# SASTRA DEEMED TO BE UNIVERSITY
# DEPARTMENT OF CSE, BTECH MINI PROJECT,2024-2025
# ZEROTH REVIEW

## FINE-TUNING ALZHEIMER'S DISEASE DIAGNOSIS USING IMPROVED WAVELET CONVOLUTION NEURAL NETWORK [IWCNN]


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## Advancing early diagnosis of Alzheimer's disease with next-generation deep learning methods

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Dataset link: https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images

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ABSTRACT

Alzheimer's disease, characterized by cognitive decline and memory impairment, poses a significant healthcare challenge. This study presents a specially designed CNN model, utilizing contemporary approaches, to distinguish between various types of Alzheimer's disease. This model can serve as an early diagnostic tool to prevent the disease from progressing towards more pronounced and severe dementia symptoms. In this context, the performance of various transfer learning models has been examined, leading to the development of a specialized model integrating compression and excitation blocks, an innovative Avg-TopK pooling layer, and the SMOTE technique to handle data imbalance. The ablation study results demonstrate the critical role of these components, highlighting the model's effectiveness and innovative design. This study is novel in that it combines modern methodologies for detecting Alzheimer's disease, resulting in a model with state-of-the-art accuracy of 99.84% and improved computing efficiency. Grad-CAM analysis further demonstrates that the model focuses on cortical areas during classification, underscoring its potential as a robust diagnostic tool. These innovations represent a significant advancement over existing models, positioning this study as a pioneering effort in the early diagnosis of Alzheimer's disease. This study aims to contribute significantly to both academic research and medical applications by focusing on integrating artificial intelligence methodologies into medical diagnosis.

### 1. Introduction

Alzheimer's disease (AD) is a neurodegenerative disease primarily observed in the elderly population, characterized by cognitive decline, memory impairment, and behavioral changes [1,2]. As the disease progresses, cognitive abilities, including thinking skills and the ability to recall information, begin to deteriorate. AD is a leading cause of death worldwide, affecting individuals, families, and healthcare systems [3,4]. AD was initially identified by Dr. Alois Alzheimer in 1907. The disease was diagnosed in a 51-year-old female patient who was undergoing treatment at the psychiatric hospital in Frankfurt am Main. As the disease progressed, the patient exhibited various complex symptoms and experienced significant memory loss. It was observed that she could correctly name a series of objects when shown to her, but shortly after, she would forget everything. Additionally, difficulties in comprehension, hallucinations, and reading problems were detected. The disease process lasted for approximately four and a half years, and the patient passed away at the end of this period [5]. The World Health Organization (WHO) has indicated that approximately 10 million new cases are reported each year, and globally, more than 55 million people live with dementia, with over 60% of these residing in low and middle-income countries. Dementia is currently the seventh leading cause of death and leads to disability and dependency among the elderly population worldwide [6].

AD is one of the most common diseases in elderly individuals, characterized by a gradual slowing and deterioration of cognitive abilities. Early symptoms of the disease include difficulties in recent memory recall, word-finding difficulties, repetition, multitasking impairments, and mood or behavioral changes. As the disease progresses, individuals may experience more pronounced memory loss, lose simple functions such as dressing or bathing, encounter difficulties in language and comprehension, exhibit aggression, engage in wandering behavior, and even experience hallucinations. The severity of symptoms corresponds to the extent of nerve cell damage in the brain [7–9].

The rapid and accurate diagnosis of AD is crucial for effective disease management and treatment. Recently, CNN models have achieved notable success in various fields, including healthcare services [10–16]. Despite their success, current methodologies often face constraints such as high computational requirements and inefficiencies when dealing with imbalanced datasets. These challenges highlight the need for innovative approaches that are both effective and resource-efficient.

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## PROBLEM STATEMENT:

- Alzheimer's disease remains challenging to detect in its early stages, limiting timely intervention and effective treatment. Existing diagnostic methods, including traditional assessments and AI-based models, often struggle with accuracy and reliability.
- One major challenge is the imbalance in MRI datasets, where fewer cases of severe Alzheimer's leads to biased models that underperform on underrepresented categories. Additionally, conventional CNNs primarily extract spatial features but struggle to capture crucial frequency-based patterns, reducing classification accuracy. Moreover, deep learning models often function as black boxes, offering little transparency in their decision-making process, which makes clinical adoption difficult.

## OBJECTIVES:

- Develop a CNN architecture integrating *improved wavelet convolution* for more accurate Alzheimer's classification.
- Incorporate Squeeze and Excitation (SE) blocks and Avg-TopK pooling to improve feature representation in MRI scans.
- Apply SMOTE to balance the dataset, ensuring fair classification across all Alzheimer's severity levels.
- Utilize Grad-CAM to highlight important brain regions, improving transparency and clinical trust in AI predictions.
- Optimize the model's structure to achieve high accuracy with reduced computational complexity, making it suitable for real-world applications.

## DATASET DESCRIPTION :

The research uses an Alzheimer's disease brain MRI dataset from Kaggle, which contains 6,400 images classified into four different classes:

- Non-Demented
- Very Mild Demented
- Mild Demented
- Moderate Demented

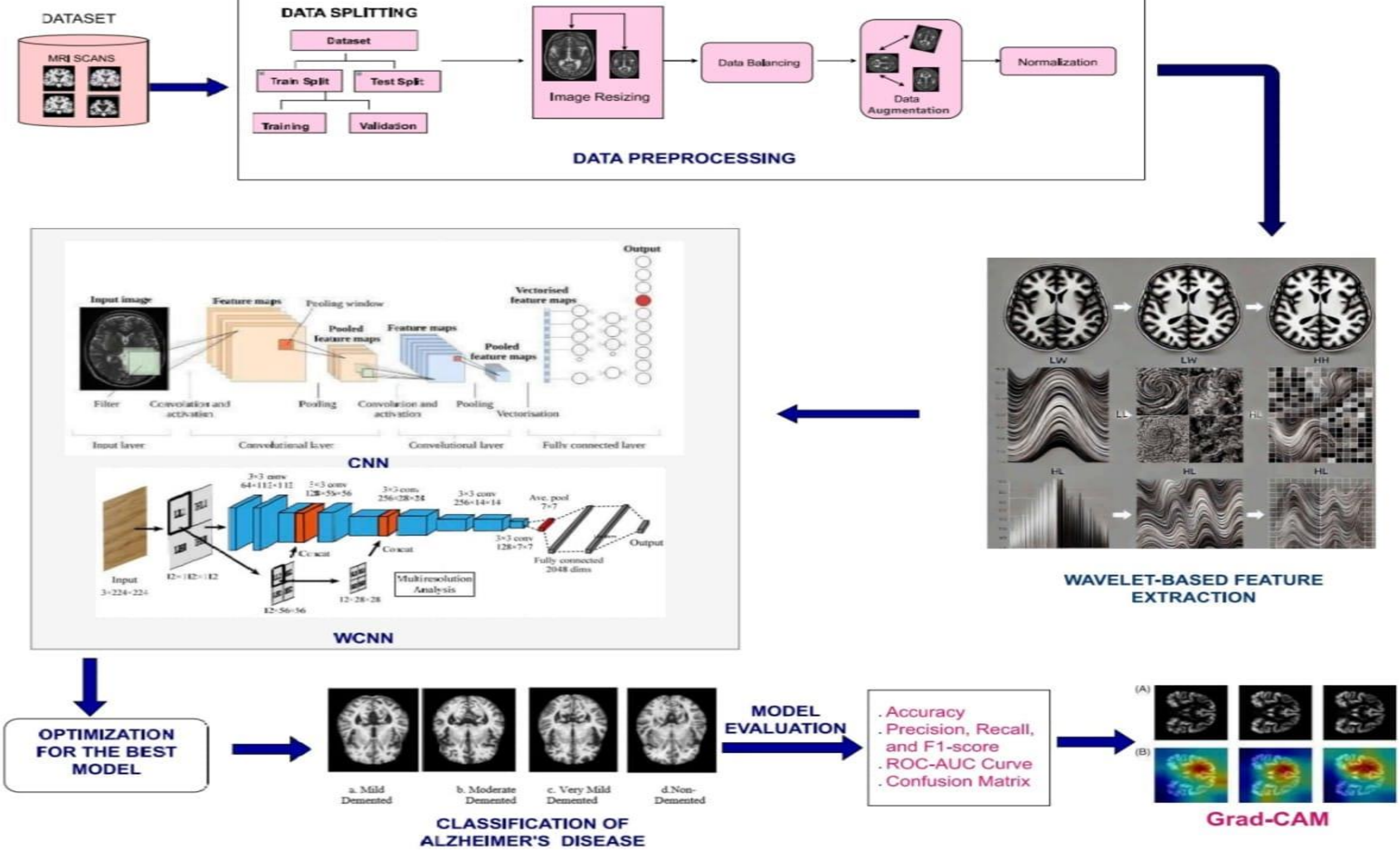
**Dataset Link:**
https://www.kaggle.com/datasets/borhanitrash/alzheimer-mri-disease-classification-dataset

# LITERATURE REVIEW

| S.NO | TITLE | JOURNAL | YEAR | AUTHOR(S) | TECHNIQUES USED | MERITS | DEMERITS |
|---|---|---|---|---|---|---|---|
| 1. | **Pipelined Deep Learning Architecture for the Detection of Alzheimer's Disease** | Biomedical Signal Processing and Control (Science Direct) | 2024 | T. Prasath, V. Sumathi | Pipelined LeNet (PLN) architecture, Image Fusion, MRI preprocessing | High classification accuracy (99.5%), faster execution time (0.65 ms) | Limited evaluation on real-world diverse datasets |
| 2. | **Machine and Deep Learning Approaches for Alzheimer's Disease Detection Using Magnetic Resonance Images: An Updated Review** | Measurement (Science Direct) | 2024 | M. Menagadevi, Somasundaram Devaraj, et al. | CNN, SVM, Transfer Learning, Preprocessing (Histogram Equalization, Contrast Stretching) | Comprehensive review covering 2013-2023 studies, highlights key ML and DL techniques | Lacks experimental validation of reviewed techniques |
| 3. | **Bio-Inspired Deep Learning-Personalized Ensemble Alzheimer's Diagnosis Model for Mental Well-Being** | SLAS Technology (Science Direct) | 2024 | Ajmeera Kiran, Mahmood Alsaadi, et al. | Personalized dynamically ensemble CNN (PDECNN), Attention Mechanism | Improves classification accuracy by 4%-11%, adapts to variations in brain degeneration | High computational complexity |

| s.no | TITLE | JOURNAL | YEAR | AUTHOR(S) | TECHNIQUES USED | MERITS | DEMERITS |
|---|---|---|---|---|---|---|---|
| 4. | **Fine-Grained and Multiple Classification for Alzheimer's Disease With Wavelet Convolution Unit Network** | IEEE Transactions on Biomedical Engineering | 2023 | Jinyu Wen, Yang Li, Meie Fang, et al. | Wavelet Convolution Unit (WCU), Multi-scale Wavelet Decomposition, Diffusion Tensor Imaging (DTI) | Achieves state-of-the-art fine-grained classification accuracy (97.89%) | Requires extensive computational resources |
| 5. | **Detection of Alzheimer's Disease Using Deep Learning Models: A Systematic Literature Review** | Informatics in Medicine Unlocked | 2024 | Eqtidar M. Mohammed, Ahmed M. Fakhrudeen, et al. | Various CNN architectures (ResNet, AlexNet, GoogleNet, EfficientNetB7), RNN, Deep Belief Networks | Summarizes 45 research papers on AD detection using deep learning | Lacks focus on non-imaging biomarkers |

# WORK PLAN


DATASET
MRI SCANS
DATA SPLITTING
Dataset
Train Split
Test Split
Training
Validation
Image Resizing
Data Balancing
Data Augmentation
Normalization
DATA PREPROCESSING
Output
Input image
Feature maps
Pooling window
Pooled feature maps
Feature maps
Pooled feature maps
Vectorised feature maps
Filter
Convolution and activation
Pooling
Convolution and activation
Pooling
Vectorisation
Input layer
Convolutional layer
Convolutional layer
Fully connected layer
CNN
Input
3×224×224
Concat
Concat
Multiresolution Analysis
Ave. pool 7×7
Fully connected 2048 dims
Output
WCNN
LW
LW
HH
LL
HL
HL
HL
HL
WAVELET-BASED FEATURE EXTRACTION
OPTIMIZATION FOR THE BEST MODEL
a. Mild Demented
b. Moderate Demented
c. Very Mild Demented
d.Non-Demented
CLASSIFICATION OF ALZHEIMER'S DISEASE
MODEL EVALUATION
. Accuracy
. Precision, Recall, and F1-score
. ROC-AUC Curve
. Confusion Matrix
(A)
(B)
Grad-CAM

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***THANK YOU!***