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Alzheimer’s Disease Class Prediction by Dynamic Feature Selection and Learning Model: A Review

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Abstract- Alzheimer's disease is a progressive brain disorder that mainly affects memory. Diagnosing it manually can take a lot of time and is often subject to mistakes because of the large number of patients. Many techniques exist for diagnosing and classifying Alzheimer's, but there is still a strong need for better methods for early detection. This paper looks at different techniques proposed by researchers for classifying the patient report into specific categories. Paper has list various image features used for the disease diagnosis. Different set of image category were also brief used for diagnosis of Alzheimer disease. Finally paper list various evaluation parameters that were used for the comparison of models.

Keywords: Alzheimer’s Disease, Brain MRI, Convolutional Neural Network, VGG Net.

I. INTRODUCTION

Alzheimer’s disease is a brain disorder that gradually destroys memory and thinking skills. It eventually affects a person’s ability to perform even basic tasks. In most cases, symptoms appear later in life. Estimates differ, but experts believe that over 6 million Americans, primarily those aged 65 and older, may have Alzheimer’s. Alzheimer’s is now the seventh leading cause of death in the United States. It is also the most common cause of dementia in older adults. Dementia is the loss of cognitive functions, such as thinking, remembering, and reasoning, along with changes in behavior. This decline affects a person's daily life and activities.

Alzheimer’s disease is named after Dr. Alois Alzheimer. In 1906, Dr. Alzheimer observed changes in the brain tissue of a woman who had died from an unusual mental illness. Her symptoms included memory loss, language issues, and unpredictable behavior. After her death, he examined her brain and identified many abnormal clumps, now called amyloid plaques, and tangled bundles of fibers, now known as neurofibrillary or tau tangles. These plaques and tangles in the brain are still regarded as key features of Alzheimer’s disease. Another feature is the loss of connections between neurons in the brain. Neurons carry messages between different areas of the brain, as well as from the brain to muscles and organs throughout the body.

Stages of Alzheimer's disease

Mild Alzheimer’s disease: As Alzheimer's progresses, individuals begin to experience increased memory loss and difficulties with cognitive functions. This can manifest as disorientation, such as wandering and getting lost, challenges managing finances or paying bills, and repetitive questioning. Completing routine tasks often takes more time, and personality or behavioral shifts, including irritability or apathy, may emerge. This is often the stage when a formal diagnosis is made.

Moderate Alzheimer’s disease: During this stage, brain areas responsible for language, reasoning, conscious thought, and sensory perception, such as recognizing sounds and smells, undergo further damage. Memory loss and confusion intensify, leading to difficulties in identifying familiar faces and close relations. People may find it challenging to learn new skills, complete tasks that require multiple steps, such as dressing, or adapt to new environments. Additionally, hallucinations, delusional thoughts, paranoia, and impulsive behaviors may occur as the disease continues to progress.

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Severe Alzheimer's disease: In the final stage, plaques and tangles spread extensively throughout the brain, causing significant tissue shrinkage. Individuals with severe Alzheimer's are unable to communicate verbally and become entirely dependent on others for their care. As the disease nears its end stage, individuals may become bedridden as bodily systems shut down.

II. LITERATURE REVIEW

Several previous studies that have constructed in trails in Alzheimer's disease detection in the following:
The paper by Waleed Al Shehri et al. reviews AD detection strategies for this permanent neurological disorder which mainly impacts elderly patients. The article highlights the importance of early precise diagnosis through detailed discussion about labor-intensive manual processes that lead to repeated errors. The suggested method employs DenseNet-169 and ResNet-50 CNN architectures for deep learning techniques to classify AD stages between Non-Dementia and Very Mild Dementia and Mild Dementia and Moderate Dementia. The DenseNet-169 architecture achieved its training accuracy at 0.977 and its testing accuracy at 0.8382 according to the results presented in [1].

Suriya Murugan et al. performed research on DEMNET which represents a deep learning model built for early dementia and AD diagnosis through analysis of MRI pictures. The model achieves high performance levels on the Kaggle dataset by reaching 95.23% accuracy and 97% AUC which enables the system to address class imbalance problems. Convolutional Neural Network architecture within the model allows both risk assessment of AD in individuals and the extraction of distinctive features. The model achieves accuracy of 84.83% during its robustness evaluation by validating performance using data from the Alzheimer's disease Neuroimaging Initiative (ADNI) database [2].

Sunday Adeola Ajagbe et al. ,their research focuses on the early diagnosis of Alzheimer's disease using deep convolutional neural networks (DCNN) for image classification of magnetic The study by Sunday Adeola Ajagbe et al. uses deep convolutional neural networks (DCNN) to interpret magnetic resonance imaging (MRI) pictures and identify early Alzheimer's disease stages. This study integrates traditional diagnosis methods with DCNN demonstration of its superior feature extraction properties to examine digital diagnostic tools in healthcare. Thirty-two models face challenges due to limited real-world data and slow calculating speed during an analysis of their performance and accuracy insights using six evaluation measures that include accuracy and F1-score. Deep learning approaches applied in the results allow for faster and more precise identification of Alzheimer's disease [3].

Bangyal Waqas Haider et al. Successful brain tissue damage prevention during AD treatment depends heavily on early detection according to the study because it explores the deep learning approach toward AD domain ontology construction. The study highlights the necessity of ontologies in biological research because we lack sufficient knowledge about Alzheimer's disease in the domain of knowledge. A Kenn-trained for AD detection analyzes data obtained from Kaggle using a convolution neural network together with multiple machine learning approaches. CNN achieves an accuracy of 94.61%. The results show deep learning provides a solution to improve ontology development which results in enhanced scalability with increased robustness [4].

Shukla GP et al. in [5] introduced innovative pre-processing techniques that markedly enhanced the classification accuracy of MRI images. Additionally, these methods substantially reduced the training time for various existing learning algorithms. The data for their research was derived from the Alzheimer's disease Neuroimaging Initiative (ADNI), with MRI images transformed from a 4D to a 2D format. Pre-processing steps included selective clipping, grayscale conversion, and histogram equalization. Following these steps, three learning algorithms were proposed for Alzheimer's disease (AD) classification: Random Forest, XGBoost, and Convolutional Neural Networks (CNN). Evaluation of the model on the dataset demonstrated superior performance, achieving an accuracy of 97.57% and a sensitivity of 97.60%.In their study, Liu, Yuyang et al. [6] employed a statistical approach combined with unsupervised learning to differentiate MRI scans among several groups: (1) cognitively normal (CN) versus Alzheimer's disease (AD); (2) stable mild cognitive impairment (sMCI) versus progressive mild cognitive impairment (pMCI); and (3) CN versus pMCI.

This was done using a limited number of labeled structural MRI scans. Regions of interest (ROIs) between each group pair were identified through two-sample t-tests, and an unsupervised learning neural network was used for feature extraction from these regions. The extracted features were then clustered to discriminate between groups. Their method was validated using baseline structural MRI scans from 715 individuals from the ADNI database, consisting of 231 CN, 198 AD, 152 sMCI, and 134 pMCI participants. In study [7], Gaussian descriptor-based features were proposed as novel biomarkers for differentiating between AD, Mild Cognitive Impairment (MCI), and Normal Controls (NC) using T1-weighted MRI images. Features such as the Gaussian shape operator, Gaussian curvature, and mean curvature were extracted and applied to a Support Vector Machine (SVM) for classification.

Calculations were initially performed separately for the Hippocampus and Amygdala, followed by feature fusion across regions. Authors in [8] developed a deep learning model for detecting Alzheimer's-related dementia using retinal photographs alone. Utilizing the EfficientNet-b2 network as the primary model architecture, features from optic nerve head-centered and macula-centered images from both eyes were extracted. Supervised deep learning models were created and enhanced with an unsupervised domain adaptation technique to address dataset discrepancies across six different studies. Shah et al. [9] implemented hard and soft voting algorithms to identify early stages of Alzheimer's disease.

Their dataset included 437 patients aged 60 to 96, with 72 being non-demented and 64 demented. They trained the algorithm on 70% of the data and tested it on the remaining 30% using classifiers such as hard voting, soft voting, decision trees, and SVM. The hard voting classifier achieved an accuracy of 84%. Huanhuan et al. [10] developed a method for early dementia detection using convolutional neural networks (ConvNets) and MRI scans. Gray and white regions of brain scans were classified using data from 615 MRI scans sourced from the ADNI database. Preprocessing involved statistical parameter mapping to reduce head movement, resizing images to 192×192×160, and applying classifiers like a 50-layer Residual Network and Neural Architecture Search Network.

Adding a dropout layer minimized overfitting, yielding accuracy rates of 97.65% to 88.37% for MCI and AD detection. Razavi et al. [11] focused on unsupervised feature learning using a two-step process. They extracted features from raw data through scattered filtering and an uncontrolled neural network layer, followed by sparse filtering and softmax regression to classify healthy versus unhealthy subjects. Methods like Boltzmann machines and dispersed coding distributed data collected from ADNI datasets, with 51 AD and 43 MCI patients. Using MRI data from 1.5T scanners, their model achieved a peak accuracy of 98.3% with softmax regression. Islam et al. [12] used deep learning CNN models to analyze brain MRI images for AD detection, including various disease stages.

Their CNN architecture comprised four layers: deep neural, batch processing, pooling, and ReLU layers. The method also effectively handled imbalanced datasets. Using the 3D MRI data from the OASIS dataset (416 samples), the model achieved high precision rates (0.81 and 0.82) with Inception-v4 and ResNet models. Danso et al. [13] applied two tree-based algorithms to build machine learning models predicting AD risk in European datasets and utilized transfer learning for UK datasets. SHAP was employed to visualize risk factors at population and individual levels. In study [14], a two-layer Random Forest (RF) model was designed for diagnosing AD and detecting disease progression. The first layer classified AD, MCI, and Normal Controls (NC), while the second predicted MCI-to-AD progression.

The model, trained on biological and clinical data from 1048 subjects, utilized SHAP for explaining RF classifiers globally and individually. Chang et al. [15] proposed an ensemble CNN model to classify AD stages based on brain shape. Their model combined the visual geometry group network (VGGNet) with a 1D CNN that transformed visual line segment information into vectors. This enhanced model utilized parallel 1D convolution layers for precise brain shape analysis, merging shape data with original image features for improved performance over existing methods. Amar Shukla et al. examine different approaches for detecting Alzheimer's Disease (AD), noting the rising global prevalence of the condition.

The paper explores the effectiveness of Automatic Pipeline Methods and Machine Learning Techniques, which have achieved over 95% accuracy in single and binary classifications. However, challenges persist in multi-class classification, especially in differentiating between AD and Mild Cognitive Impairment (MCI). From the research, it can be seen that multi-modal techniques are vital for cross-checking AD detection for extra accuracy validation. The goals of improving diagnostic accuracy and more sophisticated methods for the detection of AD and its stages are the aspirations of the study [16] While speaking about the problems in identifying Alzheimer’s disease, P. Kishore et al. have drawn attention to limitations in current methods that rely on behavioral and social history reports.

It is proposed that the machine learning methods should also be used along with AI to help improve the precision of diagnosis. The research utilizes a dataset which includes MRI scans along with other variables for the purpose of exploring relationships and improving classification accuracy. Since Alzheimer’s disease has no known effective treatment at this time, it emphasizes the importance of diagnosis at an early stage for appropriate therapy. As per the findings, Support Vector Machine using the linear kernel model is more accurate than the other methods examined in the study [17]. The increasing rate of dementia cases among the older generation has been addressed by C. Kavitha et al. by applying machine learning models for the early-stage detection of Alzheimer’s disease (AD).

The research highlights the problems faced at the stage of diagnosis as well as the benefits associated with treatment at an early stage. Their research has implemented several machine learning techniques such as Decision Tree, Random Forest and Support Vector Machine to analyze the data especially from the Open Access Series of Imaging Studies (OASIS). The proposed method of classification is better than existing methods with an average validation accuracy of 83%. These findings are aimed at assisting physicians in diagnosing AD in order to provide early treatment and potentially reduce mortality rates [18].

Deep learning technique for Alzheimer's disease (AD) is proposed by Hadeer A. Helaly et al. which incorporates convolutional neural networks (CNN) to augment deep learning approaches to aid in the recognition of early stage AD. It employs neuroimages consisting of 2D and 3D graded structural scans of the brain from the ADNI database to carry out medical image categorization of the various stages of AD. The system employs dual strategies like the transfer learning with architectural VGG19 model and some primary settings of CNN. The suggested web application for remote AD validation boosts the classification accuracy to 93.61% and 95.17% for 2D and 3D [19].

Using MRI data, Swathi S. Kundaram et al. also explore a deep learning approach for the classification of Alzheimer's disease (AD). It introduces a deep convolutional neural network (DCNN) that classifies participants into three groups: normal control (NC), moderate cognitive impairment (MCI), and Alzheimer's disease (AD). The technology achieves a 98.57% accuracy rate on the ADNI dataset, surpassing conventional machine learning approaches requiring handcrafted features. For proper patient care and possible future therapy, the authors of the article emphasize that an early diagnosis is important [20]. M. El. Assy et al. conducted research on a fresh convolutional neural network (CNN) design for Alzheimer's disease (AD) detection and classification using magnetic resonance imaging (MRI) data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database.

The designed model incorporates multiple CNNs with different filters for extensive detection which resulted in triple classification accuracy rates of 99.43% and 99.57% and 99.13%. Its design successfully interprets essential image features found in MRI studies to support accurate AD subtype identification and stage assignment necessary for developing personalized interventions [21]. Y N Fu'adah et al. proposed a study focused on Alzheimer's disease that presents memory loss because brain neurons responsible for cognitive processes become damaged.

Researchers developed a classified system to examine MRI datasets by employing Convolutional Neural Networks (CNN) based on AlexNet architecture. Using a total of 664 MRI scans, the study categorizes Alzheimer's into four stages: The stages in the analysis are non-demented, very mildly demented, mildly demented and moderately demented. The analysis method demonstrates a 95% accuracy rate making it a valuable diagnostic tool for Alzheimer's disease stages that provides healthcare providers with essential treatment information [22]. R.R. Janghel et al. developed a special deep convolutional neural network (CNN)-based system to detect early Alzheimer's disease through diagnosis processes.

The novel preprocessing method for Alzheimer's picture datasets within this system leads to improved detection accuracy. Clinical evaluation enabled the team to achieve an impressive 99.95% diagnostic accuracy for Alzheimer's disease through fMRI scans thanks to data training from the Alzheimer's Disease Neuroimaging Initiative (ADNI). A research approach demonstrates how deep learning strengthens diagnosis procedures for Alzheimer's disease while implementing multiple classification methods [23]. Manu Raju and associates suggested the study addresses the difficulties in detecting Alzheimer's disease because of comparable brain patterns by concentrating on the multilayer categorization of the condition using MRI images.

It achieves 99% predicted accuracy by using deep learning techniques, particularly transfer learning with the VGG16 model. Correct staging of Alzheimer's disease between four phases including mild dementia to very mild dementia stands as a critical matter according to the research. The application of deep learning in medical imaging is proven through the proposed approach which delivers superior outcomes compared to previous studies [24].

The paper by Nagaraj Yamanakkanavar et al. outlines deep learning methods for MRI segmentation, improving classification accuracy for Alzheimer's disease (AD) detection. It discusses various state-of-the-art methods for classifying AD versus healthy controls and mild cognitive impairment stages.The authors highlight the challenges in tracking AD transitions due to limited MRI data in the ADNI dataset. Competitive classification performance was achieved using independent training and testing sets. The study emphasizes the importance of convolutional neural networks in analyzing brain structures for AD diagnosis [25].

Robin Wolz et al. achieved 93% sensitivity and 85% specificity for HC/AD classification using combined features. For S-MCI/P-MCI, the results were 67% sensitivity and 69% specificity. The combination of features improved classification accuracy compared to individual MR-based features. The best individual feature results were 90% sensitivity and 84% specificity for HC/AD classification. The research demonstrated that combining multiple MRI features enhances predictive power in early AD detection. Significant improvements in classification accuracy were noted when all features were combined. The study utilized 834 ADNI baseline images for evaluation [26].

Avinash Bhagat et al. suggested the study achieved 96.6% accuracy for multi-class Alzheimer's disease stage classifications using the MobileNet model. The research developed a novel framework for identifying different stages of Alzheimer's disease. The MobileNet model outperformed other models like VGG16 and ResNet50 in medical image analysis. The approach utilized transfer learning with pretrained health data classification models for improved results. The findings indicate that the CNN architectures effectively reduce computational burden and overfitting [27]. Dr. Rachna Jaina et al. proposed the method achieved an accuracy of 95.73% for the 3-way classification of Alzheimer's disease, MCI, and cognitively normal subjects. The study utilized a pretrained VGG16 network as a feature extractor for classification tasks. Various metrics were computed to support the performance of the classification model.

The results were compared with past methods, demonstrating the effectiveness of the proposed approach [28]. Junhao Wen et al. presents the paper to identifies that about 50% of surveyed studies may report biased results due to data leakage. It highlights the difficulty in comparing classification performance across studies due to variations in participant selection and preprocessing. The research emphasizes the lack of reproducibility in studies due to unavailable frameworks and implementation details. The study concludes that AE pre-training's impact on performance remains unproven due to suspected data leakage in previous research. The paper presents an open-source framework for AD classification, integrating various tools for data processing and evaluation [29].Ruhul Amin Hazarika et al. introduces the study on the DenseNet-121 model achieved an average performance rate of approximately 89% in classifying Alzheimer's disease (AD) using brain MR images.

The modified DenseNet-121 model improved performance to 90.22% and execution time was enhanced by using depth- wise convolution layers. MobileNet-V1 classified AD efficiently with an average performance of around 88.11%. EfficientNet-B0 showed poor performance with an average performance of 73.94% in AD classification. VGG-16 achieved an average performance of around 80% in classifying AD. Inception-V1 provided an average performance of 83% in AD classification. The paper emphasizes the need for further modifications and data acquisition for improved classification accuracy [30].

Author	Description	Methods	Performance Measure
Chang-Min Kim and Woobeom Lee	The paper addresses Alzheimer's disease (AD) diagnosis using MRI.	CNN VGG-16 (Feature Extractor)	Accuracy- 98.6%
Suriya Murugan et al.	The model was trained using a variety of datasets.	CNN	Accuracy- 95.23%
Waleed Al Shehri et al.	Model has ability to extract features from complex medical images.	CNN DenseNet-169 ResNet- 50	DenseNet-169 Accuracy- 83.82% ResNet-50 Accuracy- 81.92%
Waqas Haider Bangyal et al.	Multimodal feature extraction techniques, such as Random Forest, MLP, SVM, etc.	CNN	Accuracy- 94.61%
Shagun Sharma et al.	The model incorporates activation function such as ReLu and SoftMax.	CNN VGG-16 (Feature Extractor)	Accuracy- 90.4%
Sunday Adeola Ajagbe et al.	Reduces computation time by removing redundancy from the dataset.	DCNN VGG-19 (Feature Extractor)	Accuracy- 77.66%

III. IMAGE FEATURES

Color feature: Image is a matrix of light intensity values, these intensity values represent different kind of color. so to identify an object colure is an important feature, one important property of this feature is low computation cost.

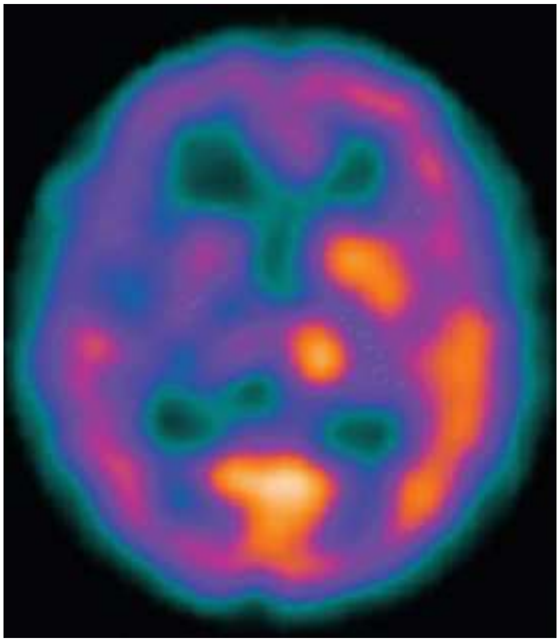

Fig. 1 Represent the HSV (Hue Saturation value) format of an image.

Different Image files available in different color formats like images have different colure format ranging from RGB which stand for red, green, and blue. This is a three-dimensional representation of a single image in which two-dimensional matrix represent single color and collection of that matrix tends to third dimension. In order to make intensity calculation for each pixel gray format is use, which is a two dimension values range from 0 to 255. In case of binary format which is a black and white color matrix whose values are only 0 or 1. With the help of this color feature face has been detected efficiently in [8].

Edge Feature: As image is a collection of intensity values, and with the sudden change in the values of an image one important feature arises as the Edge as shown in figure 4. This feature is use for different type of image object detection such as building on a scene, roads, etc. [5]. There are many algorithms has been developed to effectively point out all the images of the image or frames which are Sobel, Prewitt, canny, etc. out of these algorithms canny edge detection is one of the best algorithms to find all possible boundaries of an images.

Texture Feature: Texture is a degree of intensity difference of a surface which enumerates properties such as regularity and smoothness [1]. Compared to color space model, texture requires a processing step. The texture features on the basis of color are less sensitive to illumination changes as same as to edge features.

Histogram Feature: In this step image vector obtained after pre-processing is used where histogram of the image is found at one bin. This can be understand as let scale of color in fig. 4.2 is 1 to 10, than count of each pixel value is done in the image. So as per above vector Hi=[0, 0, 0, 4, 3, 5, 2, 1 2, 0] where H represent the color pixel value count and i represent the position in the H matrix with color value.

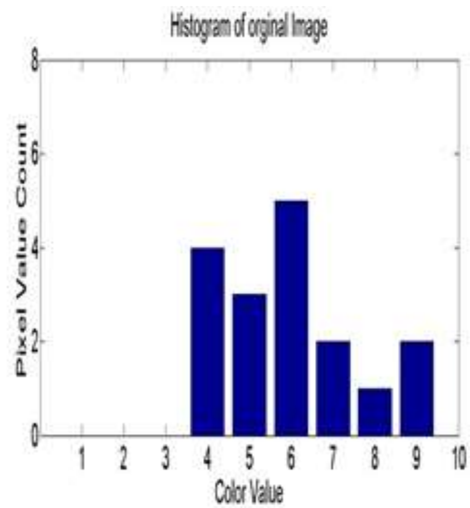

Fig. 2 Histogram of the original image.

Corner Feature: In order to stabilize the video frames in case of moving camera it require the difference between the two frames which are point out by the corner feature in the image or frame. So by finding the corner position of the two frames one can detect resize the window in original view. This feature is also use to find the angles as well as the distance between the object of the two different frames. As they represent point in the image so it is use to track the target object.

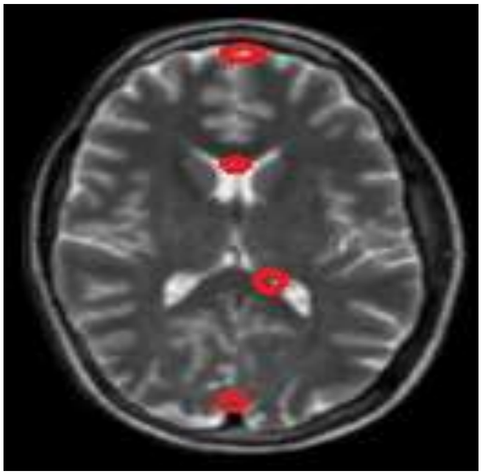

Fig 3 Represent the corner feature of an image with green point.

DWT (Discrete Wavelet Transform): LL: In fig. 4 upper left part is term as LL block. This block of image is obtain by filtering the image rows from the low pass filter then pass same to the low pass filter but here column are filter for the analysis. This block contain flat region of the image which do not have any edge information, so this is term as approximate version of the image.

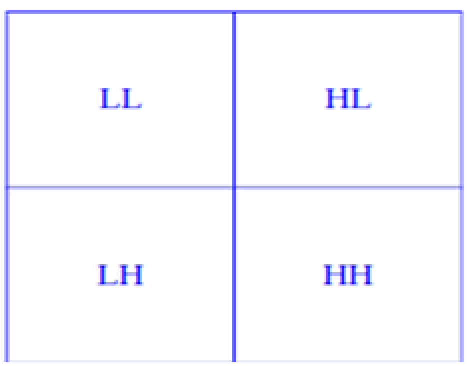

Fig. 3.1 DWT of image from [8].

HL: In fig. 4 upper right part is term as HL block. This block of image is obtain by filtering the image rows from the high pass filter then pass same to the low pass filter but here column are filter for the analysis. This block contain horizontal edge region of the image which do not have any flat information.

LH: In fig.4 lower left part is term as LH block. This block of image is obtain by filtering the image rows from the low pass filter then pass same to the high pass filter but here column are filter for the analysis. This block contain vertical edge region of the image which do not have any flat information.

HH: In fig. 4 lower right part is term as HH block. This block of image is obtain by filtering the image rows from the high pass filter then pass same to the high pass filter but here column are filter for the analysis. This block contain diagonal edge region of the image which do not have any flat information.

IV. HEALTH IMAGE

Brain Imaging

Alzheimer's-related dementia stems from the gradual degeneration of brain cells. This degeneration can be observed in different ways through brain scans, although imaging alone is not sufficient for diagnosis. This is because changes seen in Alzheimer's may overlap with normal age-related changes. However, brain imaging serves critical roles in:

- Ruling out other conditions such as hemorrhages, brain tumors, or strokes.
- Differentiating between various degenerative brain disorders.
- Establishing a baseline for the degree of brain tissue degeneration.

The most commonly utilized imaging methods include:

Magnetic Resonance Imaging (MRI):

MRI is widely used for structural brain assessment. It produces high-resolution images through strong magnetic fields and radio waves, enabling visualization of cortical thinning, hippocampal atrophy, and ventricular enlargement. Volumetric MRI is particularly effective in quantifying medial temporal lobe atrophy, a hallmark of early AD (Jack et al., 2010) [36].

Computerized Tomography (CT):

CT scans employ X-rays to generate cross-sectional brain images. While less sensitive than MRI for subtle structural changes, CT is effective for detecting gross abnormalities such as strokes, tumors, or extensive brain atrophy (Knop man et al., 2001) [37]. Due to lower cost and higher availability, CT is often used as an initial screening tool in dementia evaluation.

Positron Emission Tomography (PET):
PET provides functional and molecular imaging insights by utilizing radioactive tracers:

Fluorodeoxyglucose (FDG) PET: Measures regional cerebral glucose metabolism, with reduced uptake commonly observed in the temporoparietal cortex and posterior cingulate gyrus in AD (Mosconi, 2005) [38].

Amyloid PET: Uses tracers such as Pittsburgh Compound B (PiB) to detect amyloid-β plaques, enabling in vivo visualization of one of AD's pathological hallmarks (Klunk et al., 2004) [39].
Tau PET: A more recent advancement, tau-specific tracers allow the detection of neurofibrillary tangles, correlating closely with disease severity and cognitive impairment (Ossenkoppele et al., 2016) [40].

Although amyloid and tau PET scans have transformed AD research by improving diagnostic accuracy and tracking disease progression, their use remains limited in clinical practice due to high cost and limited accessibility.

V. EVALUATION PARAMETERS

Evaluation Parameters for Alzheimer's Disease Detection The performance of Alzheimer's disease (AD) detection systems is assessed using several key metrics:

- **Accuracy:** Overall proportion of correctly classified cases (AD and non-AD).
- **Sensitivity (Recall):** Ability to correctly identify AD cases; critical to avoid missed diagnoses.
- **Specificity:** Ability to correctly identify non-AD cases; reduces false alarms.
- **Precision:** Proportion of true AD cases among those predicted as AD.
- **F1-Score:** Harmonic mean of precision and sensitivity; useful in imbalanced datasets.
- **ROC Curve & AUC:** Measure overall discriminative ability; higher AUC indicates stronger performance.
- **Kappa Statistic:** Assesses agreement between model predictions and clinical diagnoses beyond chance.
- **Processing Time:** Ensures clinical feasibility through efficient computation.

VI. CONCLUSION

Recent advances in brain imaging and AI have significantly improved Alzheimer's disease (AD) detection. Deep learning models, particularly CNNs and ensemble approaches, achieve high accuracy in classifying AD, Mild Cognitive Impairment (MCI), and normal controls, though multi-class classification remains challenging. Various image features were used by the different work but frequency-based feature has increased the detection accuracy of the work. Further paper has found that image pre-processing is important by removing unwanted information in the image. Different types of images techniques were discussed in the paper where MRI has increases the work performance in various works. Future research should focus on improving the detection accuracy with noisy image.

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