CODEN [USA]: IAJPBB ISSN: 2349-7750

INDO AMERICAN JOURNAL OF
PHARMACEUTICAL SCIENCES

SJIF Impact Factor: 7.187
https://zenodo.org/records/10644229

https://www.iajps.com/volumes/volume11-january-2024/36-issue-01-january-24/

Available online at: http://www.iajps.com *Research Article*

NEW AUTOMATED MODELS FOR THE EARLY DIAGNOSIS OF ALZHEIMER'S DISEASE USING MRI IMAGES

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Abstract:

Alzheimer's disease (AD) is a progressive and irreversible neurodegenerative disorder that is the leading cause of dementia. It is characterized by the accumulation of abnormal protein deposits in the brain, disrupting normal brain cell function. Symptoms develop slowly and worsen over time, including memory loss, difficulty with language and problem-solving, confusion, and changes in mood and personality. Researchers have proposed and implemented a hybrid framework that combines the Gray wolf optimization algorithm (GWO) and multiple discrete wavelets transform (DWTs) algorithms to achieve early detection using a support vector machine (SVM) and convolutional neural network (CNN). This framework involves several essential steps, including data acquisition, preprocessing, and image-to-signal transformation; feature extraction using four discrete wavelet transform systems (demy, semy, bior1, db8); feature selection through a Gray wolf optimization algorithm (GWO), and SVM-based classification and convolutional neural network (CNN). These steps are critical for developing accurate and reliable machine and deep-learning models for Alzheimer's disease detection. The study's results demonstrate the effectiveness of the proposed system, achieving an average accuracy of 94.5% using a support vector machine and 95.4% using a convolutional neural network in detecting Alzheimer's disease. The integration of machine learning and deep learning algorithms such as SVM, CNN, and Gray wolf optimization for feature selection significantly contributes to the model's accuracy. This research emphasizes the importance of early detection of Alzheimer's disease and showcases the machine's potential and deep learning techniques using brain magnetic resonance images (MRI) to accomplish this objective.

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Please cite this article in press** Yahea Alzahrani **et al., New Automated Models For The Early Diagnosis Of Alzheimer's Disease Using MRI Images**., **Indo Am. J. P. Sci, 2024; 11 (01).

INTRODUCTION:

Alzheimer's disease (AD) is a common neurodegenerative disease associated with the accumulation and deposition of cerebral beta-amyloid, which impairs cognitive function. Memory loss, disorientation, and impairment of daily tasks are among the symptoms [1]. While it is an incurable disease, some therapies can help control symptoms and limit their course, such as medication, exercise, and social interaction. The ultimate objective of the disease's study is to discover a cure, as it is a significant worldwide health concern [2]. The unpredictability of disease development, overlapping symptoms with other disorders, absence of a conclusive diagnostic test, difficulties recognizing the disease in its early stages, and restricted access to diagnostic equipment make it difficult to diagnose Alzheimer's disease [3]. Despite these drawbacks, work on creating novel biomarkers and diagnostic instruments has advanced [3]. To get above these obstacles and enhance early and precise Alzheimer's disease diagnosis, more research is required [4].

Detecting Alzheimer's disease is challenging due to its complexity and the absence of definitive diagnostic tests [5]. Key challenges include overlapping symptoms with normal aging or other dementia types, the lack of specific biomarkers, late diagnosis at advanced stages, variability in progression, limited access to specialized facilities, and lack of awareness [3]. Addressing these challenges requires ongoing research for better diagnostic tools, raising awareness, and improving access to specialized facilities [6]. Early detection and intervention can potentially improve management and future therapeutic interventions for Alzheimer's disease [7].

Early detection of Alzheimer's disease is essential for planning future care, improving patient outcomes, furthering research, and participating in clinical trials [1]. Early identification lowers healthcare costs, permits prompt intervention and treatment, makes it easier to gather crucial data for research, and permits involvement in clinical trials for novel medications and treatments [8]. Various methods, including cognitive testing, brain imaging, bio-marker testing, genetic testing, and machine learning, are used to detect Alzheimer's disease [9].

The role of neuroimaging in Alzheimer's disease (AD) diagnosis is undergoing a paradigm shift. Traditionally employed to rule out other etiologies, it increasingly contributes to accurate disease identification, extending beyond its historical limitations to later stages (Figure 1) [10]. Recent advancements in neuroimaging modalities, encompassing both structural and functional Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) studies, unveil characteristic brain changes not only in symptomatic but also in prodromal and even presymptomatic phases of AD. This paves the way for earlier diagnosis and intervention, potentially revolutionizing our approach to this neurodegenerative disease [11, 12].
The chance of Alzheimer's disease may also be predicted by deep learning and machine learning algorithms using vast data sets of medical history, demographic data, cognitive test results, and brain imaging data [13].

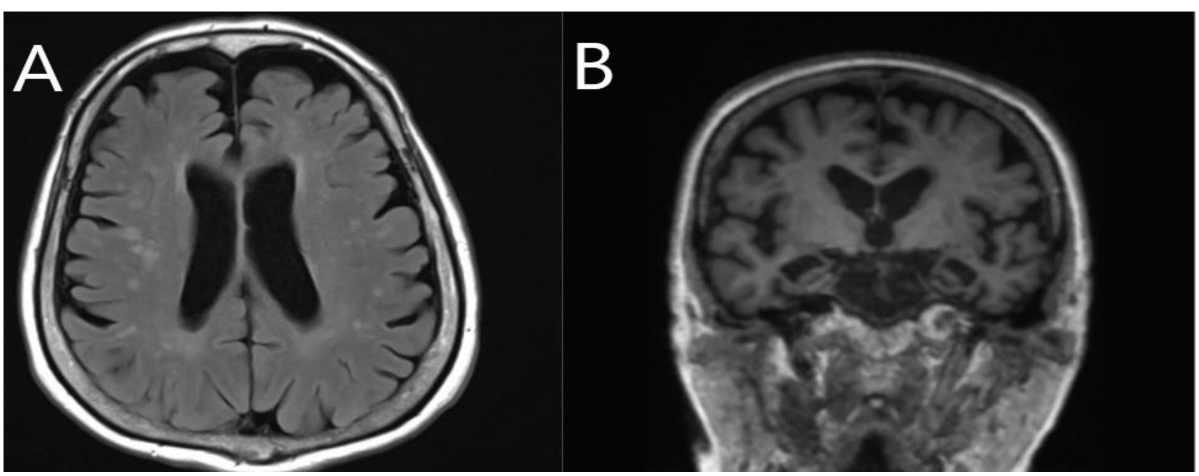

Figure 1. (A) Axial Fluid-attenuated inversion recovery (FLAIR) and (B) *T1-weighted* images of the patient with Alzheimer's disease demonstrate generalized cerebral volume loss; this is most pronounced in the hippocampi, which are symmetrically atrophied. There are multiple white matter hyperintensities in keeping with chronic small vessel ischemic white matter changes.

Detecting Alzheimer's disease early is vital for timely intervention and treatment, allowing for symptom management and improved quality of life [14]. It enables planning, informed decision-making, and access to supportive services for individuals and their families. Early detection facilitates research, clinical trials, and the development of new treatments [1]. It enables personalized care plans and strategies for disease management, including medication and lifestyle modifications [15]. It also supports financial and social planning, ensuring adequate support and engagement in meaningful activities. It enhances interventions, empowers decision-making, and improves the well-being of individuals affected by Alzheimer's disease [2,16].

This study investigates several research questions on using machine learning to diagnose Alzheimer's disease. Thus, these are the main issues that our study will try to answer: What are the best machine or deep learning architectures for detecting Alzheimer's disease? Which characteristics or indicators are the most informative for diagnosing Alzheimer's disease? How can machine and deep learning algorithms handle multi-modal data efficiently?

Several crucial processes are needed for both our study and common practice when utilizing machine and deep learning to diagnose Alzheimer's disease [17]. These include data collection, preprocessing, model construction and training, model assessment, hyperparameter tweaking, and classification [18]. These actions are essential for creating machine and deep learning models that reliably and accurately identify Alzheimer's disease. Data collection includes obtaining pertinent information from both healthy and patients with Alzheimer's disease. Data preprocessing is ensuring the quality of the collected data by cleaning and preparing it. To maximize the model's performance and guarantee its correctness and dependability, model creation for feature extraction and selection, model training, assessment, and hyper-parameter adjustment are prerequisites [19,20].

The rest of this paper is organized as follows: Section 2 presents the related work, and Section 3 introduces the proposed methodologies. The experiment results and discussion are in Section 4. Finally, Section 5 contains conclusions and future work.

2. Related Work

The difficulties in identifying Alzheimer's disease are covered in [21], along with how deep learning algorithms may be able to increase the precision and effectiveness of diagnosis. The authors examine several deep-learning architectures that have been used in the diagnosis of Alzheimer's disease, including Deep Belief Networks (DBNs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs). Additionally, they stress how crucial feature extraction and data pretreatment are to improving the functionality of deep learning models. The study concludes by pointing out that deep learning algorithms have shown encouraging results in identifying Alzheimer's disease and may enhance early diagnosis and treatment. To confirm these models' performance on bigger and more varied datasets, however, and to investigate the possibilities of various deep learning architectures and methodologies for Alzheimer's disease detection, additional study is required.

A technique is shown in [22] to extract characteristics from MRI data and categorize them into four classes: mixed dementia, Alzheimer's disease, normal control, and moderate cognitive impairment. The method incorporates Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) network. Using a dataset of 416 patients, the scientists assessed the suggested method's performance and contrasted it with other cutting-edge techniques. With an accuracy of 94.79%, the findings demonstrated that the suggested strategy performed better than the other approaches. According to the paper's conclusion, the suggested approach utilizing brain MRI data has the potential to increase the efficacy and accuracy of Alzheimer's disease diagnosis. It may also result in earlier identification and improved treatment results.

A suggested method in [6] employs a Long Short-Term Memory (LSTM) network to categorize electroencephalogram (EEG) spectral pictures into healthy control and Alzheimer's disease categories after a Convolutional Neural Network (CNN) has extracted characteristics from the images. A dataset of 86 people was used in the study to assess the technique's effectiveness and compare it with alternative ways. The method outperformed the others, with an accuracy of 91.86%. The scientists hypothesize that by employing non-invasive EEG data, this method might enhance treatment results and enable an early diagnosis of Alzheimer's disease.

The authors in [23]examined 42 research that made use of several neuroimaging modalities, such as MRI, PET, and SPECT, as well as different deep learning architectures, such as CNNs, Auto-encoders, and Generative Adversarial Networks (GANs). The performance of the models, the significance of feature extraction and data preprocessing, and the possibilities of transfer learning were among the main conclusions they outlined. The authors conclude that deep learning methods can potentially improve diagnosis efficiency and accuracy and have demonstrated encouraging results in detecting Alzheimer's disease from neuroimaging data. Further investigation is necessary to validate the efficacy of these models on more extensive and varied datasets and investigate the possibilities of alternative deep learning architectures and methodologies in the identification of Alzheimer's disease.

A CNN is used in the suggested method in [14] to extract characteristics from neuroimages and categorize them as either normal control or Alzheimer's disease. A dataset of 355 participants was used in the study to assess the technique's effectiveness and compare it with alternative ways. The method outperformed the others, with an accuracy of 94.2%. According to the scientists, the use of neuroimaging data in the diagnosis of Alzheimer's disease might be enhanced by this deep learning-based method, perhaps resulting in earlier identification and improved treatment results.

In [2], The study focuses on the application of deep learning techniques to automatically analyze structural MRI scans for AD diagnosis. The authors propose a 3D CNN architecture that takes the volumetric MRI data as input and learns to extract meaningful features for classification. The CNN model is trained on a dataset consisting of MRI scans from AD patients and healthy individuals. The performance of the proposed method is evaluated using various metrics, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). The results demonstrate that the 3D CNN approach accurately distinguishes AD patients from healthy individuals, highlighting its potential for accurate AD diagnosis. The paper discusses the advantages of using 3D CNNs over traditional methods, such as manual segmentation and feature extraction, for AD diagnosis. It emphasizes the ability of deep learning models to automatically learn discriminative features from raw MRI data, eliminating the need for manual feature engineering.

In [16], The authors trained the normative model on the UK Biobank dataset, consisting of 11,034 healthy controls, and then applied it to patients with mild cognitive impairment (MCI) and AD from various datasets. They aimed to assess the severity of brain anatomical alterations in these patient groups and identify the specific brain regions associated with such deviations. Additionally, the performance of the normative model was compared to traditional classifiers in distinguishing between patients and healthy controls. The results of the study demonstrated that the normative model successfully captured deviations in patients' brain patterns according to the severity of their clinical condition. Key regions implicated in the deviations included the medial temporal cortex and the ventricular system, consistent with previous neuroimaging studies of MCI and AD. The researchers found that the normative model exhibited comparable cross-cohort generalizability to traditional classifiers.

In [24], The authors focus on a predictive framework that utilizes brain volume trajectories for the early detection of Alzheimer's disease. The paper discusses the methodology and findings of the study conducted by the researchers. The framework proposed in the study aims to identify individuals at risk of developing Alzheimer's disease by analyzing brain volume changes over time. The authors highlight the significance of early detection in improving management and treatment outcomes for the disease. The review provides insights into the potential of brain volume trajectories as a predictive biomarker for Alzheimer's disease and contributes to the existing literature on early detection methods.

In [25], The review focuses on the analysis of features associated with Alzheimer's disease and the detection of its early stage using functional brain changes observed in magnetic resonance images (MRI) with a fine-tuned ResNet18 network. The authors describe the methodology employed in the study and present the findings. The study aims to identify early signs of Alzheimer's disease by analyzing functional brain changes captured in MRI scans. The fine-tuned ResNet18 network is utilized as a deep learning model to extract relevant features and classify individuals into different stages of the disease. The review contributes to the existing literature by exploring the potential of functional MRI and deep learning techniques for early detection of Alzheimer's disease, offering insights into the analysis of disease-related features in MRI data.

In [26], The review focuses on the use of 3D convolutional neural networks (CNNs) for diagnosing Alzheimer's disease using structural magnetic resonance imaging (MRI) data. The authors describe the methodology employed in the study and present the key findings. The study aims to develop an accurate diagnostic model by leveraging the capabilities of 3D CNNs to extract spatial features from structural MRI scans. The review contributes to the literature by exploring the potential of deep learning techniques, specifically 3D CNNs, for the diagnosis of Alzheimer's disease based on structural MRI data. The findings provide insights into the effectiveness of this approach and its potential implications for clinical applications.

3. The proposed methodology

Using Support Vector Machine (SVM), Convolutional Neural Networks (CNN), and Gray wolf optimization (GWO) algorithm to identify Alzheimer's disease, the proposed methodology , as shown in (Figure 2), consists of the following stages: Gathering an MRI scan dataset from both healthy and Alzheimer's disease patients, preprocessing the data to make it ready for the model's input and turning the images into signals, extracting features to find patterns, then using the Gray Wolf optimization algorithm to choose the most relevant features, fine-tuning the model to increase accuracy, testing the model's performance on an additional MRI scan dataset, and using the trained and tested model to predict Alzheimer's disease by inputting new preprocessed MRI scans, are the steps involved in this process.

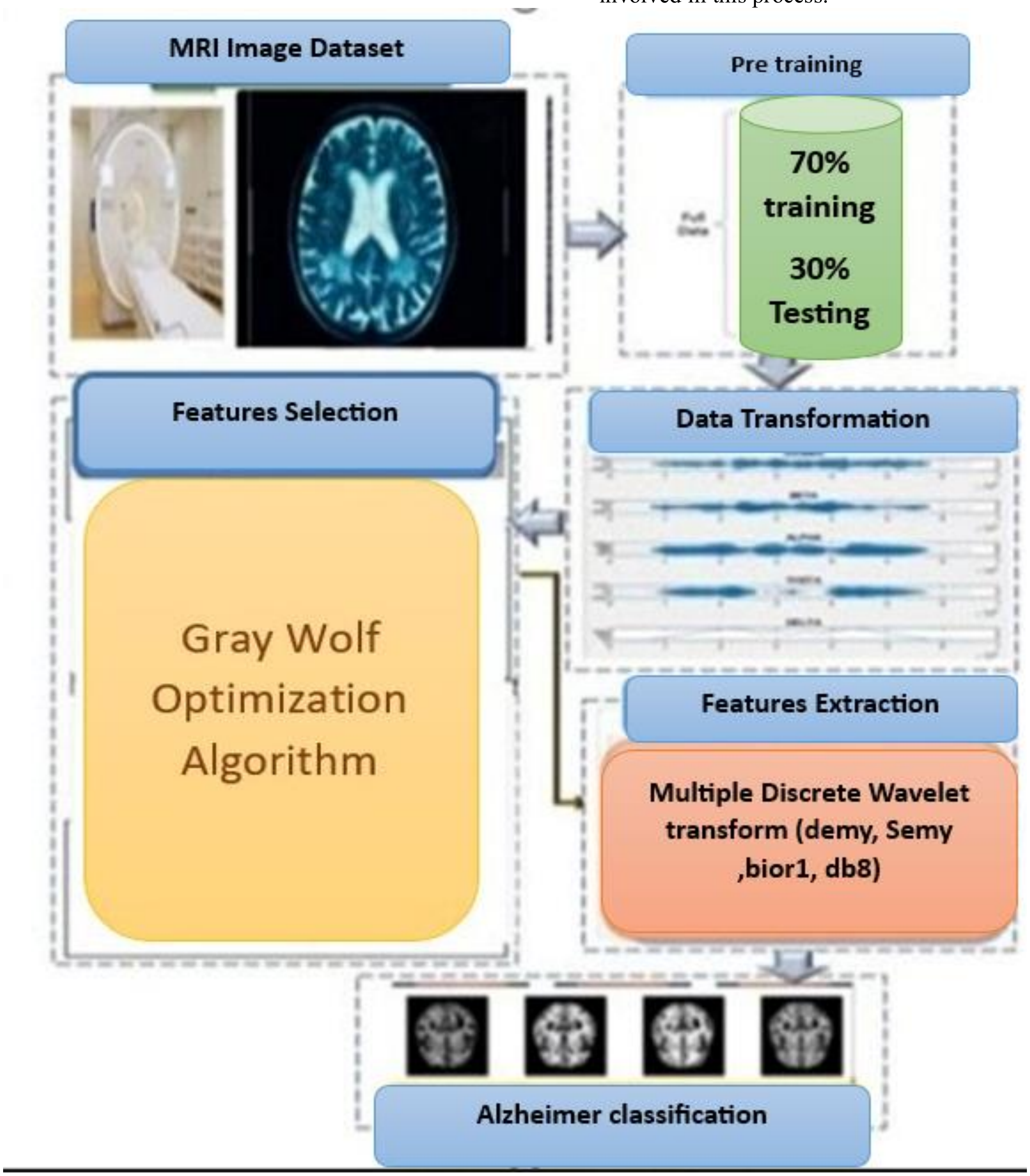

Figure 2. The proposed framework for Alzheimer's Detection.

3.1 Data acquisition

The objective of this work is to evaluate MRI images from an AD dataset to build sophisticated algorithms that can enhance the early diagnosis of Alzheimer's disease (AD). The dataset evaluated in this research is publicly available on: https://www.kaggle.com/tourist55/alzheimers-dataset-4-class-of images. This dataset consists of over 6400 MRI images, divided into four categories: Very Mild Dementia (2240 images), Non-Dementia (3200 images), Moderate Dementia (64 images), and Mild Dementia (896 images).

3.2 Image transformation

In our study, the images are converted into signals, (Figure 3), and each signal is further split into sub-signals (alpha, beta, theta, delta, and gamma). Alpha, beta, theta, delta, and gamma are different frequency bands observed in brain signals, such as electroencephalogram (EEG) or magnetoencephalography (MEG) recordings [17]. Each band represents specific patterns of neural activity and is associated with various cognitive and physiological processes. Alpha waves (8-12 Hz) are seen when a person is awake but relaxed with closed eyes, mainly in the occipital region. They reflect a state of mental relaxation. Beta waves (12-30 Hz) are higher-frequency oscillations related to alertness, active thinking, and concentration. They are commonly observed in the frontal and central regions of the brain. Theta waves (4-8 Hz) are present during drowsiness, deep relaxation, or light sleep [19,24]. They play a role in memory formation and spatial navigation and are typically seen in the temporal and frontal regions. Delta waves (0.5-4 Hz) are the slowest brain waves and are prominent during deep sleep or unconscious states. They contribute to restorative processes and overall brain health, primarily in the frontal and central regions. Gamma waves (>30 Hz) have the highest frequency range and are associated with active cognitive processing, attention, and sensory perception [18]. They are observed in the cortical regions and are involved in integrating information across brain regions. These frequency bands represent specific neural activities and contribute to various cognitive functions and states of consciousness [25]. Analyzing their power, coherence, or phase relationships can provide insights into brain function and be applied in research and clinical settings related to cognition, sleep, neurological disorders, and brain-computer interfaces. Several characteristics, including mean, Shannon entropy, min, max, skewness, normalized sd, avp, and others, are retrieved for each of the signals.

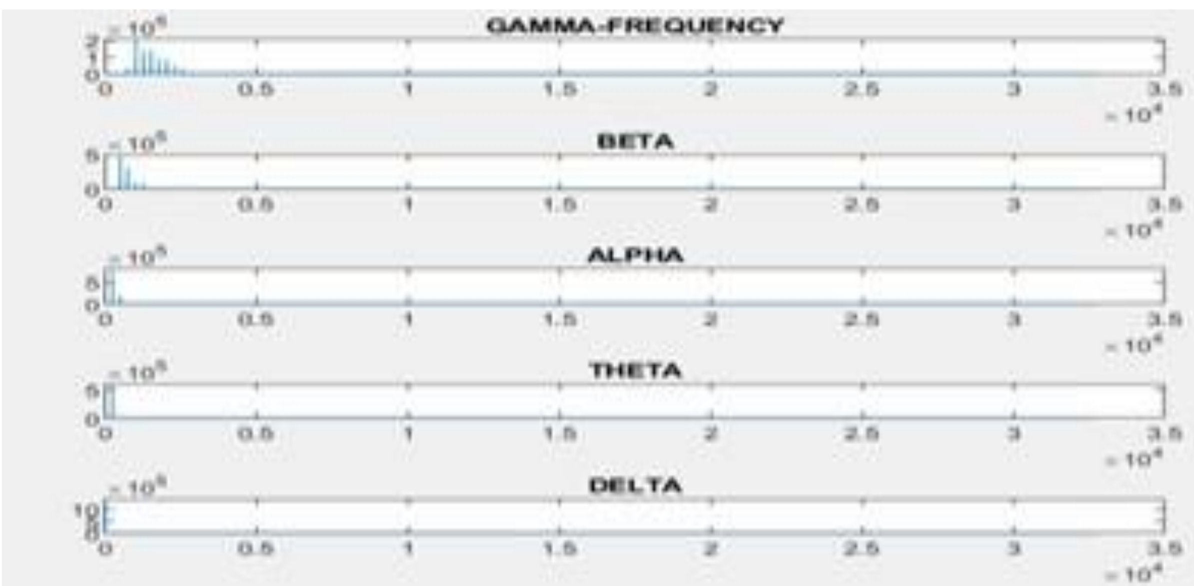

Figure 3. Dividing the signal into subbands.

3.3 Features Extraction

To improve the detection system's accuracy and efficiency, it is essential to extract pertinent elements from brain imaging data regarding Alzheimer's disease. Several Discrete Wavelet Transform (DWT) families, including demy, semy, bior1, and db8 are combined with statistical characteristics, including entropy, min, max, skewness, standard deviation, and mean, and others in our feature extraction process [26].

A signal may be broken down into several frequency sub-bands (Figure 3 and 4) using the DWT signal processing approach, which reveals the frequency content of the data. The brain imaging data is preprocessed to reduce noise and artifacts before being broken down into different frequency sub-bands using the DWT, such as alpha, beta, delta, theta, and gamma, in the feature extraction process utilizing DWT and statistical features [27,28]. Next, each sub-brand's statistical properties are extracted to provide details about the distribution and texture of the data [21]. A feature selection technique is then used to rank the extracted features according to their relevance to the disease detection job [18,24]. This ranking is then used to train a classification model, such as SVM, CNN to identify whether or not a person has Alzheimer's disease [6]. The wavelet functions db8, semy, bior1, and demy, which are renowned for their time-frequency localization capabilities and effective signal representation were employed in our work. The high-pass filter in these wavelet functions breaks down signals into high-frequency components [20,29]. It is frequently used with the low pass scaling function to create the filter bank that the DWT uses.

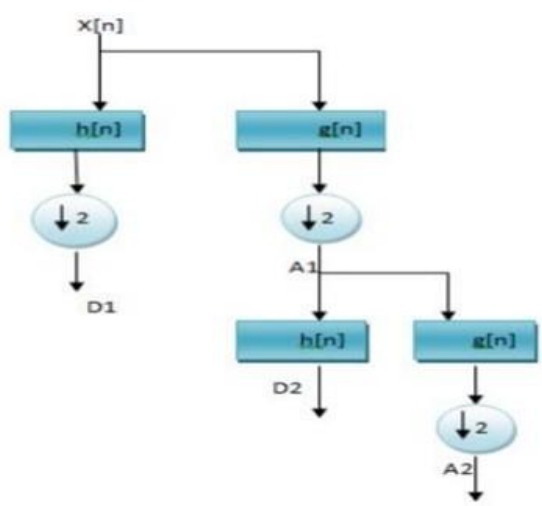

Figure 4. Signals division using DWT families.

3.4 Features Selection

The Gray Wolf Optimization (GWO) algorithm is a metaheuristic optimization algorithm inspired by the social hierarchy and hunting behavior of gray wolves in nature. It was proposed by Mirjalili et al [30]. In 2014. The GWO algorithm is used to solve optimization problems, aiming to find the optimal solution or approximate the global optimum in a search space. It is particularly effective for solving complex optimization problems with multiple variables and non-linear objective functions [3]. The algorithm is based on the social behavior and hunting mechanism of gray wolves, which involves cooperation, communication, and leadership within a pack [2,31]. The algorithm mimics this behavior by defining three main roles for the wolves alpha, beta, and delta. The alpha wolf represents the best solution found so far in the search space. It is responsible for leading the pack and coordinating the search process [32]. The beta wolf is the second-best solution found. It supports the alpha wolf and helps in the exploration of the search space. The delta wolf represents the third-best solution obtained. It assists the alpha and beta wolves in the search process [9].

The GWO algorithm starts with an initial population of candidate solutions, represented as a group of wolves. Each wolf corresponds to a potential solution to the optimization problem [4,33]. The positions of the wolves in the search space are updated iteratively based on their social interaction and hunting behavior. During each iteration, the position of each wolf is updated by three main operations: Exploration: The wolves explore the search space to discover new promising regions. They update their positions by considering the alpha, beta, and delta wolves' positions. Exploitation: The wolves converge towards the best solutions found so far. They adjust their positions by considering the alpha wolf's position and modifying it [34]. Encircling and trapping: The wolves try to encircle and trap the prey (optimal solution) by adjusting their positions accordingly [3].

The GWO algorithm continues the iterative process until a stopping criterion is met, such as reaching a maximum number of iterations or achieving a desired level of convergence [35,36]. The final positions of the wolves represent the approximate optimal solutions to the optimization problem. The GWO algorithm has been applied to various optimization problems, including engineering design, image processing, data clustering, and machine learning. It is known for its simplicity, effectiveness, and ability to handle complex optimization landscapes [1].

3.5 Features Classification

Classification using Support Vector Machines (SVM) is a popular machine-learning technique for solving classification problems [3]. SVM is a supervised learning algorithm that aims to find an optimal hyperplane that separates data points belonging to different classes (Figure 5) [20]. It is particularly effective in cases where the data is not linearly separable by transforming the data into a higher-dimensional space.

The SVM algorithm works by mapping data points into a higher dimensional feature space and finding the best hyperplane that maximizes the margin, which is the distance between the hyperplane and the nearest data points from each class. The hyperplane is chosen such that it can generalize well to unseen data, minimizing the risk of overfitting [9]. The SVM algorithm can handle both linear and nonlinear classification tasks by using different types of kernels. A kernel function calculates the similarity between data points in the higher-dimensional space without explicitly computing the transformation. Common types of kernels used in SVM include linear, polynomial, radial basis function (RBF), and sigmoid kernels [14].

To classify new data points, the SVM algorithm determines which side of the hyperplane they fall on, assigning them to the corresponding class [30,37]. SVMs have been widely used in various applications, including image recognition, text categorization, bioinformatics, and financial analysis, due to their ability to handle complex classification problems and their robustness against overfitting [24]. It's important to note that while SVMs are powerful classifiers, they may have limitations with large datasets or noisy data. In such cases, appropriate preprocessing techniques and parameter tuning may be necessary to achieve optimal performance.

Another algorithm that we used in this work is Convolutional Neural Networks (CNNs) (Figure 6). CNNs are deep learning architectures used for analyzing visual data like images and videos [2]. They have transformed computer vision by introducing specialized layers that efficiently learn and extract hierarchical representations from raw pixel inputs. Key components of CNNs include convolutional layers that extract local features, pooling layers that downsample feature maps, activation functions for non-linearity, fully connected layers for high-level feature combinations, and backpropagation for training [24]. CNNs can leverage pre-trained models for transfer learning and have been successful in tasks like image classification, object detection, and semantic segmentation. They can also be adapted for other data types through modifications like 1D or 2D convolutions, making them a crucial tool in deep learning for visual analysis [3]. Convolutional Neural Networks (CNNs) are highly effective for visual analysis tasks. Their key characteristics, including local receptive fields, shared weights, hierarchical feature extraction, translation invariance, spatial downsampling, non-linear activation functions, backpropagation training, pre- trained models for transfer learning, parallelization with GPU acceleration, and versatility in handling various data types, contribute to their success. CNNs excel in tasks such as image classification, object detection, image segmentation, and more.

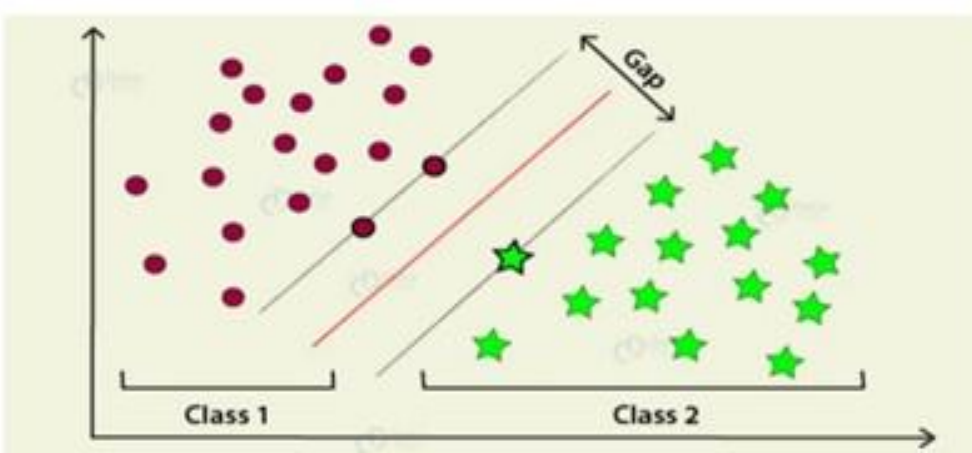

Figure 5. Support vector machine.

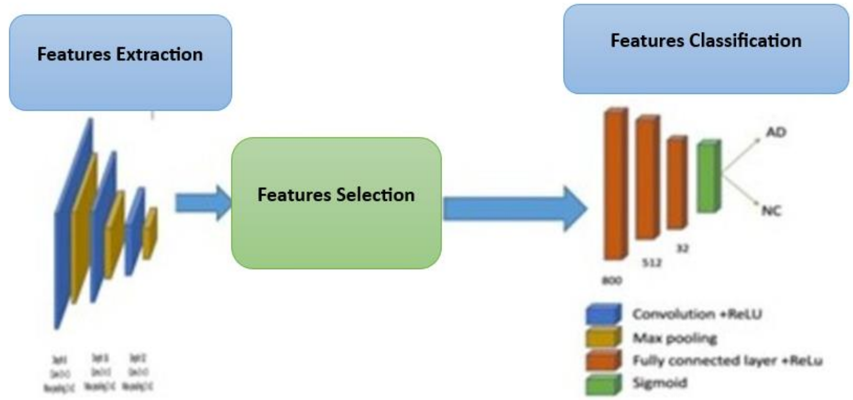

Figure 6. Convolutional Neural Network.

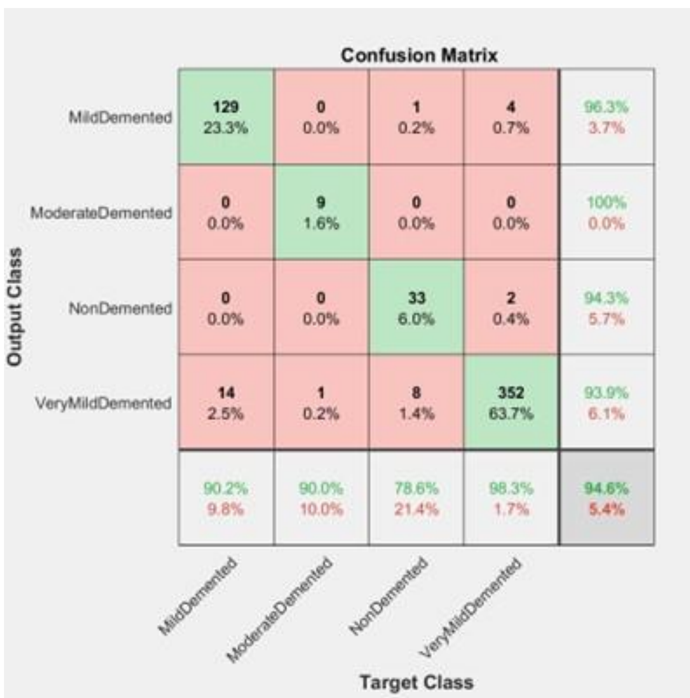

Figure 7. SVM classifier confusion matrix.

4. RESULTS AND DISCUSSION:

A separate test set of MRI scans not used during training provides an unbiased evaluation of the trained model's performance. Our study assesses the model's performance using evaluation metrics to measure the accuracy of this test set, where in our work, we divide the data into 70% training and 30% testing data. The 'evaluate' method of the model is called to obtain the loss and metric values for the model in 'test mode,' and the testing accuracy is displayed for evaluation. In Alzheimer's disease detection, the classification model's performance is evaluated using values such as true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). TP refers to correct instances classified as positive, FP refers to instances that are incorrectly classified as positive, FN refers to instances that are incorrectly classified as negative, and TN refers to instances that are incorrectly classified as negative. These values are used to calculate performance metrics like accuracy. This metric provides insights into the model's strengths and weaknesses and can be helpful in optimizing the model for better performance.

Figure 8. CNN classifier confusion matrix.

A confusion matrix is (Figures 7 and 8) a Table that compares the predicted and actual class labels of a dataset to evaluate the performance of a classification model. In multi-class classification, where there are more than two classes, the confusion matrix includes the counts of (TP), (TN), (FP), and (FN) for each class. The confusion matrix for multi-class classification is a square matrix with the same number of rows and columns as the number of classes. The rows represent the actual class labels, and the columns represent the predicted class labels. Each cell in the matrix indicates the count of instances that belong to the actual class and were predicted to belong to the predicted class. False positives (FP) occur when the actual class is a normal brain. However, the predicted class is abnormalities in the brain, and false negatives (FN) occur when the actual class is abnormalities in the brain. However, the predicted class is a normal brain. The accuracy is calculated using the following equation: $Accuracy = TP + TN/(TP + FP + FN + TN)$

In (Figure 9), from the provided data, we observe the accuracy scores of different classifiers for a particular task. In KNN (K-Nearest Neighbors), It has the lowest accuracy score of 43.26%. KNN is a simple algorithm that classifies data based on the majority class of its nearest neighbors. However, it seems to perform poorly compared to other classifiers in this case. The decision tree classifier achieves an accuracy of 74.22%. Decision trees create a tree-like model to make decisions based on feature values. Although it performs better than KNN, it is still outperformed by other classifiers. Rule induction achieves an accuracy of 69.6 %. Rule induction algorithms generate a set of if-then rules to classify data. It performs slightly better than the decision tree but falls short compared to other classifiers. The Naive Bayes classifier achieves an accuracy of 74.6%. Naive Bayes is based on Bayes' theorem and assumes independence between features. It performs similarly to the decision tree but does not surpass the performance of more advanced models. The generalized linear model achieves a significantly higher accuracy of 88.29%. This model is a flexible framework that includes linear regression, logistic regression, and other models. It performs well compared to the previous classifiers but is still surpassed by deeper learning models. The deep learning model achieves an accuracy of 78.32%. Deep learning models, such as neural networks with multiple layers, can learn complex patterns and relationships in data. While it performs better than some earlier classifiers, it is still not the top performer. The combination of our proposed methodology with Support Vector Machines (SVM) achieves an impressive accuracy of 94.5%. SVM is a powerful classification algorithm that finds an optimal hyperplane to separate data points. The combination of it with our proposed methodology further enhances its performance. The combination of our proposed methodology with Convolutional Neural Networks (CNN) achieves the highest accuracy of 95.4%. CNNs are specifically designed for visual analysis tasks, making them well-suited for the given task.

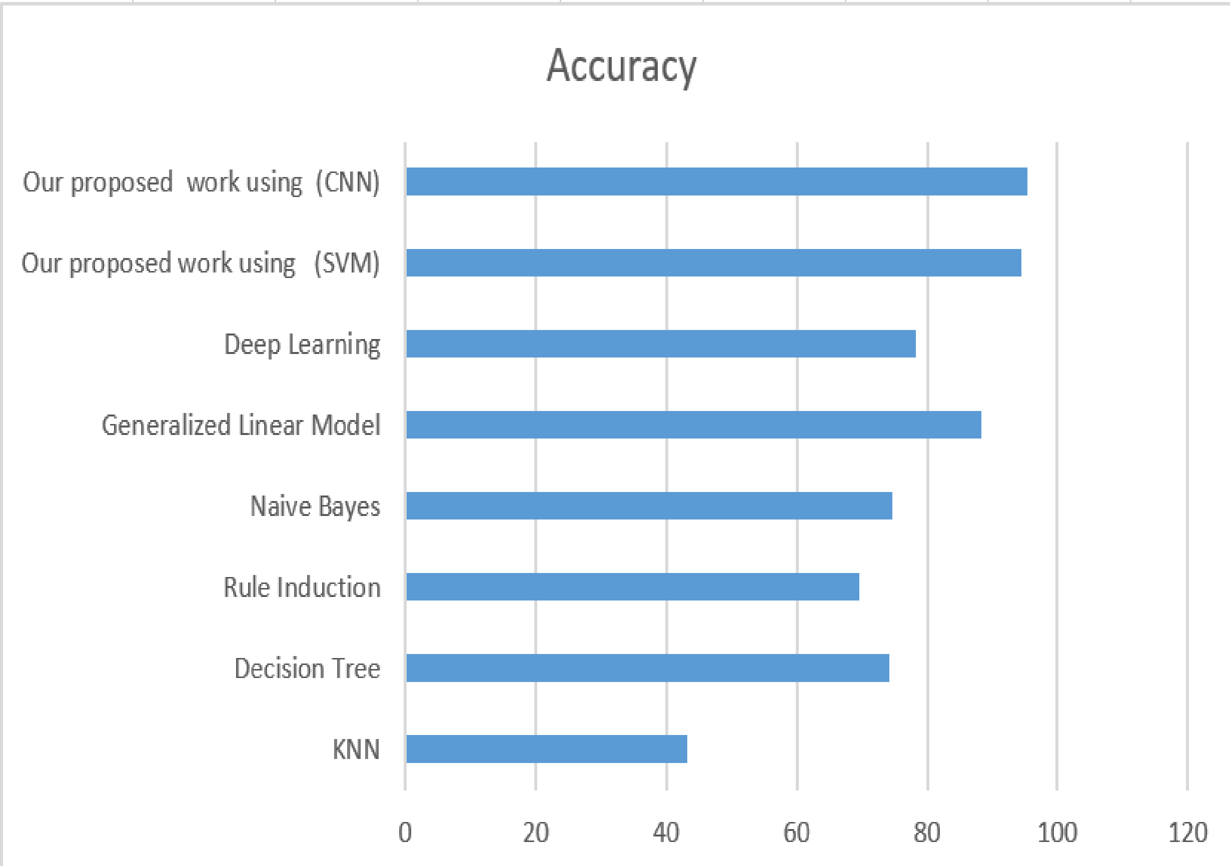

Figure 9. Comparing our Results with previous Results

In (figure 10), the provided data compares the accuracy of SVM and CNN models across different stages of dementia and provides the total accuracy for the combined CNN and SVM models. In Mild Demented, The SVM model achieves an accuracy of 96.3% in identifying mild dementia cases. The CNN model achieves a slightly lower accuracy score of 95.6% for mild dementia cases. In Moderate Demented, the SVM model achieves a perfect accuracy score of 100% in identifying moderate dementia cases. In CNN Accuracy, the CNN model also achieves a perfect accuracy score of 100% for moderate dementia cases. In Non-Demented: The SVM model achieves an accuracy of 94.3% in correctly identifying non-demented cases. In CNN Accuracy, the CNN model outperforms the SVM model with a perfect accuracy score of 100% for non-demented cases. In Very Mild Demented, The SVM model achieves an accuracy of 93.3% in identifying very mild dementia cases. In CNN Accuracy: The CNN model performs slightly better with an accuracy score of 94.9% for very mild dementia cases. In Overall (CNN + SVM): Combined Accuracy: The overall accuracy of the combined CNN and SVM model is 94.6%. This represents the accuracy of the combined model across all stages of dementia.

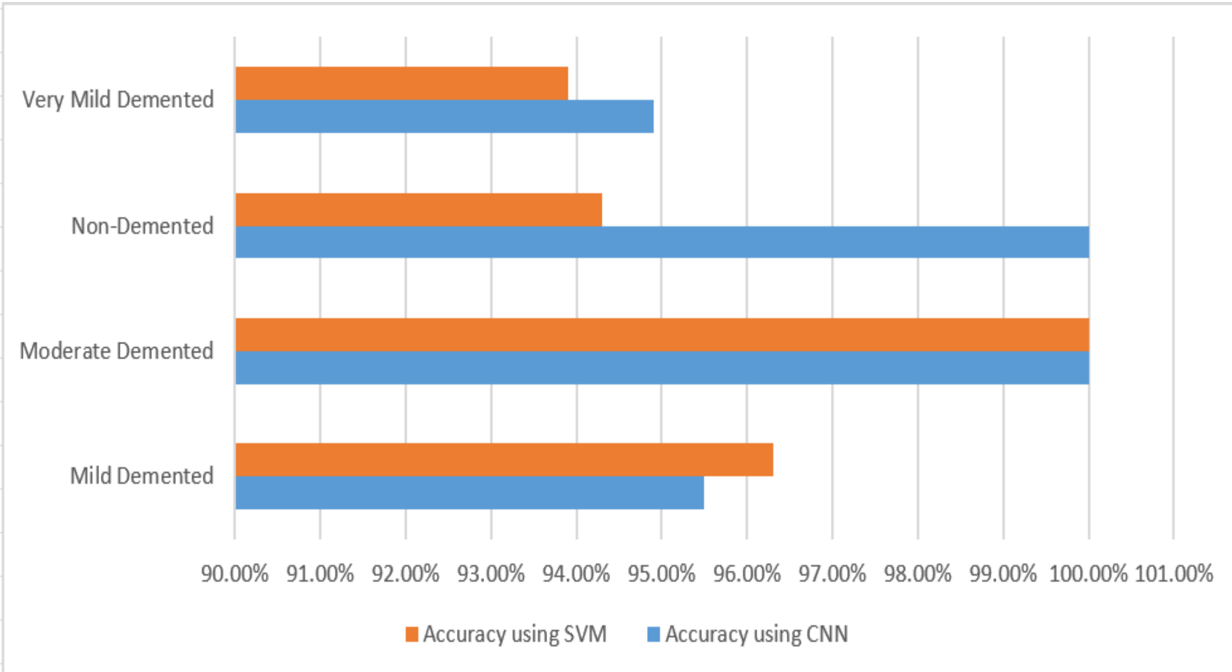

Figure 10. Accuracy of stages using both SVM and CNN.

5. CONCLUSION:

In conclusion, the use of Support Vector Machines (SVM) and convolutional neural network (CNN) in conjunction with Discrete Wavelet Transform (DWT) for detecting Alzheimer's disease using brain MRI images has yielded promising results, achieving an overall accuracy of 94.5% and 95.4% respectively. The SVM algorithm and CNN, known for its effectiveness in classification tasks, was employed to classify different stages of Alzheimer's disease based on the provided MRI images dataset. By leveraging the DWT technique, which analyzes signals in both time and frequency domains, the model was able to extract relevant features from the data and improve the classification accuracy. The obtained accuracy of 95.4% suggests that the CNN-DWT approach is highly effective in identifying Alzheimer's disease. This level of accuracy indicates that the model correctly classified the majority of cases within the MRI images dataset, demonstrating its potential as a valuable tool for early detection and diagnosis. Furthermore, it is essential to validate the results on larger and more diverse datasets to ensure the generalizability and robustness of the SVM and CNN -DWT approach. Additional research and testing are needed to evaluate its performance against different populations and to assess its reliability in real-world clinical settings.

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