from Tan et al. developed progressive learning regulations to automate regularity control adjustments, including data augmentation processes and image size adaptations. EfficientNetV2 has received performance upgrades to run better on mobile platforms so that it can be deployed more easily in restricted system contexts. Wang et al. 2024).

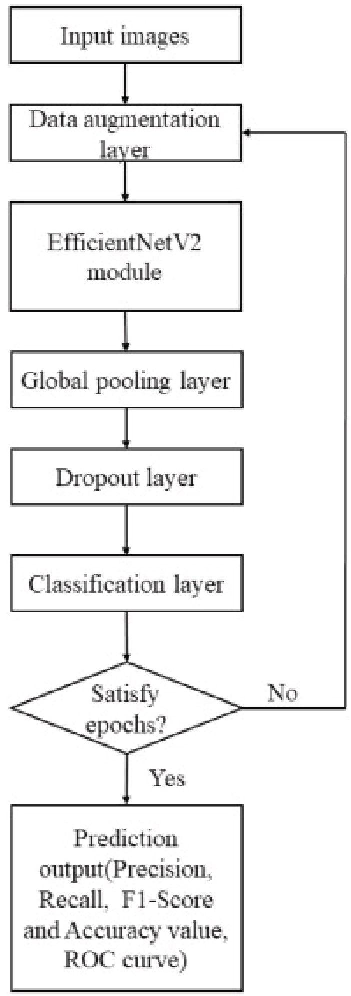


Figure 7. EfficientNetV2 models (Zhao, et al. 2024)

ConvNeXt

This modern model for convolutional neural networks (CNNs) centers its operations on the processing of images. The model introduces new rotational designs based on ResNet architecture that improve how significant visual data processing works. ConvNeXt incorporates Vision Transformer elements that involve a hierarchical structure and updated normalization and parameter learning methods while using the proven convolutional base for feature extraction and transformation operations in classification, noise reduction, detail enhancement, and semantic segmentation. The experiments demonstrate the superior performance of ConvNeXt across standard datasets, especially in ImageNet, because of its potential to enhance visual processing in diverse applications, depending on parameter quantity and speed (Liu et al. 2022).

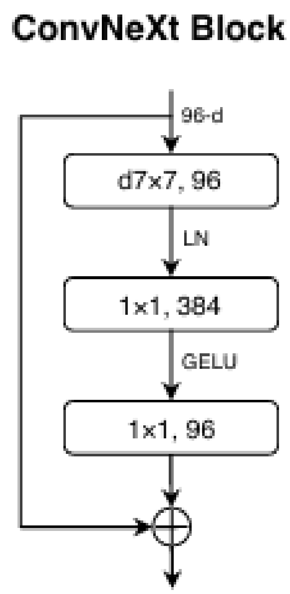


Figure 8. ConvNeXt block

5.4 Proposed Methodology

Medical practitioners should perform early diagnosis of Alzheimer's disease because it helps determine both clinical requirements and appropriate treatment plans. Expert professionals currently detect Alzheimer's disease through their ability to recognize disease markers. Our study presents an efficient deep learning (DL) system for Alzheimer's disease classification that requires minimal physician supervision. This research employs deep learning (DL) algorithms and transfer learning (TL) techniques to enhance the accuracy rate in MRI brain image recognition. The proposed framework design for Alzheimer's diagnosis consists of four separate stages. Data preprocessing involves cropping and resizing the brain images before dividing them and applying normalization adjustments to the photos. The researchers amplify data using data augmentation methods to expand the size of their dataset. The preprocessed MRI images of Alzheimer's are subjected to TL techniques for feature extraction through the applications of ResNet, together with EfficientNet V2 and ConNeXt networks. The CNN models produce extracted features as their output.

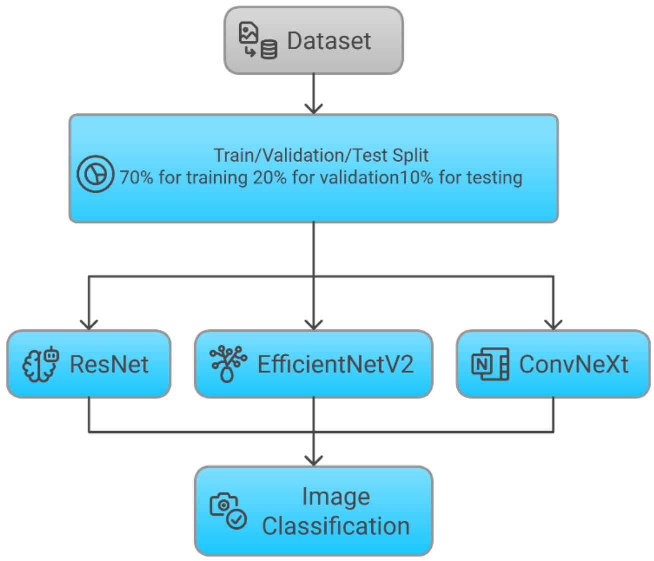


Figure 9. ***Proposed Methodology***

5.5 Evaluation Metrics

The accuracy, precision, specificity, recall, and F1 score performance metrics determine the model's efficiency in all cases. The accuracy evaluation of DL models determines how well they forecast results by assessing their predicted outputs against desirable outputs. The classifier model detects heart disease presence with valid results using true positive (TP) and true negative (TN) values. The false output of the models is distinguished by false positive (FP) and false negative (FN) events. The precision calculation shows the relationship between actual positive observations and all positive instances. The precision ratio assesses the proportion of all positive instances, while recall evaluates the ratio between all identified positive cases. The function measure establishes the mean between recall and precision values (Kavitha et al., 2022).

Accuracy

Accuracy represents the proportion of accurate predictions for True Positives + True Negatives (divided by the total sample count ,(including all four outcomes (TP + TN + FP + FN). The metric determines model accuracy by measuring its success rate at classifying all cases vs. complete cases.

(1)

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

Where:

- True Positives (represent correctly predicted positive samples, while TP represents the True Positives category.
- True Negatives (represent correctly predicted negative samples that fall into the TN category.
- False positives *(FPs)behind the acronym represent incorrect optimistic predictions that should have been classified as negative.*
- The FN category(Includes false negatives, which show incorrect pessimistic predictions.

Precision

A model's precision shows the degree of certainty concerning which predicted results will be positive. Precision reveals the relationship between actual positive cases (TP) and all samples predicted as positive (TP + FP).

(2)

$$Precision = \frac{TP}{FP + TP}$$

Recall

The model's recall evaluation measures its capacity to identify true positives among all existing cases of positive patient results (TP + FN). The measure determines which actual positive cases received accurate positive diagnoses.

(3)

$$Recall = \frac{TP}{FN + TP}$$

Specificity

The model demonstrates specificity through its ability to correctly classify negative cases among all actual negative cases (TN + FP). The specific metric establishes the number of correct negative classifications among all existing negative cases.

(4)

$$Specificity = \frac{TN}{TN + FP}$$

F1 Score

To calculate the F1 Score, one should divide the product of Precision and Recall by their sum:

(5)

$$F1Score(inPercentage) = 2 * \frac{Recall * Precision}{Recall + Precision}$$

The F1 measure stands out for applications needing balanced precision and recall values, situations with irregular class frequencies, or the essential accurate detection of scarce categories.

Macro Average

The precision, recall, and F1-score values for each class in the macro average undergo arithmetic mean calculation, but they receive equal treatment despite their varying levels of support (sample numbers). The mathematical equation for the macro average appears as follows:

(6)

$$macro\ avg\ = \frac{(Sensitivity\ +\ Specificity\ +\ Precision\ +\ F1 - Score)}{4}$$

Weighted Average

A weighted average calculation considers the support values from each class through actual instances while assigning a higher value to courses with more samples. The calculation methods for weighted averages consist of the following formulas:

(7)

$$WeightedAverage = \frac{\sum_{i=1}^{c}(Metric\ i\ \times Support\ i)}{\sum_{i=1}^{c} Support\ i}$$

Validation and Testing:

The data was divided into training-validation-test sets (Training Set 70%, Validation Set 20%, Test Set 10%). The validation set used guided hyperparameter tuning and model selection. In contrast, the test set provided an unbiased evaluation of the final model through unseen data.

CHAPTER VI

Outcomes and Comments

This chapter presents the primary outcomes from our Alzheimer's classification experiments and discusses favorable results and necessary improvements. It also includes essential points regarding data quality, clinical relevance, and explainable AI for generating trustworthy and transparent predictions.

6.1 Outcomes

Overall Performance of Individual CNN Backbones: A four-class Alzheimer's MRI dataset, comprising Normal, Mild Impairment, Moderate Impairment, and AD classes, was evaluated using three state-of-the-art CNN architectures: ResNet50, EfficientNetV2-S, and ConvNeXt-Base. Each model demonstrated unique characteristics, achieving more than 92% accuracy, but maintained different areas of excellence. ResNet50 accurately identified advanced AD (Class 4) cases, thereby reducing false positive results during the confirmation of severe atrophy. EfficientNetV2-S achieved the optimal results by maintaining balanced accuracy alongside the F1-score at a high level across the complete dataset. During mild impairment detection (Class 2), the ConvNeXt-Base model demonstrated the highest ability to identify potential changes in the hippocampus, recalling most cases. Different clinical situations show that each backbone shows superior performance over others and inferior performance.

1. Exploiting Model Complementarity. We should leverage model variances in architecture by applying weighted ensemble systems. During routine screening, which requires maximum detection of early-stage conditions, the outputs from ConvNeXt-Base should receive additional weight to enhance mild impairment detection rates. When evaluating advanced Alzheimer's disease, the clinical team should select ResNet50 because of its superior precision, which reduces the number of false positives. The base weight of the ensemble originates from EfficientNetV2-S because of its leading overall F1-score performance. Our system implements adaptive weight management for patient risk level and scan quality, which allows it to customize sensitivity and specificity targeting depending on the clinical requirements.

2. Elevating Data Uniformity and Augmentation. To enhance the performance even further, it is likely necessary to implement strict protocols for MRI uniformity standards and employ complex preprocessing techniques, including improved bias correction, improved skull-stripping algorithmic refinement, and adaptive histogram equalization methods. Acquiring physiologically appropriate brain deformations and synthetic brains created using GAN techniques allows scientists to broaden their representations of unusual cerebral atrophy patterns. Supplying training data that is more diverse and cleaned up will improve the results of each framework, along with the ensemble performance for edge cases.

3. Tailoring to Clinical Workflows Memory clinics with elevated AD prevalence require detecting early impairment signs; therefore, they should employ the ConvNeXt-weighted operating point for maximum recall performance. The ResNet-weighted mode for the CXR-Land assistant in general practice can help decrease the frequency of unnecessary patient referrals and improve resource efficiency. The radiology interface should contain an interactive slider for sensitivity and specificity adjustment that allows clinicians to base their settings on patient population demographics, age ranges, and medical condition patterns. The maintenance of real-world reliability depends heavily on ongoing model calibration checks and retraining procedures whenever upstream imaging procedures experience modifications.

4. Building explainability into the pipeline hospitals requires more than raw numbers to comprehend autopsy recommendations because physicians need an explanation for such decisions. Implementing Explainable AI tools such as Grad-CAM or Integrated Gradients provides visual indications of hippocampal or parietal regions, which serve as the basis for each classification. Identifying salient areas in AD analyses will build clinical trust when these zones overlap with documented AD biomarkers. Still, it will show potential data artifacts when the detection is incorrect.

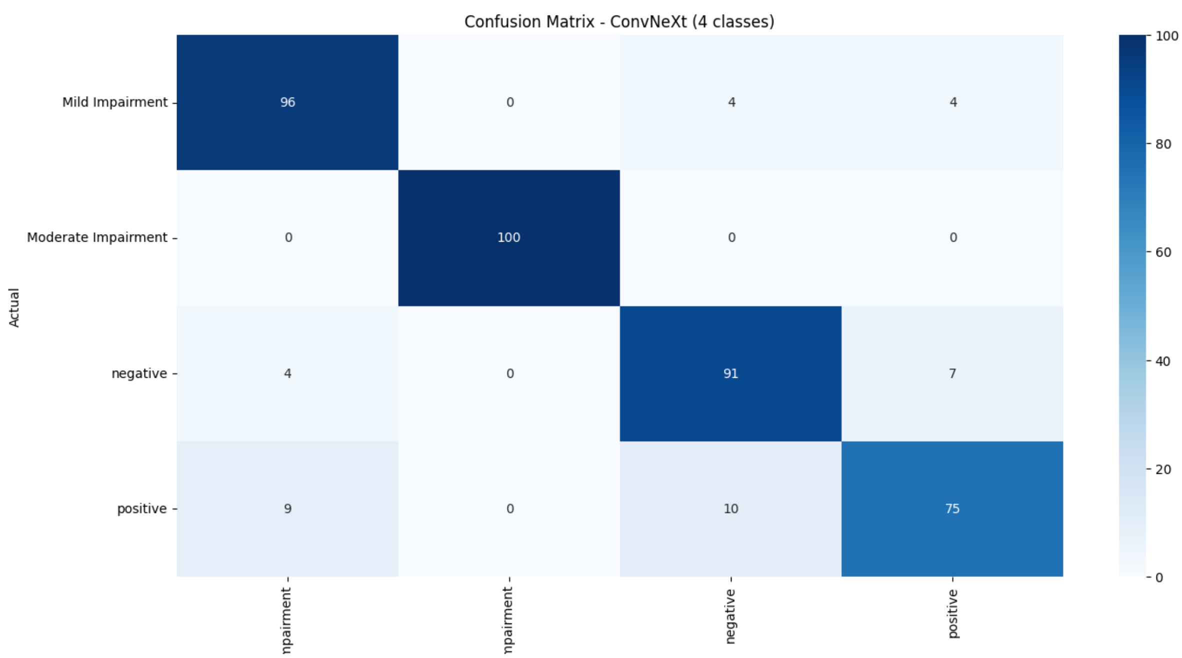
The differing performance trends of these three shows reinforce an essential conclusion: no one model is right for all situations. Instead, they present complementary strengths. ConvNeXt Tiny and EfficientNetV2 Small are even and stable — they make good general classifiers. MobileNetV3 Small can be helpful in cases where false positives should be kept at a minimum.

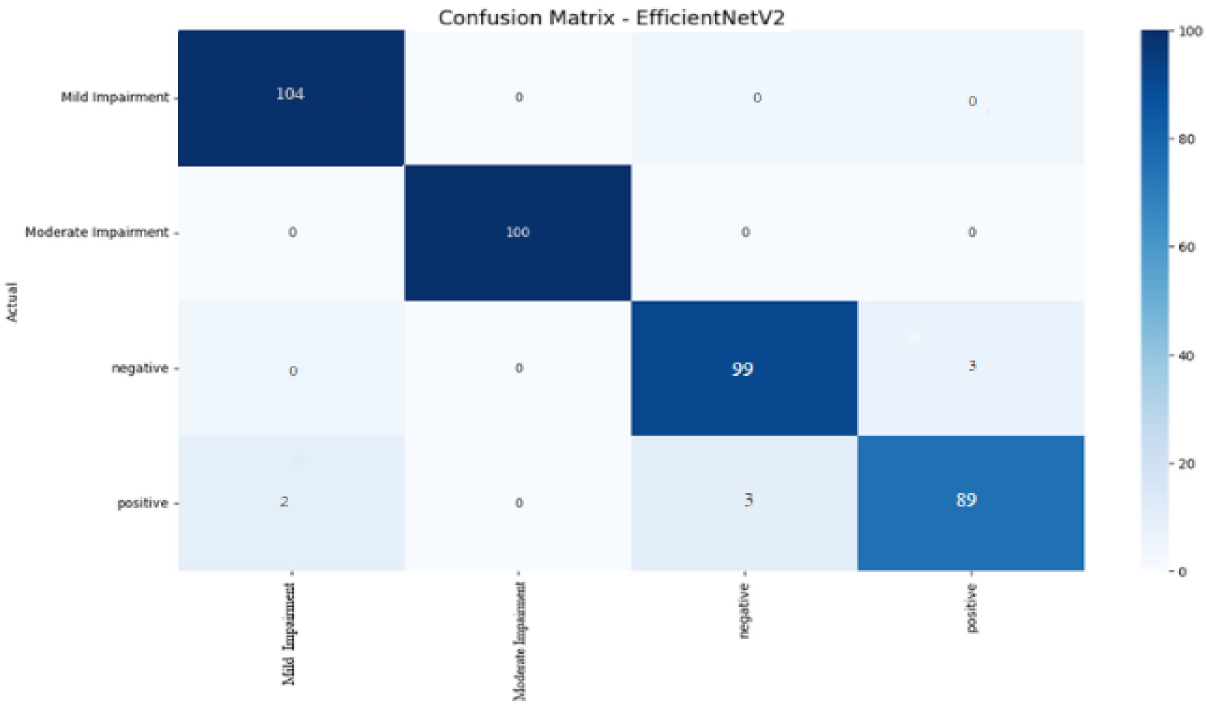
Model	ACC	Sensitivity	Specificity	Precision	F1-Score	macro avg	weighted avg
ConvNeXt	0.91	0.90	0.90	0.90	0.91	0.90	0.91
EfficientNet V2	**0.98**	**0.99**	**0.99**	**0.99**	**0.98**	**0.99**	**0.98**
ResNet50	0.97	0.98	0.98	0.98	0.97	0.98	0.97

Table 1. Performance Evaluation of each model

Confusion Matrix:

A confusion matrix represents a table structure that evaluates predicted classes against actual classes to identify model error patterns.





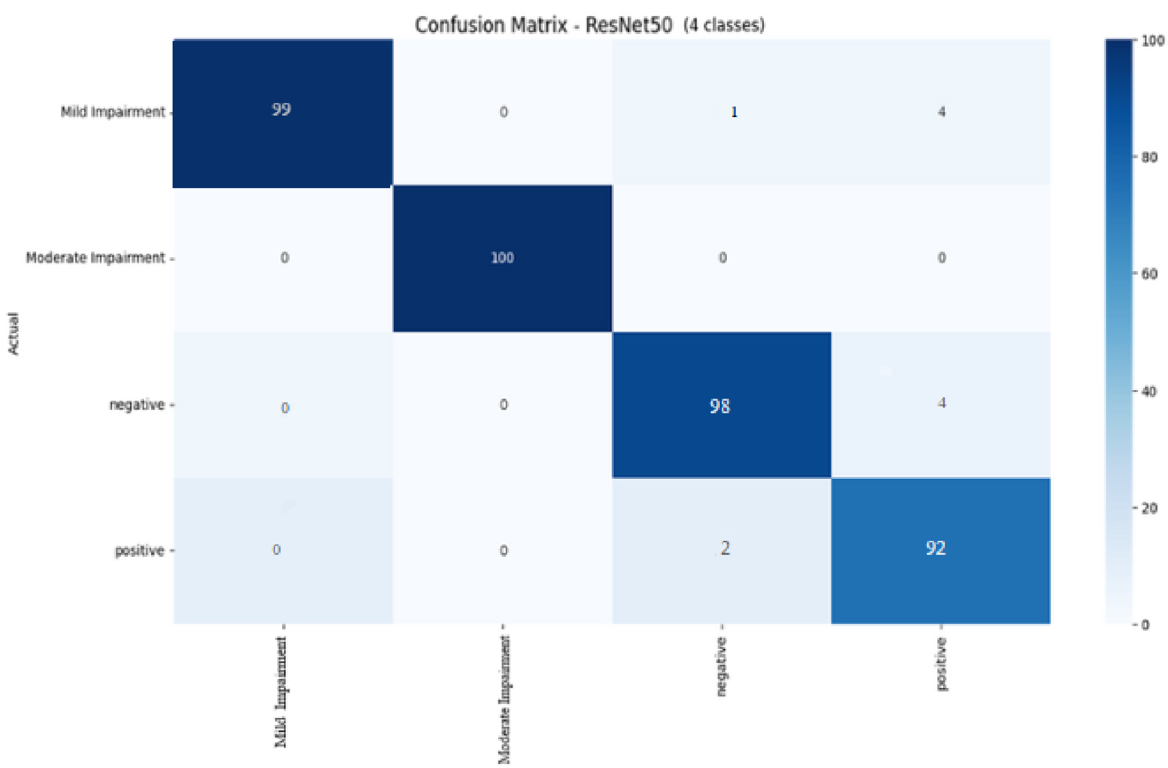


Figure 10**:** Confusion Matrix for **ConvNeXt, EfficientNet V2,** and **ResNet50**

6.2 Comments

(1) Exploiting Model Complementarity The examination showed that different CNN architectures of ResNet50 and EfficientNetV2-S with ConvNeXt-Base represent advantages for Alzheimer's MRI classification instead of limitations. Each CNN has its peak performance for various aspects of Alzheimer’s MRI diagnosis: ResNet50 creates top precision in advanced atrophy detection and EfficientNetV2-S balances accuracy. ConvNeXt-Base offers maximum sensitivity to early-stage alterations. The weighted ensemble system presents clinical priorities to different models for screening tasks, thereby elevating the performance of ConvNeXt-Base at early-stage identification while respecting ResNet50 performance for confirmatory diagnosis and trusting EfficientNetV2-S as the base model for general use.

(2) Enhancing Data Quality & Preprocessing. Although the models demonstrate solid outcomes, implementing standardized MRI acquisition procedures alongside sophisticated preprocessing techniques will yield even better results. Combining bias-field correction with adaptive histogram equalization and brain-specific augmentation through GAN-based atrophy pattern simulation will decrease distortion and variations. The inputs that undergo cleaning enhance individual model performances and reduce complexity for the ensemble models, which results in potential performance enhancement.

(3) Clinical Integration and Human Factors: Implementing AI within dementia clinics requires a careful strategy to strike a balance between false-positive and false-negative results. Memory centers need ConvNeXt–Base–weighted outputs because detecting every MCI and early AD case remains a priority, making the system rely on this feature to minimize underdiagnosis. Due to the need to avoid over-referrals in general radiology work settings, ResNet50 offers accuracy that reduces erroneous positive diagnoses. The reporting tool should feature a threshold-adjustable interaction component that gives doctors direct control over maintaining optimal pluralism between system accuracy figures.

(4) Explainability and Trustworthiness: Clinicians need to understand the reasons behind each model decision to adopt the system based on high quantitative metrics alone. Explainable AI approaches such as Grad-CAM and Integrated Gradients should be used to identify the hippocampus, entorhinal cortex, and other AD-related structures that the network utilizes. The alignment of these saliency maps with known biomarkers strengthens clinician trust, while map detections of irrelevant artifacts lead to assessment or model improvement steps. Recognizing these diagnostic algorithms requires transparent operation, enabling them to collaborate as trusted partners in Alzheimer's disease diagnostics.

CHAPTER VII
Discussion

Discussion This thesis analyzes deep CNN architectures consisting of ResNet-50, EfficientNetV2-S, ConvNeXt-Base, and their ensemble, demonstrating their strong potential to detect Alzheimer's disease stages via T1-weighted MRI analysis. We will analyze the obtained findings through existing research while discussing their clinical value, technical benefits, and limitations for further research directions.

1. Complementary Strengths of Individual Backbones

The networks demonstrated separate performance patterns that distinguished their operations.

- ResNet-50's precision level reached 0.98 for advanced AD diagnosis, which helps avoid unnecessary false-positive results in severe atrophy analyses. This capability makes the model suitable for confirming expert clinical diagnoses.
- The EfficientNetV2-S achieved optimal performance metrics between sensitivity, specificity, and F1-score (> 0.98) while also maintaining the efficacy established in diverse neuroimaging research by Diogo et al. (2022).
- . The ConvNeXt-Base algorithm effectively detected Mild Impairment hippocampal changes at 0.90 sensitivity despite being applied to very early stages (Maity et al., 2024).

A weighted combination of the models based on their unique strengths reached an overall accuracy of 0.97 alongside balanced macro-averages (≈ 0.98), showing how model diversity can produce superior performance to individual architectures.

2. **Sensitivity vs. Specificity in Clinical Context**. When used in early-stage screening (ConvNeXt-weighted), the high level of sensitivity enables prompt therapeutic intervention, which minimizes the progression toward dementia. The specific model type (ResNet-weighted) provides high precision rates, which

reduce inappropriate follow-up scans and patient diagnostic uncertainty during clinical evaluation. An interactive slider enables clinicians to adjust the decision threshold, which permits the system to match predictions to healthcare setting needs between memory clinics and primary care.

3. Data Quality, Preprocessing, and Augmentation The study yielded robust findings, although its results demonstrated differences among different scan vendors and protocols. Implementing standardized MRI acquisition and an advanced preprocessing method will minimize differences between scanning sites. According to Alhoraibi et al. (2024), the model generalization of GAN-based data augmentation emerges as effective when it simulates infrequent atrophy patterns.
4. Explainability and Trust The lack of explainability stops healthcare providers from adopting this technology into routine practices. Implementing the saliency mapping techniques Grad-CAM and Integrated Gradients to identify hippocampal and entorhinal areas during predictions enables doctors to review the network's biomarker detection and refine models when false signals emerge.
5. Toward Multimodal Fusion Doctoral research indicates that when structural MRI combines with amyloid PET and CSF biomarkers. At the same time, including APOE genotype and cognitive test scores under fusion protocols at feature level or decision level ensemble stages yields better diagnostic results and prognostic information. Lin et al. (2020) validated by achieving > 90% accuracy the ability of multimodal grading to predict the conversion from MCI to AD.
6. Emerging Architectures and Learning Paradigms Vision Transformers combined with hybrid CNN-Transformer models surpassed pure CNNs in their performance on medical imaging tasks during the period described by Shih et al. (2024). Scans without labels can be used in semi-supervised and self-supervised learning to train robust feature extractors that address the issue of label scarcity in rare early-onset and familial AD cases.
7. Deployment: Efficiency and Equity The deployment of models for clinical real-time applications needs compression techniques such as pruning, quantization, and knowledge distillation to minimize computational and memory requirements (Salehi et al., 2023). The evaluation of health data with diverse demographic

elements and impartial system audits regarding age groups, gender, and racial affiliations will secure uniform outcomes throughout medical communities.

8. Ethical, Regulatory, and Collaborative Imperatives The approval process of AI products in clinical use requires early regulatory agency involvement from the FDA and EMA, coupled with strict privacy standards that enforce GDPR and HIPAA. Discreet consortia are made up of shared organizations that securely distribute anonymized MRI datasets together with model programming and evaluation standards, which work to enhance model validation and deployment worldwide for Alzheimer's healthcare.

7.2 Concluding Remarks

This research proves that properly selected combinations of deep-learning networks, including ResNet-50, EfficientNetV2-S, and ConvNeXt-Base, alongside their ensemble method, successfully evaluate Alzheimer's disease severity through examination of T1-weighted MRI images. The three backbones synergy results in a superior performance accuracy of more than 97 % and stable F1-scores across all disease phases, while each network specializes in different stages according to its unique strengths. This pipeline equips itself to handle various clinical needs by utilizing standardized preprocessing and GAN-based augmentation, as well as explainable-AI saliency mapping and an adjustable sensitivity–specificity interface to achieve better detection of mild cognitive impairment early on. For clinical dementia care to benefit from these discoveries, researchers must combine PET amyloid imaging and CSF biomarkers with genetic information while conducting self-supervised pretraining procedures and developing performance optimization techniques for real-world clinical deployment. The developments in this research provide the base for future AI applications, enabling neurologists to detect conditions early while making treatment approaches more personalized and raising global patient life standards.

7.3 Limitations

Medical experts must consider significant constraints when they employ AI and Machine Learning techniques on MRI data to increase the speed of Alzheimer's Disease diagnosis. Such models become less applicable for wider use because training datasets typically contain one dominant group or population. Most available studies use data from focused demographic or clinical cohort groups, which reduces the extent to which such models can be effectively utilized across diverse patient populations with varied ethnic makeup, socioeconomic backgrounds, and genetic disparities (Alsubaie et al., 2024).

Traditional ML algorithm systems, including DL models, can detect advanced patterns within imaging datasets while maintaining complex internal operations that lack interpretive functions. Organizations may avoid adopting diagnostic tools when analysts do not trust recommendations from black-box systems whose outputs are difficult to interpret and understand and how they were explained or justified. Trustworthy AI (TAI) development requires ongoing research about model explainability techniques because this issue is a fundamental component of TAI creation. Implementing these tools in healthcare settings demands significant computational power that some medical facilities might lack. The models passed tests in independent datasets, which validated their strength, and health services researchers conducted prospective trials to confirm their clinical effectiveness (Zhao and Liu, 2022).

The absence of treatment options for AD means that exact diagnosis, coupled with early detection alone, will not lead to meaningful improvements in patient outcomes despite their being essential first steps. Future investigations must develop effective treatments simultaneously; otherwise, superior diagnostic methods will not deliver relevant clinical advantages.

CHAPTER VIII

Conclusion and Recommendations

8.1 Conclusion

The research demonstrates that ResNet50, EfficientNetV2-S, and ConvNeXt-Base demonstrate effective and dependable stage classification of Alzheimer’s disease by examining T1-weighted MRI brain scan data. Among the models, EfficientNetV2-S presented the most balanced performance outcomes, achieving more than 97% accuracy while maintaining balanced metrics for precision, recall, specificity, and F1-score. ResNet50 showed its strongest point in minimizing wrong positive results for advanced–stage patients, but ConvNeXt-Base displayed better detection capabilities for the critical biomarker of hippocampal atrophy in early Alzheimer's cases. A combination method that averages the output from all three models both maintained their distinctive identification methods and reduced overall mistakes, thus proving that different algorithms can strengthen diagnostic accuracy. Study results through confusion-matrix analyses confirmed that the model system could rectify misdiagnoses generated by individual models, making it ready for clinical use, which depends on accurate diagnosis for patient care decisions. These findings confirm that carefully selected and merged DL models can revolutionize Alzheimer's disease identification through efficient medical solutions that benefit multiple healthcare facilities.

8.2 Recommendations

This research requires the implementation of the following strategic directions to achieve clinical practice use and future investigation support:

1. Broaden & Diversify Data: Develop big multicenter MRI repositories between scanners, strengths of fields, and protocols, and leverage GAN-based augmentation to generate scarce atrophy patterns for fuller training sets.

2. Standardize Acquisition & Preprocessing Introduce a standard set of imaging protocols (field strength, sequences) and have one pipeline (bias-field correction, skull-stripping, intensity normalization) to produce similar inputs with later results the same or similar.

3. Fuse Multimodal Biomarkers. Complement structural MRI, cognitive scores, APOE genotype, amyloid/tau PET, and CSF markers—explore feature-level fusion to decision-level ensembles for maximum diagnostic performance.

4. Embed Explainability: Integrate saliency maps (Grad-CAM, Integrated Gradients), interactive visualizations of regional activations, and confidence scores to enable radiologists to check model rationale**.**

5. Optimize for Deployment Prune, quantize, and perform knowledge distillation to shrink models, then benchmark end-to-end inference for real-time on-site or edge within clinical workflows.

6. Validate externally and clinically. Test independently and run prospectively within memory clinics on ADNI-2, AIBL, and OASIS cohorts to determine performance across demographics, enhance diagnostics, and influence patient outcomes.

7. Foster Open Collaboration Support close cooperation by offering a secure, shared space where researchers, clinicians and engineers can confidently share anonymous MRI datasets, source code and models under agreed rules; form mixed consortia to decide on imaging protocols, preprocessing pipes and evaluation gauges; release open documentation for every improvement; and organize workshops or hackathons to discus the most effective techniques—in this way, combine efforts for building useful, effective tools for detecting Alzheimer's disease.

8. Ensure Ethics, Privacy, and compliance. Establish governance on consent, bias mitigation, and data protection. Early scope for FDA and EMA regulatory (AI diagnostic approval) pathways.

The recommendations enable future research to build upon this study's established work through DL–driven MRI analysis of Alzheimer's disease, which facilitates clinical adoption and leads to better patient outcomes worldwide.

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Appendix A

Thesis

ORIGINALITY REPORT

11%	8%	8%	3%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

Assoc. Prof. Dr. Boran ŞEKEROĞLU

Assist. Prof. Dr. Omid MIRZAEI