CLASSIFICATION OF ALZHEIMER'S DISEASE STAGES USING A DEEPAQUILA CONVOLUTIONALNEURAL NETWORK

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ABSTRACT

Alzheimer's disease (AD) is the primary cause of death in the elderly, and diagnosing the disease in its early stages can be difficult with traditional manual methods. Additionally, machine learning (ML) methods have successfully demonstrated their reliability and efficacy as a reliable early diagnosis option for Alzheimer's disease. Due to the heterogeneous dimensions and composition of ailment data, diagnosing it is more challenging, so a proper classification process is required.Therefore, in this paper, we develop a deep learning-basedAquila-CNN for detecting the AD in the early stages. Initially, ADNI database is used to estimate the effectiveness of different combinations of MR-based features for improving classification accuracy.The MRI images are pre-processed using adaptive median filter to remove unwanted distortions in the input images. Afterwards, the relevant features are extracted from the pre-processed images using CNN, which is optimized with aquila optimizer (Aquila-CNN). Consequently, based the extracted features the proposed which classifies the MRI images into normal, EMCI (early-mildcognitive impairment), LMCI(late-mildcognitive impairment) and AD. The proposed Aquila-CNN achieves a high accuracy range of 96.78%, 95.45%, 95.08% and 96.12% for classifying normal, EMCI, LMCI and AD respectively. The proposed Aquila-CNNmodel was compared with traditional MLalgorithms like SVM, kNN, RF and XGBoost. The comparison analysis evidently reveals that the proposed Aquila-CNN exhibits better results for classification than the traditional classifiers.

Keywords: Alzheimer's disease, MRI images, Classification, Convolutional neural network, Aquila optimizer.

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1. INTRODUCTION

AD is a progressive disease that affects the memory and overall functioning of the brain. It is a general cause of dementia that mostly affects the elderly population above the age of 65 and older live with Alzheimer's disease [1]. In recent days approximately 44 million cases were reported all over the world, it is estimated as the sixth leading cause of death [2]. The degeneration of brain cells and some variations in the volume of brain are the major cause of AD. It is caused due to the abnormal build-up of two proteins named amyloid that stores plaques around the neurotransmitter and another protein called tau that stores tangles inside the neurotransmitter. The increase in amyloid protein increases cell death and interrupts signal transmission [5]. The early signs of AD include insensible to the past events or communications. As the disease progresses, a person with AD develops severe loss of memory and loss the capacity to carryout day-to-day chores.

A variety of neuroimaging practices, that comprises computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET), as well as deep learning techniques, that has been evolved to categorise such abnormalities for early diagnosis and treatment plans[7]. The proper execution of machine learning (ML) methods has also demonstrated their efficacy and dependability as one of the improvedchoices for an early analysis of Alzheimer's disease. However, the disease data's heterogeneous dimensions and composition have apparently made diagnostic tests more challenging, necessitating an adequate model selection to ease the process [10]. Therefore, the present work focuses on deep learning techniques to diagnose Alzheimer's as early as possible. The key contributions of the proposed work are as follows,

- ✓ MRI images are gathered from ADNI database to evaluate the effectiveness of different combinations of MR-based features for improving classification accuracy.
- ✓ The MRI images are pre-processed using adaptive median filter to remove unwanted distortions in the input images.
- ✓ The Aquila CNNis employed to extract the relevant features and based on these features the Aquila CNN classifies the MRI images into normal, EMCI, LMCI and AD.
- ✓ The proposed Aquila-CNN technique is evaluated based on its specificity, sensitivity, and accuracy.

The remainder of this paper was prearranged as follows. Section 2 outlines with the literature survey, Section-3 includes the proposed methodology using Aquila-CNN, Section-4 contains results and discussion and finally Section-5 encloses with conclusion and future enhancement.

2. LITERATURE SURVEY

Alzheimer's is consideredas the progressive mental decline that typically befalls in old-aged people due to the degradation of brain regions. In addition, more research has been conducted in recent years to accurately detect AD, and some of them are discussed briefly in this section.In 2021P.Kishore, *et al.,*[3] had developed a new approach to predict and analyze Alzheimer's dependent on different machine learning techniques. The proposed system was mainly focused on supervised learning for classification and regression. SVM along with linear kernel model was used for accuracy. By using this technique AD can be predicted in the early stage.

In 2021 Fanar, E.K.*, et al.,* [4] had designed a deep learning technique to detect Alzheimer in early stage based on the MRI. This technique mainly focused on the Alzheimer Network (Alznet) were created by training a CNN structure using 2D slices to differentiate the healthy and affected brain. The range of accuracy is 99.30% based on the OASIS datasets. In 2020 Mehmood A., *et al.,* [6] had devised a Siamese CNN on basis ofVGG-16 to categorizethe stages ofdementia. This approach wasextendedfor the imbalanced and inadequate data was used for augmentation approaches. The experiments are conducted on theOASIS dataset and achieves accuracy of 99.05% for classification.

In 2019 Garam Lee*., etal.,*[8] had developed multimodal deep learning to predicting the transformation from MCI to alzheimer. The classification was done by using the 4-modalities like cognitive performance, MRI biomarker along with demographic,CSF, and cross-sectional data.In 2019 D.Chitradevi and S.Prabha [9] had introduced a deep learning method to analyze AD in the brain sub-regions by using optimization techniques. The classification was done in the brain sub-regions by using the Grey wolf algorithm. This algorithm gave the optimal results with high accuracy, but this technique is not applicable in MCI diagnosis.

From the literature review, various ML and DL learning techniques were focused on accuracy for detecting AD in early stages. The proposed Aquila-CNN model also focuses on improving the accuracy rate by accurately classifying the four stages of AD for early diagnosis.

3. PROPOSED METHODOLOGY

In this section, we introduce a novel Aquila-CNNapproach for prognosing the Alzheimer's from MRI images. The proposed Aquila CNNtechnique for automatic diagnosis of AD is based on a hybridization of CNN which is optimized with aquila optimizer. The method includespre-processing of MRI, feature extraction phase, and classification of AD stages and the overall workflow of the proposed approach is depicted in fig.1.

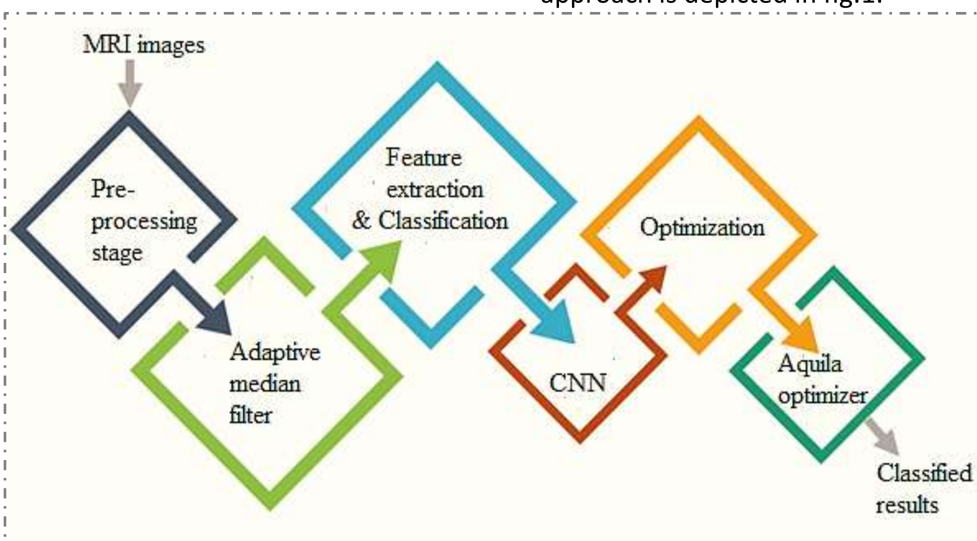


Figure.1: The overall work flow of the proposed methodology

3.1 Dataset description

In this study, Alzheimer's Disease Neuroimaging Initiative-3 (ADNI-3) dataset is employed, which is an open-source database. It encompasses the previous datasets like ADNI-1, ADNI-2 and ADNI-GO combining the endeavour to evaluate the relation between clinical, imaging, cognitive, biomarker, and genetic features of the AD stages. ADNI-3 encompasses 59 research centres; in addition to the previous data, additional 133 elderly-CN, 151-MCI, 87-AD medical data. ADNI-3 extends to develop, optimise, standardise, and validate clinical trial measurements and biomarkers for Alzheimer's disease research.

3.2 Data pre-processing

Pre-processing the input data plays a vital step for reducing the noise and enhancing the subtle changes of medical images. Skull stripping is used to remove the outer cortical and skull region, to improve the cortical region. The noise reduction, non-linear, levelling, and edge preserving filter is the adaptive median filter. This filter executes spatial dispensation to evaluate which pixels in an MR images have been afflicted by noise. This median filter describes each pixel in an MR image as noise by comparing it to its neighboring pixels. It simultaneously normalizes the brightness across an image and increases contrast.

3.3 Feature extraction phase

Feature extraction is a vital phase that is used for eliminating the redundant and irrelevant data present in the pre-processed MRI images. These images are fed into the deep CNN for extracting the relevant features such as Hippocampal volume, Cortical thickness, etc. and the CNN model was optimized with Aquila optimizer for selecting theoptimum features and improve the accuracy.

3.3.1 Convolutional neural network

In deep learning, convolutional neural network (CNN) are well-known models that are used to solve image classification problems. In contrast to traditional ML techniques that depend on hand-crafted feature extraction, CNNs can efficientlyanalyze and characterized as complex features. In addition to their ability to distribute weights across multiple layers, CNNs are also known for reducing model complexity. CNN comprises of convolutional layer, pooling layer, and fully-connected layers. A convolutional layer employs a nonlinear ReLU activation function, succeeded by dropout regularization. A convolution layer is made up of various convolution kernels that are used to extract input data. The input data is given to the convolution kernels of the convolution layer, which then apply the convolution operation to the data, resulting in the extracted features. The procedure for performing a one-dimensional convolution operation is as follows,

$$x_j^L = \sum_{i=1}^{n} x_j^{L-1} * k_j^L + b_j^L \quad (1)$$

where x_j^{L-1}defines the i-th feature map of the layer *L-1*,x_j^L denotes the j^{th}feature map of the layer *L*, k_j^Ldenotes the j^{th}convolution kernel, b_j^L represents the bias, the convolution operation is defined as *** and *n* is represent as the number of input feature maps. Once a feature has been identified, its specific position is less relevant as much as its estimated position in relation to other features is retained. Each layer with ReLU function is used to the standardized input data and it derived as,

$$R(x_j^L) = \max\{0, x_j^L\} \quad (2)$$

The CNN catches the variants in the sequential variations of the input data by wide across the time series with a filter of a certain size. The different sections of the data are described by feature maps. The next layer achieves a local averaging, called pooling and down-sampling minimize the identity of the feature map and reduce the intensity of probable shifts and alterations of the output. This procedure may result in the omission of important information and the max-pooling process is defined as,

$$P_L^{L+1}(j) = max_{(j-1)w<t<jw}\{Q_i^L(t)\} \quad (3)$$

Where $P_L^{L+1}(j)$represents the certain value acquired later max-pooling process of the j^{th}operating state of the i^{th}feature map, $Q_i^L(t)$ denotes the t^{th} neuron of the i^{th}feature map of layer *L* and*w* defines the width of the pooling region.To attain the last feature representation of each input sample, the generated feature map is pooled inorder to extract the most relevant features, and these are down-sampled according to learning criteria, so the model can train rapidly for better classification results.

3.3.2 Aquila optimizer

An AQU algorithm generally mimics the social behavior of Aquila to capture its prey. It is the population-based optimization algorithm, same as other metaheuristics, which initiates with an initialize the population of *N* agents. The agents in the existing population are upgraded until they find the best solution based on this best agent and the AQU. Equation (4) is used to generate the initial population *Z* that is composed of *N* solutions.

$Z_i = lb + R\ and\ (1, D) * (ub - lb)$ (4)

where *D*refers to the number of features. *R and (1, D)*denotes a random-vector with *D* values. *ub*and *lb*are the search spaceboundaries. Then, convert Z_i to binary using equation (5)

$$BZ_{ij} = \begin{cases} 1 & if\ Z_{ij} > 0.5 \\ 0 & otherwise \end{cases}$$ (5)

As a result of Equation (5), the number of selected features is reduced by neglecting theirrelevant features that correspond to zero values inBZ_i. Then the value of fitness is determined as,

$$fitness = \beta * \gamma_i + (1 - \beta) * (\frac{|BZ_i|}{D})$$ (6)

where $\beta \epsilon [0,1]$denotes the weights used to balancethe ratio between relevant features$\frac{|BZ_i|}{D}$and classificationerror γ_i.Afterwards, the optimal fit and its equivalent agent Z_b is determined. In the testing set, features are reduced according to the binary ofZ_b. Based on the reduced features, several performance metrics are calculated to determine the quality of the classification process.

4. RESULTS AND DISCUSSION

The experimental setup of the paper was implemented by using MATLAB 2019b, a machine learning toolbox. In this result analysis, the MRI images from ADNI dataset was used for identifying and categorizing the stages of Alzheimer into normal, EMCI, LMCI and AD.

4.1 Performance analysis

In this study, the efficiency of the Aquila-CNNmodel is evaluated based on specificity, accuracy and sensitivity.

$$specificity = \frac{tn}{tn+fp}$$ (7)

$$sensitivity = \frac{tp}{tp+ fn}$$ (8)

$$accuracy = \frac{tp+tn}{total\ no.of\ samples}$$ (9)

wheretp and *tn* refers to true positives and negatives of the samples, *fp* and *fn* refers to false positives and negatives of the samples.

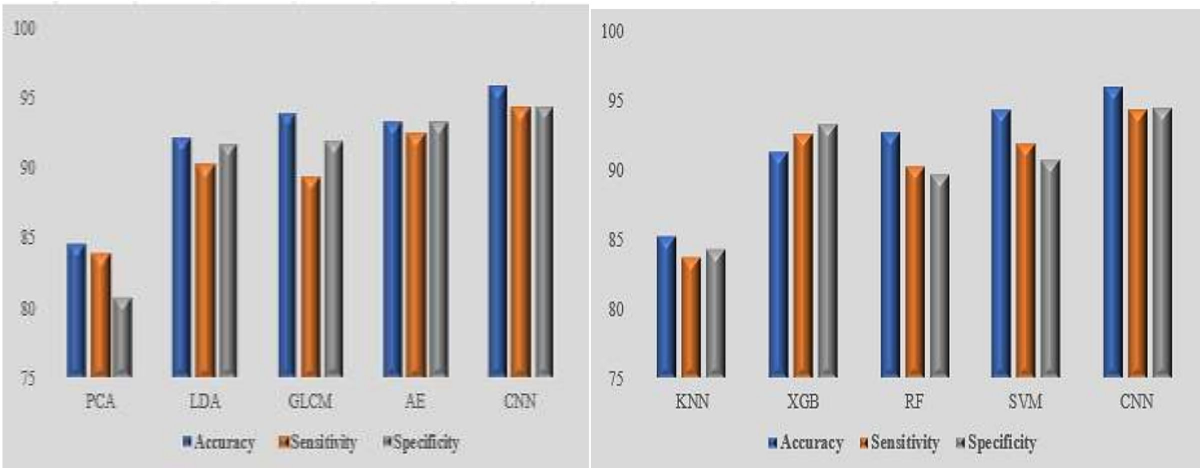
Table.1: Performance analysis of the proposed model

Classes	Accuracy	Specificity	Sensitivity
Normal	96.78	95.25	95.02
EMCI	95.45	94.28	94.14
LMCI	95.08	92.47	93.01
AD	96.12	95.22	95.18

From table.1, it is obviously clear that the Aquila-CNN achieves high accuracy for four classes. The accuracy range is differed for different classes. The proposed Aquila-CNN achieves a high accuracy range of 96.78%, 95.45%, 95.08% and 96.12% for classifying normal, EMCI, LMCI and AD respectively.

4.2 Comparative analysis

The performance of each machine learning classifier was evaluated to show that the result of the proposed technique is more efficient. The classification is based on the specificity, sensitivity and accuracy of each classifier and the accuracy obtained by Aquila-CNN classifier is 96.78% for normal. The classification accuracy rate is obtained through the integration of aquila optimizer with CNN is more efficient than the existing models.



(a) (b)

Figure.2: Graphical comparison of (a) ML feature extractors (b) ML classifiers

The comparative analysis is performed between the proposed model and four machine learning feature extractors such as PCA, LDA, GLCM and Autoencoder is shown in figure.2(a). The comparative analysis is performed between the proposed model and four machine learning classifiers namelykNN, SVM, RF and XGBoost is shown in figure.2(b). The overall accuracy obtained by the CNN is 95.85% which is comparatively higher than the existing machine learning classifiers and feature extractors. The overall specificity obtained by the CNN is 94.30% and the overall sensitivity obtained by the CNN is 94.33% which is also higher than the traditional ML models. In the future, the proposed classification Aquila-CNN model will be trained in order to accurately predict the various stages of AD using advanced deep learning and various optimization techniques.

5. CONCLUSION

In this work, we introduce a deep Aquila-CNN for detecting the AD in the early stages. Initially, ADNI database is used to estimate the effectiveness of different combinations of MR-based features for improving accuracy inclassification phase. The MRI images are pre-processed using adaptive median filter to remove unwanted distortions in the input images. Afterwards, the relevant features are extracted from the pre-processed images using CNN, which is optimized with aquila optimizer (Aquila-CNN). Consequently, based the extracted features the proposed which classifies the MRI images into normal, EMCI, LMCI, and AD. The proposed Aquila-CNN achieves a high accuracy range of 96.78%, 95.45%, 95.08% and 96.12% for classifying normal, EMCI, LMCI and AD respectively. The Aquila-CNN was compared with traditional MLalgorithms like SVM, DT, RF and NB. The comparison analysis evidently reveals that the Aquila-CNN provides better classification results than the traditional classifiers.

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