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An Intelligent Metaheuristic Technique Assisted Feed Forward Neural Network (FFNN) for Alzheimer Disease Classification System

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Abstract:

One of the prevalent and general kind of dementia is Alzheimer Disease (AD). Only few people detects the incidence of disease at the early stage, since there is no specific symptom. Distinct reason for cause and cure of AD is not identified. When the disease is identified at the early stage, it can be managed and treating the patient also effective. This context necessitated early identification of disease with the assistance of computational technologies. The performance of disease classification is influenced by the dimensionality, irrelevant feature selection and misclassification. In this research work, shortcomings in the existing disease identification is improved by introducing optimization and deep learning techniques. The issues in handling dimensionality is handled by Linear Discriminant Analysis (LDA) and optimal features are retrieved by Fireworks Algorithm (FA). The optimal feature are trained and disease is classified using Feed Forward Neural Network (FFNN). The classification result is investigated by comparing with the existing state-of-art classification algorithms. The proposed LDA-FA-FFNN outperforms the existing approaches and achieves 93% accuracy.

Keyword: Alzheimer disease, deep learning, classification, optimization, feature selection and normalization.

Introduction

Alzheimer disease is a kind of neurodegenerative damage of brain, which is general and most prevalent dementia. Although Alzheimer's disease is not now treatable, its progression can be slowed if it is discovered early or mildly [1]. Pathological alterations in the brain are caused by Alzheimer's disease, and these modifications can be recognised before clinical symptoms appear. Eventually, pathological

changes damage cause death of neurons. This context motivated numerous researcher and scientist to develop computational algorithms for the identification of alzheimer disease [2, 3].

The main objectives in Alzheimer's disease (AD) and mild cognitive impairment (MCI) studies are to assess the rate of disease course, evaluate treatments' effectiveness, and to discover objective markers that enable timely and accurate diagnosis [4]. In their work, researchers encounter methodological difficulties in identifying the biomarkers that can effectively differentiate between AD, MCI and other diseases, as well as in determining the parameters of people's vulnerability to AD. Magnetic Resonance Imaging (MRI) is one of the most significant diagnostic non invasive procedures in this area, which provides images of internal body structures using high magnetic fields, radiofrequency pulses, and computers [5].

MRI-derived parameters including cortical parameters, volumetric evaluations, and hippocampal features and texture are incorporated to distinguish between AD, MCI, and asymptomatic NC. This paper is inherently interdisciplinary, as it combines computational modeling with neuroimaging both to model and analyze the processes in the brain of both healthy and diseased populations. Due to recent progress in deep learning and meta-heuristic algorithms, various high volumetric biomedical datasets including neuroimaging and related biological fields have seen an exponential rise [6]. These computational tools help to achieve the automatic classification of diseases, thus allowing diagnostic systems to classify cases without the need for posing hypotheses about marker diseases. This has spurred the use of high, complicated data sets in arriving at tools, which can predict disease prognosis and plans of treatment based on individual patient data [7].

Such tools also help not only in improving clinical knowledge but also contribute to such a field as a personalized approach, early diagnosis, and individualized therapy plans [8, 9]. In conclusion, the goal is to develop automatic diagnostic tools based on them with the help of MRI to diagnose Alzheimer's disease at an early stage, improve the chances of rehabilitation for those who are at high risk for AD pathology. Thus, under these developments, computational neuroscience aims at developing reliable approaches to disease detection and prevention that can enhance the lives of high-risk people.

This research describes how to use MRI brain image processing techniques to analyze normal and Alzheimer's patients. Alzheimer's disease (AD) is a neurodegenerative illness that causes alteration in the shape of the brain. Monitoring the progression of the pathological illness is critical in certain complex situation [10]. Multifaceted spatial structural modification in the brain occur as the disease advances, including expansion of the ventricles, volume decrease in the GM, HC, and CC, and shrinking of the periventricular structures. The examination of these structural alterations necessitates a clearly defined procedure for describing the structures and their modifications [11]. Feature selection is required to fully characterize the deformation and to express a link between the structure and functions [12].

Several optimization strategies are used to delineate the complicated structure of the brain. These approaches are capable of dealing with complicated brain deformations. In image analysis and pattern recognition, statistical metrics sensitive to the geometry of structures, such as curvatures and connectedness, have been intensively researched [13, 14]. In this research work, different pre-processing approaches are utilized and pre-processed MRI is utilized for feature selection that is done

by linear discriminant analysis (LDA) based firework algorithm (FA). Optimal feature vector generated from optimization approach is used for classification using feed forward neural network (FFNN).

The remaining of the article is organized as follows: various research in Alzheimer disease identification is discussed in Section 2, proposed feature selection and classification technique is given in Section 3, results generated from existing and proposed approach is compared in Section 4, research article is concluded with future perspective in Section 5.

1. Related Work

The discrete wavelet transform (DWT) method was used to produce feature wavelets for categorization of Alzheimer's disease to aid diagnosis. This does not provide illness identification; extra processing is necessary using machine learning methods [15]. Machine learning algorithms are the most accurate at accurately classifying Alzheimer's disease [16]. The support vector machine is the most prominent of these methods. To categorise the illness as AD and healthy controls (HC), a framework employs a feature-based ranking algorithm using SVM [17]. SVM is used to create predictive classification models that extract high-dimensional, useful features from MRI [18]. However, this necessitates the retrieval of brain structures, which is tedious and time intensive, which necessitates the assistance of professionals.

Machine learning and feature selection approaches are initiated to rectify the computational complexity in traditional approach. The majority of approaches to treat brain features is to separate variables, disregarding anatomical and geographic correlations (for example, voxelwise grey matter concentration maps from brain MRI). The author has developed a new SVM-based learning approach for Alzheimer's disease (AD) classification that takes into account spatial-anatomical data. The SVM model promotes spatial neighbours in the same anatomical region to have similar weights in this method [19].

The back propagation neural network (BPNN) has a high level of accuracy and dependability when it comes to classifying stages of disease and providing accurate diagnoses. The training phases of deep learning approaches, on the other hand, take a long period. Image processing methods are used to decrease the quantity of input sent to the neural network, reducing training and testing time while improving performance and accuracy for issues with a restricted number of classes [20]. Deep learning algorithms are a subset of machine learning algorithms. Without the need for human involvement, deep learning systems extract features automatically [21].

Deep learning algorithms learn the high-level representation from the raw data since there are many hidden layers available that is popular in the field of computer vision [22]. Multilayer perceptron [23] is a distinct variety of neural network that has numerous perceptron layers to classify the information. Machine learning approaches faces complication in retrieving feature and redundant feature leads to misclassification. Handling of numerous feature also complicated one and necessitates dimensionality reduction approach. In certain deep learning approach, error occurred during classification that makes degradation of accuracy. By considering all these drawbacks, an effective AD classification framework is designed with linear discriminant analysis with firework algorithm (LDA-FA) and feed forward neural network (FFNN) [24-26].

2. Proposed Methodology: Alzheimer Disease Classification

This section discusses about alzheimer disease classification with deep learning and optimization approach. Entire process of processing MRI for AD classification is elucidated with prominent aspects.

2.1. Image Acquisition

MRI images of brain is utilized to segment the internal portions of brain for the classification of disease. The MRI images are taken from the scanner of MRI and has the thickness of about 5mm with 1mm spacing that has the resolution of 256 x256. About 1296 images of normal and AD subjects are considered in this research of diverse age group and gender.

2.2. Pre-Processing

The process of double window median filter is performed twice where performance is enhanced and assures high quality filtering. Occurrence of distortion is eliminated. The estimation of median is attained by the pixel values of the image. Outcome of row estimation is gathered in buffer region and new column value is replaced. Entire median value in buffer is transferred to the filter's exit position. The data of outcome of paired comparison of pixel value is investigated and indicated in matrix format.

2.3. Normalization: Pixel Feature Normalization

Pixel feature normalization, normalizes the size and shape of the image and it prevents attributes with greatest numeric levels from dominating minimal numeric levels. The process of normalization is attained by the maximum minimum technique that is given as

$$p_{new} = \frac{(p - p_{min})}{(p_{max} - p_{min})}$$

where p_{min} and p_{max} are the maximum and minimum feature vectors of the images.

2.4. Feature Extraction: Z-Score Standardization

Feature extraction normally requires changing the input image pixel values from their raw form and into a format that is more helpful to further process and analyze. The method of normalization often used in feature extraction includes scaling pixel values while making their distribution to be approximately normal, for instance in this case, normalizing pixel values so that they have a mean of 0 and a standard deviation of 1. In this regard, the z-score technique is used, where each pixel is shifted according to the overall distribution of the data set. In detail, the z-score is computed for each pixel to normalize the data that centers the data and flattens it, making the succeeding changes direct with minimized data variance and in turn, enhances the model by amplifying the relative differences of the data. The value of z-score is equated as,

$$z - score = \frac{score - mean}{standard\ deviation}$$

This feature extraction retrieves the correlation among the normalized and original MRI images whereas it is considerably minimizes the election bias. After completing the feature extraction process feature selection approaches are incorporated and the feature extraction makes the learning approach easier.

2.5. Feature Selection: Linear Discriminant Analysis based Firework algorithm

In firework algorithm (FA), every firework can be considered as optimal solution across solution space where the explosion process is considered as optimal solution searching. In the solution space, distinct count of fireworks are generated randomly and every solution is depicted as subset of feature. The quality of firework is investigated by fitness function and it is estimated with the assistance of linear discriminant analysis (LDA). LDA based FA algorithm encompasses the process of dimensionality reduction technique and feature selection. LDA has huge interpretation probability that is lack in firework algorithm. Linear combination among the variables assures effective handling of feature vectors. The process of generation of score is attained by

$$FS = \beta_1 v_1 + \beta_1 v_1 + .. + \beta_d v_d$$

$$S(\beta) = \frac{\beta^T \mu_1 - \beta^T \mu_2}{\beta^T M \beta}$$

$$S(\beta) = \frac{FS_1 - FS_2}{FS\ variance\ in\ the\ group}$$

Calculation of linear co-efficient maximizes the feature score that is estimated in relevant to the subsequent equation. Linear co-efficient model is indicated as β, matrix of covariance is indicated as M and average of feature vector is indicated as μ.

$$\beta = M^{-1}(\mu_1 - \mu_2)$$

$$M = \frac{1}{(n_1 + n_2)}(n_1 M_1 + n_2 M_2)$$

The Mahalanobis (Δ) is utilized to estimate discriminant among group of vectors. The variation among the vectors is V and probabilities P. At the end, features are acquired as,

$$\Delta^T = \beta^T(\mu_1 - \mu_2)$$

$$\beta^T \left(v - \left(\frac{\mu_1 + \mu_2}{2} \right) \right) > log \frac{P(M_1)}{P(M_2)}$$

The process of generation of amplitude is maintained with LDA and fitness value is close or equal to zero. The amplitude of explosion is tiny and sparks are placed in an identical location that attains poor interpretation probability and exploitation. This issue is handled by the LDA and equation is given as,

$$\beta_i^T = \begin{cases} \beta_{min}^T & if\ \beta_i^T < \beta_{min}^T \\ \beta_i^T & otherwise \end{cases}$$

$$\beta_{min}^T(t) = \beta_{initial} - \frac{\beta_{initial} - \beta_{final}}{evaluation_{max}} * t$$

where t is the count of function assessment at the beginning of the existing iteration. Values $\beta_{initial}$ and β_{final} are the initial and final amplitudes with minimal amplitude, while $evaluation_{max}$ indicates maximum count of investigation. The process of LDA-FW for feature selection is illustrated in Figure 1.

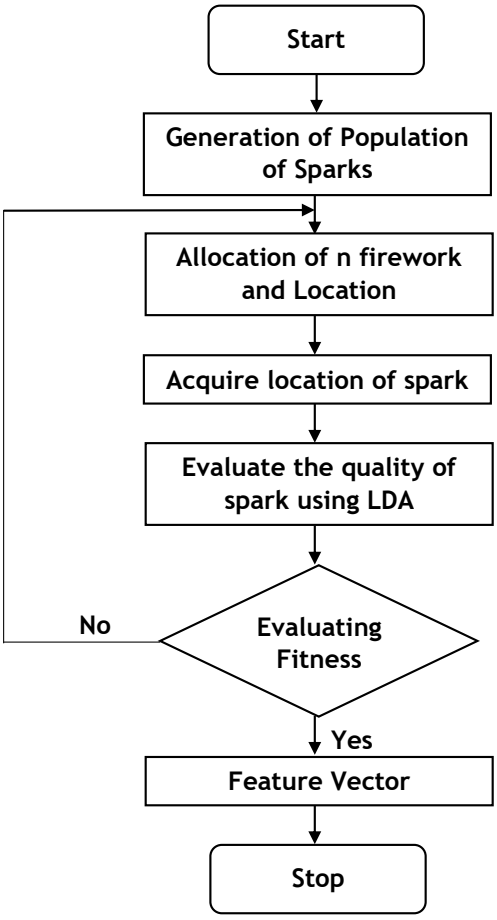


Figure 1. Feature Selection Process

2.6. Classification: Feed Forward Neural Network

The Feedforward Neural Network (FFNN) classifier was chosen mainly because of its popularity in pattern classification problems and secondly, it does not require prior knowledge of the posterior distributions or the probabilities of the classes. The FFNN was trained in batch mode for classification using a set of feature vectors that had been chosen. The specific FFNN model used in this study possesses a one-hidden-layer structure as illustrated in figure 2, which best describes the model structural simplicity and its applicability to the current classification exercise. This configuration makes it easier to generalize structures, which is particularly advisable when there is a continuum of class differences such as in medical image analysis.

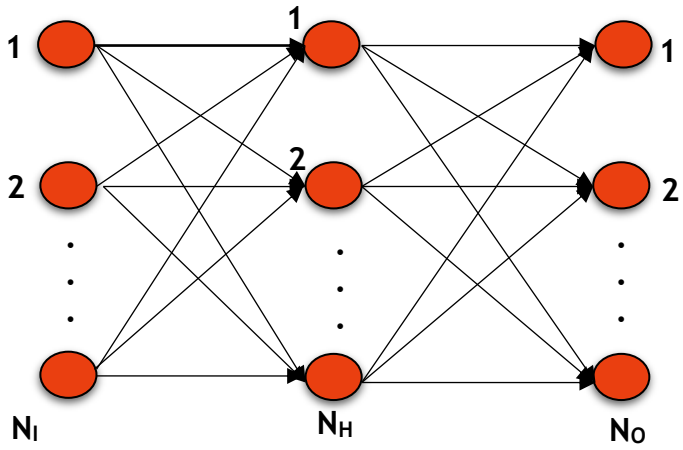


Figure 2. Overall process of FFNN

In terms of architecture, the FFNN consists of three distinct layers: each consisting of an input layer, a hidden layer and an output laye as depicted in figure 2 above. Every layer has only one connection with the nodes of the previous layer and the nodes in the subsequent layer are directly connected. As for these interactions, a numeric value is assigned to them to express the closeness level of nodes. It's illustrated in Figure 3 that in four cycles of training, weights which define connections are turned to optimize the ability of the network to classify according to these connections. The computations of the output of each neuron in the hidden layer are also performed during the initial stages to facilitate the learning and adaptation of the FFNN.

$$k_j = af_H\left[\sum_{i=1}^{N_j} \omega_i(i,j)l_i\right] \quad j = 1,2,3,\ldots\ldots,N_H$$

where i^{th} input value is indicated as l_i, j^{th} hidden layer output is indicated as k_j, and sigmoid function is utilised as activation function that is indicated as af_H. The sigmoid function is given as,

$$af_H(l) = \frac{1}{1+exp(-l)}$$

The output information of neuron in the output layer is equated as,

$$OP_k = af_{op}\left[\sum_{j=1}^{N_H} \omega_2(j,m)y_j\right] \quad m = 1,2,3,\ldots\ldots,N_o$$

Output layer's activation function is indicated as af_o and every weight is allocated with random value that is altered by delta rule in accordance with learning samples. Occurrence of error in median square error (MSE) is indicated as variation among target and output value is given as,

$$ER_i = MSE\left(\sum_{m=n}^{N_o}(OP_k - T_k)\right) \quad n = 1,2,3,\ldots\ldots,N_s$$

where authentic value of k^{th} value is indicated as T_k that is already identified as users and N_s indicates the count of samples. The fitness function of neural network is the average of MSE that is given as,

$$af(\omega) = \sum_{l=1}^{N_s} ER_i$$

The overall goal of this FFNN training is to reduce the classification error; direct changes to each feature vector to the target values. Feature vectors, derived from Linear Discriminant Analysis and Factor Analysis (LDA-FA), were incorporated to train the FFNN to improve its classification capability between normal control and Alzheimer's disease patients. The FFNN enhances classification accuracy through minimizing error rates during the learning phase. Figure 3 represents the general framework of the FFNN which explains how feature vectors are passed through several layers to complete a classification.

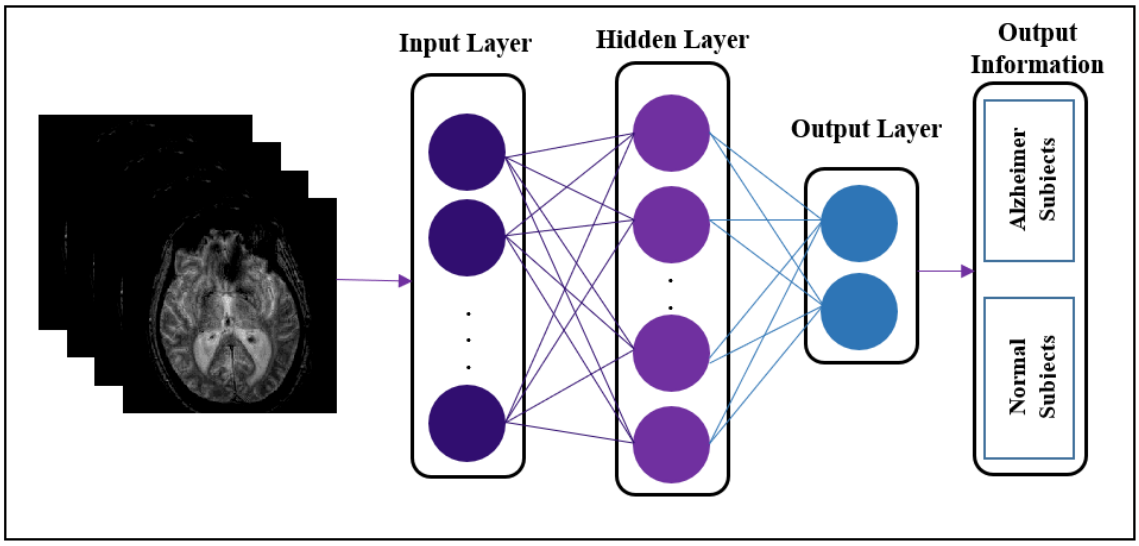


Figure 3. Architecture of FFNN

3. Result and Discussion

This section discusses about the classification of Alzheimer Disease and the implementation is accomplished using MATLAB. The performance of the existing techniques namely SVM, BPNN, MP and proposed approach LDA-FA-FFNN are compared and contrasted.

3.1. Dataset Description

Images are acquired from the kaggle dataset [27] of NDNI repository that is utilized in this research. The MRI images in NDNI repository is composed of 1296 images and five categories of Alzheimer and normal images are considered in this research. About 60% of the image is utilized in the process of training and 40% of images are utilized in testing.

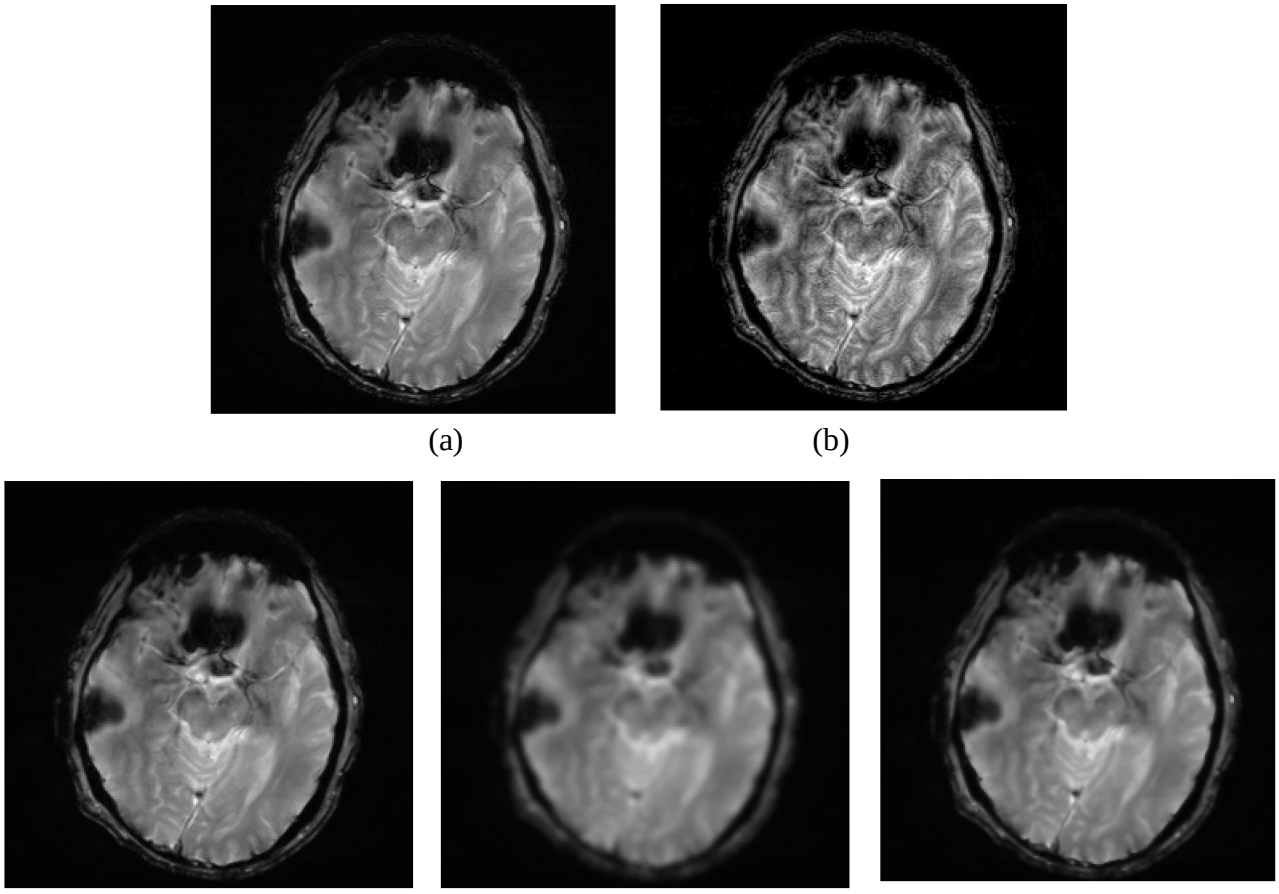
3.2. Performance Evaluation

Brain MRI's are passed through several phases, in order to enhance the performance of classification. The factors influencing performance of classification is considered and improved with the assistance

of optimization as well as deep learning approach. Incidence of disease is classified effectively by proposed approach LDA-FA-FFNN.

3.2.1. Pre-Processing

Initially pre-processing is accomplished using double window median filter where sharp edges are preserved and incidence of spiky noises are smoothened. In certain context of linear low-pass filters, certain edges are blurred that can degrade the performance of classification technique. Occurrence of noise and propagation of error is minimized by doubling of median filter. The input and pre-processed image is given in Figure 4.



(a) (b)

(c) (d) (e)

Figure 4. Pre-processed MRI images – Double Window Median Filter

In Figure 4, input image is illustrated in Figure 4(a) and pre-processed image is illustrated in Figure 4(b). The significant regions in the MRI is enhanced and sharpened for further processing. In laplacian filter, direction for edges are accessible and it can degrade further performance. Gaussian filter consumes much time to process and minimizes details whereas there is no minimization of noise. In bilateral filter, smoothing and preserving of edge region is minimal. By comparing the performance of the diverse pre-processing approaches, double window median filter is highly effective that is transmitted to feature selection process.

3.2.2. Classification of Alzheimer Disease

After completing pre-processing, MRI of brain is passed to feature selection phase and prominent features are retrieved using Firework Algorithm (FA). The process of classification is enhanced by passing needed and optimal features that is attained by nature inspired technique. Brain MRI is composed of 330 features and necessary feature for identifying Alzheimer is retrieved by FA whereby 201 features are reclaimed. Abundant feature and size of the images are handled using Linear Discriminant Analysis (LDA). It utilizes information of features to generate new axis which in turn enhances distance among variables and lessens variance. The features retrieved by LDA-FW is passed to the neural network that is used for training the classification of disease. The results acquired from the classification is discussed in the subsequent section. Different number of images are considered for evaluating performance of existing and proposed technique that utilizes performance metrics namely accuracy, sensitivity, specificity, and MSME.

Accuracy

The classification accuracy of the MRI is calculated by dividing the number of appropriate AD patient identifications by the total number of cases. The competency of the classification model is determined by the accuracy value. The accuracy is measured using true positive (TP) and true negative (TN) values generated from Alzheimer's disease classes. The most accurate classification method is known as an effective classification algorithm. An estimate of the accuracy value is as follows:

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative(TN)}{True\ Positive(TP) + True\ Negative(TN) + False\ Positive(FP) + False\ Negative(FN)}$$

Table 1. Comparison of Accuracy

Image Count	SVM	BPNN	MP	LDA-FA-FFNN
10	90.01	90.8	91.8	**91.6**
20	91	91.5	92.7	**92.1**
30	92.2	92.2	92.9	**91.8**
40	91.6	92.3	90.3	**92.6**
50	90.3	91.7	91.6	**93**

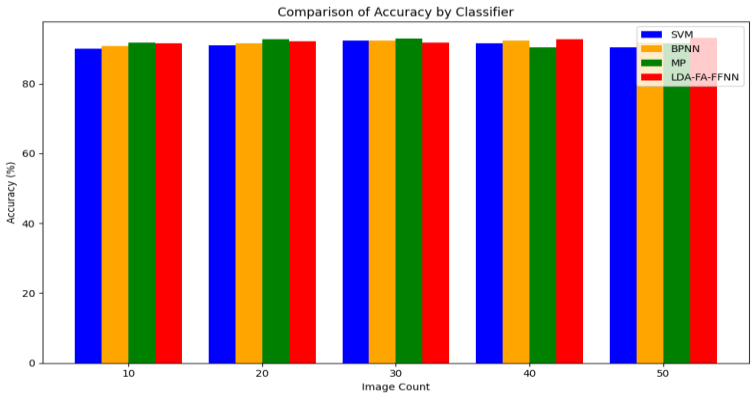


Figure 5. Comparison of Accuracy

Table 1 compares classification accuracy across four classifiers: As mentioned earlier, the performance of the different algorithms for the facial images is studied with different counts of images and the algorithms that are used are SVM, BPNN, MP, and LDA-FA-FFNN for facial images count. Significantly, the overall accuracy for LDA-FA-FFNN is higher for larger image counts, including 40 and 50 image count, for which the 50-image count model achieves an accuracy of 93% — the highest in the dataset. The performance of MP classifier exhibits moderate variation where as the SVM and BPNN exhibit a slightly lower performance. This indicates that the feature extraction process in LDA-FA-FFNN of perhaps sharpening discriminant features may be responsible for the higher classification accuracy than the other methods. Figure 5 was created from the data in Table 1 to make judging the manner in which accuracy grows with image count with respect to the classifiers easier. The figure also reveals how the performance of LDA-FA-FFNN increases with higher image counts, an indication that it learns from added information. It can also be used to check the consistency of model in terms of accuracy of the predictions when trained on different dataset sizes.

Sensitivity

Sensitivity is defined as the ratio of positive or properly identified values out of all occurrences, and it is given as the rate of TP. It determines the properly recognized test findings, with higher sensitivity lowering specificity rates and vice versa. The TP value indicates proper identification performance, and sensitivity is assessed as follows:

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

Table 2. Comparison of Sensitivity

Image Count	SVM	BPNN	MP	LDA-FA-FFNN
10	90.3	88.2	88.7	**88.3**
20	91.1	88.8	91.4	**89.2**
30	91.7	90.2	91.1	**90.5**
40	88.3	90.3	86.6	**88.6**
50	86.9	88.6	88.3	**88.9**

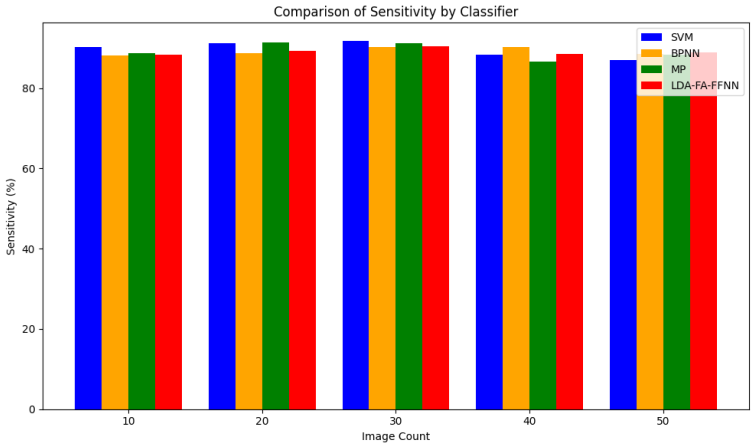


Figure 6. Comparison of Sensitivity

Sensitivity scores are presented in Table 2, where TPs are identified for classifiers. All these methods; SVM, MP, and BPNN exhibit relatively comparable sensitivity with image counts while LDA-FA-FFNN' sensitivity remains at a range of 88-90%. The sensitivity is the highest with MP with only 20 images with 91.4% while LDA-FA-FFNN maintains a satisfactory level of TP identification for all counts and this shows that LDA-FA-FFNN does not favor either positive or negative results. The sensitivity data is shown in figure 6 where it's easier to compare image counts among individual data points. This figure further supports that LDA-FA-FFNN model has stable performance and high sensitivity to identify the true cases in different data ranges. This shows that LDA-FA-FFNN is more reliable in its changes than those changes that are recorded in other methods.

Specificity

The TN rate is the percentage of negative or incorrectly classified values among all occurrences. The approach for estimating specificity, which assists in the identification of correctness throughout the whole categorization population, is as follows:

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

Table 3. Comparison of Specificity

Image Count	SVM	BPNN	MP	LDA-FA-FFNN
10	89.9	92.3	93.3	**93.6**
20	90.8	93.2	93.4	**93.1**
30	92.6	93.6	93.8	**94.5**
40	93.4	93.8	92.6	**96.4**
50	92.4	93.4	93.4	**98.8**

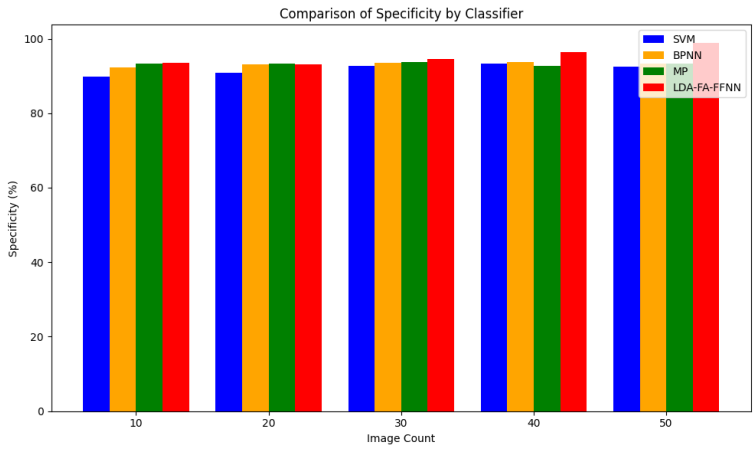


Figure 7. Comparison of Specificity

Table 2 is composed for measure of specificity which is the true negative rate, and how each classifier is able to give true negative results. LDA-FA-FFNN achieves the highest specificity values up to 98.8% in fifty images, which means the model has a high specific capability to differentiate between non-cases. BPNN and MP also achieve good accuracy, while their specificities are slightly lower indicating that this system vastly reduces false positives as seen with LDA-FA-FFNN. It is interesting

to make a comparison of specificity scores represented visually in Figure 7 based on data from Table 3. What can be seen in this figure is how specific LDA-FA-FFNN is at higher image counts – indicating that it does an excellent job of preventing false positives. This high specificity observed in LDA-FA-FFNN indicates better classification quality; especially in datasets with more images.

Mean Square Error (MSE)

The mean-square error (MSE) is utilized to compare quality of image processing. The MSE indicates the cumulative squared error among the processed and the original image. The occurrence of error during the image processing is identified by MSE. To calculate the MSE, subtract the anticipated value from the observed value and square the divergence. This process can be done for each observation. Then multiply all of the squared values by the number of observations. The MSE is estimated by

$$MSE = \frac{\sum_{M,N}[IM_1(m,n) - IM_2(m,n)]^2}{M * N}$$

where the observed values are indicated by IM_1 and IM_2, and the dimension of the images are indicated as M and N.

Table 4. Comparison of MSME

Image Count	SVM	BPNN	LDA-FA-FFNN
Normal	29.2	18.2	**13.2**
abnormal	25.6	25.3	**11.1**

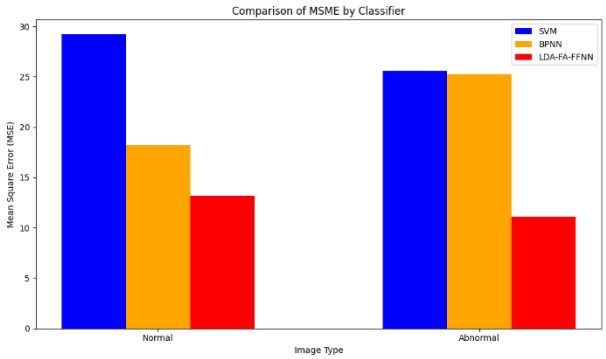


Figure 8. Comparison of MSME

In Figure 8, occurrence of error is minimal in LDA-FA-FFNN approach when compared to existing algorithms namely SVM and BPNN that shows the effectiveness of classification. Table 4 shows the MSE results of all classifiers regarding the normal and abnormal images in regards to the quality of image reconstruction. LDA-FA-FFNN has the lowest MSE values for normal (13.2) and abnormal images(11.1) which mean that processing error between the attacked and the original images is almost negligible. This is a clear indication that the LDA-FA-FFNN is efficient in preserving image identity which is an important aspect of classification. The comparison of MSE values is presented in the form of Figure 8. It supports that the LDA-FA-FFNN is effective in minimizing the processing errors than SVM and BPNN, better image quality of normal and abnormal category. They all support the fact that LDA-FA-FFNN is better in image reconstruction and error minimization than the other methods above.

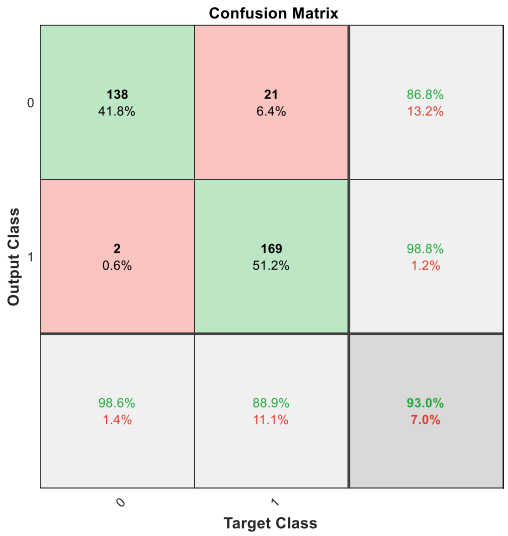


Figure 9. Confusion Matrix for FFNN

In Figure 9, the visualization of confusion matrix for FFNN based classification is given and the prediction summary is illustrated with the assistance of confusion matrix where the count of accurate and inaccurate classification is depicted as diversified classes. Figure 9 shows the result of the FFNN classifier was presented in the confusion matrix which gives information of the cases that were classified correctly and incorrectly among the classes. This matrix provides information about the accuracy of classification and distribution of error for better understanding of the diagnosis capability of FFNN. From the confusion matrix, FFNN's strong points and weak points can be seen due the detail depiction of misclassification which is useful for more model tuning.

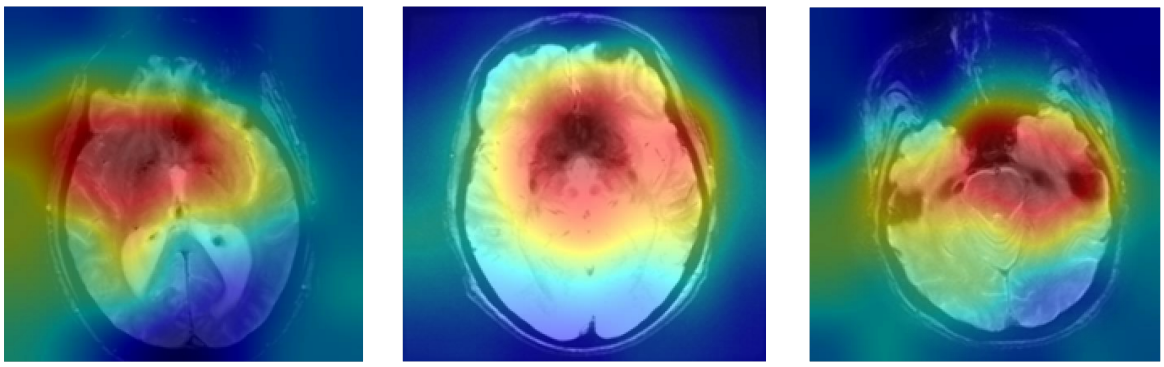


Figure 10. Gradient-weighted Class Activation Mapping

Gradient-weighted Class Activation Mapping (Grad-CAM) produces a coarse localization map emphasizing the key regions in an image by using the gradients of every target idea flowing into the final layer in FFNN. Grad-CAM provides focus to significant areas to which the network pays attention in order to make decisions; therefore, enhancing interpretability by highlighting the regions that were essential in classification. This is especially beneficial in the medical field, where knowledge of the model's attention can always improve the diagnostic dependability and credibility.

4. Conclusion

Alzheimer disease is a neurodegenerative disorder based on brain damage that has huge impact in the context of medical field. In order to attain automatic identification, new biomarkers for Alzheimer's

disease are undoubtedly significant important, but a combination of neuropsychological test scores and MRI measurements can also provide more accurate findings. This work provides a feature selection-based classification approach that allows the machine to discover excellent patterns for providing data while also improving its performance. The relevance of the feature vector in boosting the performance of classification models is demonstrated in this research, since it contains crucial information about the brain. In addition, multimodal techniques for early AD diagnosis, such as image modality with appropriate characteristics, were shown to be more accurate. With LDA-FA, 201 features are retrieved and achieved classification accuracy of 93%. In future, the approach can be extended with some other bio-inspired approach for handling the rate of convergence that can enhance the performance of the classifier.

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