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RESEARCH ARTICLE

AD-HCBL: A HYBRID CNN-BILSTM FRAMEWORK FOR ALZHEIMER'S DISEASE CLASSIFICATION USING MRI IMAGES

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Abstract – Alzheimer's disease (AD) is a neurodegenerative disorder that is progressive and causes loss of memory and cognitive performance, which significantly influences the quality of life of older adults. The accurate and early diagnosis of AD using MRI images provides complex brain structural changes, redundant features, and limited effectiveness of existing automated detection methods. To address this, a novel AD-HCBL is proposed for accurate and automated AD detection using MRI Images. The proposed AD-HCBL integrates a ResNet 50 + Grey-Level Co-occurrence Matrix (GLCM) for extracting the features from the MRI scan images. Frog Snake Prey Predation Relationship Optimisation (FSRO) is then used to extract the features and refine the exploration features to eliminate the redundancy, giving a good balance between exploitation and exploration. The MRI images are then correctly categorised into normal, mild and severe stages of AD, using a BiLSTM network. Two datasets are utilised in the implementation of the experimental results in the python, specifically, the AD Multiclass Dataset and the ADNI dataset. The proposed AD-HCBL achieves above 98% accuracy, precision, and recall when compared to the existing methods, respectively.

Keywords *– Alzheimer's disease, Grey-Level Co-occurrence Matrix, Frog Snake Prey Predation Relationship Optimisation, MRI images.*

1. INTRODUCTION

Alzheimer's is a neurologic loss disease that is usually characterised the loss of memory and decline of other mental functions as the brain cells are killed and other regions of the brain atrophy. Alzheimer Disease (AD) is a condition whose incidence and prevalence rise with age. AD has rapidly emerged as one of the major universal-level medical issues, and this is due to the increasing number of older people across all nations globally [1]. There are no specific diagnostic techniques and efficacious curative agents for AD nowadays. AD affects approximately 2% of individuals aged between 65 and 85 years. The year 2006 reported an infection in 26.6 million people, and the number is rising at an astronomical rate. Over 55 million individuals have been infected by AD in 2020, and it is projected to hit 152 million by 2050 [2-3]. The disease requires proper diagnosis to formulate the drugs required to slow the progression process, and the entire medical history of the patient is well analysed so that it can be effectively monitored [4].

The clinical procedures to detect AD currently in the mainstream include testing based on scale, the measurement of brain Magnetic Resonance Imaging (MRI) the analysis of cerebrospinal fluid, etc. Researchers are still faced with a major challenge of AD using DL [5]. Poor quality and scarcity of medical images as well as the challenge of locating regions of interest (ROI) in the brain and imbalanced class faces the challenge of AD detection. A number of MRI-based disease-diagnosis studies have employed traditional machine-learning models, although features obtained by a manual examination are more complicated and time-intensive, as well as necessitating a high degree of medical expert intervention [6].

The traditional approach lacks a specific diagnosis, leading to mistakes in diagnosis and wastage. Hence, creating a precise and efficient diagnostic model, which is automated and able to effectively obtain meaningful features of the brain MRI images and minimising reliance on manual analysis is a challenge in research [7]. These limitations are important to consider in enhancing early diagnosis, monitoring disease progression and helping in making the necessary decisions that can be used to manage AD by clinicians. To address this, a novel AD-HCBL is proposed for accurate and automated AD detection using MRI Images. The primary key contributions are

- The primary objective of this paper is to propose a novel AD classification using a hybrid CNN-BiLSTM (AD-HCBL) for an efficient and reliable MRI-based AD classification system with improved accuracy and robustness.
- The proposed AD-HCBL integrates ResNet 50 + Grey-Level for extracting the feature, FSRO is used to select the features from the MRI scan images, and

BiLSTM is used to classify the images as normal, mild, or moderate AD.

- The experimental results are evaluated using two datasets namely, the AD Multiclass Dataset and ADNI, and it confirms the effectiveness of the proposed method.

The paper has been organised as follows: section 2 will describe the literature review, section 3 will explain the proposed method, section 4 will discuss and give results and section 5 will give the conclusion and recommendations on further development.

2. LITERATURE REVIEW

In 2025, Soladoye, A.A et al., [8] designed an AD prediction algorithm on end-to-end prediction using a wide dataset of patients, and the interpretability of the models is considered through SHAP and LIME frameworks. The best results were on the optimised random forest with added feature of backward elimination method of feature selection and ant colony optimisation with 95% accuracy, 95% precision, 94% recall, 94% F1-score and 98% AUC.

In 2025, Chen, J et al.,[9] suggested a new multimodal data fusion medical model, which is labelled as MMDF, to undertake AD recognition. The designed models are joined together to form a new data fusion model in order to identify AD. Outstanding performance can be seen through the results of the experiments relative to the state-of-the-art (SOTA) method.

In 2024, Mitrovska, A et al., [10] presented an ML model that is applicable in identifying AD based on structural MRI (sMRI) images. The analysis of the presence of the following statistical differences in the trained ML models in the heterogeneous settings is simulated in the proposed procedure and necessitates the research of the differences when the training of the ML models is performed to identify AD.

In 2023, Dogan, S et al., [11] suggested a self-driven prediction model of AD using local texture features with EEG signals on a new directed graph. The model reached a 92.01% and 100% with LOSO and the tenfold cross-validation, respectively, which can testify to the discriminative power of the model in AD vs healthy classification using the KNN classifier, cross-validated tenfold and LOSO, respectively.

In 2023, Mujahid, M et al.,[12] presented an ensemble deep learning architecture comprised of EfficientNet-B2 and VGG-16 and adaptive synthetic oversampling to achieve quality and find AD early using MRI images. The experimental findings demonstrated that the suggested method had 97.35% accuracy and 99.64% AUC where the data consisted of multiple classes and 97.09% and 99.59% accuracy and AUC, respectively, on data with two classes.

In 2022, Orouskhani, M et al., [13] introduced a deep triplet network where the method of metric learning is applied to the analysis of the brain MRI and the detection of Alzheimer's. The designed method employs a profound triplet network with the conditional loss function to address the absence of a limited number of samples and enhance model accuracy. According to the experiments, the suggested model is better in terms of accuracy than the available models

In 2022, Kong, Z et al., [14] suggested an image fusion technique to merge MRI and Positron Emission Tomography (PET) images of the AD patients. According to the experiment performed with the help of the Alzheimer Disease Neuroimaging Initiative (ADNI) public data, the suggested model is more advanced in terms of accuracy, sensitivity, and specificity.

According to the literature review, AD was detected by several deep learning and hybrid models. The challenges in the existing methods include unnecessary features, non-optimal features, and poor ability in modelling multifaceted feature relationships that deteriorate classification. More computational complexity and overfitting. To tackle these issues, this work proposes a novel AD-HCBL framework that combines deep and texture feature extraction with FSRO-based feature selection and BiLSTM classification.

3. PROPOSED AD-HCBL METHODOLOGIES

In this section, a novel AD-HCBL is proposed for accurate and automated AD detection using MRI image. Figure 1 illustrates the architecture of the proposed AD-HCBL. The input brain MRI images are first processed and separated into a training and testing set. The ResNet50 network is used to extract deep features, whereas the GLCM method captures the texture information. The deep and texture features, which have already been extracted, will be fused and refined again by the FSRO-based feature selection algorithm. Lastly, a BiLSTM classifier is utilised to distinguish the MRI images into normal, mild and severe stages of AD.

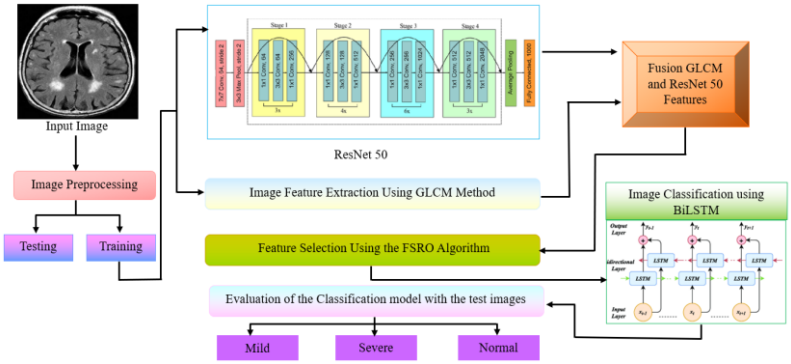

Figure 1: Architecture of the proposed hybrid CNN-BiLSTM method for Alzheimer's disease classification (AD-HCBL)

3.1 Image ResNet 50 and GLCM Method-Based Extraction of Features

A CNN is a feedforward neural network; it uses the convolution operator, among others, although most such networks are deeply structured. CNNs have also been very effective at handling multi-dimensional data, including images, and therefore, they are one of the most recognisable kinds of DL algorithms. ResNet is associated with images, including image recognition or image classification. The ResNet-50 model is a further improvement of the strength of the regular CNN with the addition of residual blocks that are joined through the shortcut connection. The ResNet 50 architecture is illustrated in Figure 2.

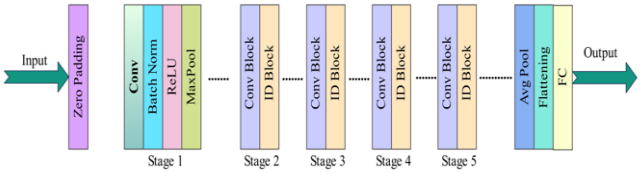

Figure 2: Architecture of ResNet50

ResNet-50 uses the concept of residual blocks to deal with the vanishing and exploding gradient issues that arise as a result of building deeper networks. Additionally, it can store extra information during training to combine the learned features with the primary nonlinear characteristics in residual blocks. Extractions of additional features of the images are carried out based on the application of such techniques like the GLCM. GLCM is also a feature-extraction process that further enhances the ability of the model in estimating the texture-based characteristics of a medical image. GLCM is particularly effective when it comes to visualising the spatial association of pixel brightness, a central activity in identifying minor variations in constant patterns of texture relative to AD. GLCM builds a matrix according to the relationship of pixels at various angles and distances to boost image features. Lastly, CNN and GLCM techniques are merged together to make a new set of features that are then utilised in the step of feature selection.

3.2 Feature Selection using Frog Snake Prey Predation Relationship Optimisation (FSRO)

The FSRO algorithm is a dynamic adaptive algorithm that changes high-level features to maximise the purpose. The model consists of two parts in which a predator (snake) and a prey (frogs) interact. The snake will proceed to lead the way of world exploration, and the frogs will aim at maximising their local and global position. The FSRO algorithm is utilised to optimally select the features by eliminating redundant features and improving the classification level

3.2.1 Movement of the Frog

The search position of each frog depends on the effects of the snake and the best position in the area, as shown in Equation (1).

$$G_d^{t+1} = G_d^t + \alpha\,(S^t - G_d^t) + \beta\left(G_d^{best} - G_d^t\right) \quad (1)$$

S^t represents the position of the snake (predator) at iteration t, G_d^{best} represents the individual's best position of the frog, α and β are the dynamic weights between local and global.

3.2.2 Movement of Snake

The snake is found to move to the best global solution and randomly selected frogs:

$$K^{t+1} = \omega K^t + \phi_1 h_1\,(N^t - S^t) + \phi_2 h_2\left(G_j^t - S^t\right) \quad (2)$$

$$S^{t+1} = S^t + K^{t+1} \quad (3)$$

Where K^t is the current global optimum, G_j^t a is the position of a frog chosen randomly, ω is the mass of the weight of inertia, ϕ_1 and ϕ_2 coefficients of acceleration, h_1 and h_2 are random numbers in [0,1].

3.2.3 Interaction of Prey Predator

The probability B_d that any frog provides an opportunity to remain in the population:

$$B_d = \frac{1}{1 + e^{-y\,(G_d)}} \quad (4)$$

where the probability of survival is low, this leads to the frog being mutated to a new random solution. FSRO is used to solve the optimisation problem by an iterative process for the convergence, or there is a fixed maximum no of iterations. The binary constraints are implemented with a sigmoid transformation as shown in Equation (5).

$$G_d^{binary} = Sigmoid\,(G_d) > 0.5 \quad (5)$$

The method maximises the amount of discriminative power in the chosen features, and minimises redundancy and sparsity.

3.3 Classification using BiLSTM

The Bidirectional Long Short-Term Memory Network (BiLSTM) is a type of optimisation network that is proposed to be the extension of the Long Short-Term Memory Neural Network (LSTM). It can operate in forward and backward directions in the time series business and can thus operate with a BiLSTM layer that has two independent hidden layers, which are towards the forward direction and the other towards the backward direction and can thus hold the past information (forward) and future information (backward) at a particular time step.

$$hf_j = f_1\left(\omega_1 l_j + \omega_2 hf_{j-1}\right) \quad (6)$$

$$hb_j = f_2\left(\omega_3 p_j + \omega_3 hb_{j+1}\right) \quad (7)$$

$$C_j = f_3\left(\omega_4 hf_j + \omega_6 hb_j\right) \quad (8)$$

where $l_1, l_2, \ldots, l_j$ denotes the input value j_{th} time step, $hf_1, hf_2, hf_3, \ldots, hf_j$ represents the forward LSTM hidden state, $C_1, C_2, \ldots,$ shows the output value at the j_{th} time step, $hb_1, hb_2, hb_3, \ldots, hb_j$ represents the backward LSTM hidden state of the backward LSTM $\omega_1, \omega_2, \ldots., \omega_j$ represents the corresponding weight matrix of each layer. The BiLSTM classifier is employed to model bidirectional dependencies among the selected features, enabling effective

learning of both low-level and the high-level feature relationships for accurate AD classification.

4. RESULTS AND DISCUSSIONS

In this section, the proposed AD-HCBL is applied to a sample of pictures of patients with Alzheimer's. It has been implemented in Python.

4.1 Dataset Preparation

The proposed AD-HCBL uses two different datasets, the Alzheimer Disease Multiclass Data set and the ADNI data set, to examine Alzheimer, to provide a large variety of demographics and images. The Alzheimer Disease Multiclass Data consists of about 44,000 MRI images in four different classes according to the severity of the Alzheimer disease. ADNI is an Alzheimer dataset that is used to trace the initial phases of the disease, meaning that it is a collection of MRI scans and 128 sagittal slices each represented as a 256x256 matrix. The two datasets are also provided by different institutions, and this adds some variability in the conditions of their acquisition, which also strengthens the model and increases its capacity to be generalised to real-world situations.

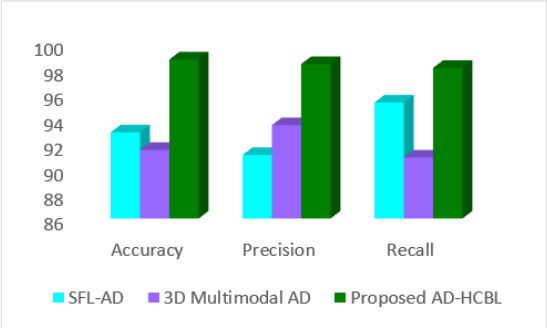

Figure 3: Performance of the proposed AD-HCBL on the Alzheimer's Disease Multiclass Dataset

Figure 3 presents the performance metrics of the proposed AD-HCBL on the OASIS MRI dataset. The existing method SFL-AD achieves a moderate accuracy and recall, and the 3D Multimodal AD achieves the lowest recall of 90.58 %. The proposed method achieves the highest accuracy (AY) of 98.23%, precision (PN) of 98.56%, and recall (RL) of 98.01% when compared with the existing designs of SFL-AD and 3D Multimodal AD.

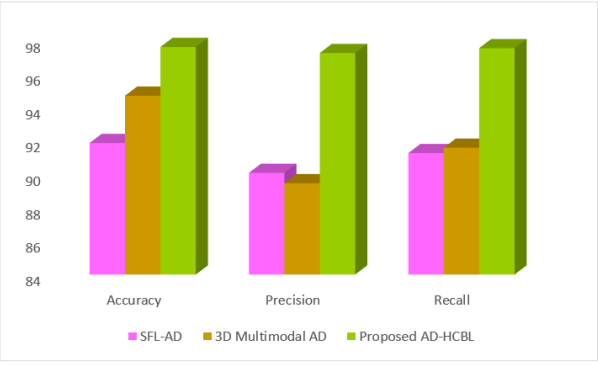

Figure 4: The proposed AD-HCBL performance on the ADNI dataset

Figure 4 illustrates the performance of the proposed AD-HCBL on the Roche AD dataset. The SFL-AD achieves a lowest precision of 89.45%and the 3D multimodal method achieves a lowest accuracy of 94.67%. The proposed method achieves the highest AN, PN and RL among all the existing methods, like SFL-AD and 3D multimodal AD. The proposed AD-HCBL achieves an AY of 97.58%, a RL of 97.51% and a PN of 97.22%.

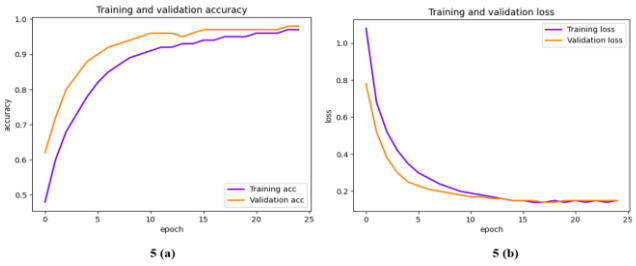

Figure 5: Training and Validation curve of the proposed AD-HBCL

Figure 5 shows the proposed AD-HCBL training and validation curve. Figure 5(a) depicts the training accuracy and validation accuracy as a function of epochs, where there is a gradual increase and convergence to accuracy values. Figure 5 (b) shows the resultant training and validation loss curves, which continuously drop over the epochs, proving effective learning and the consistent convergence of the proposed model has no overfitting.

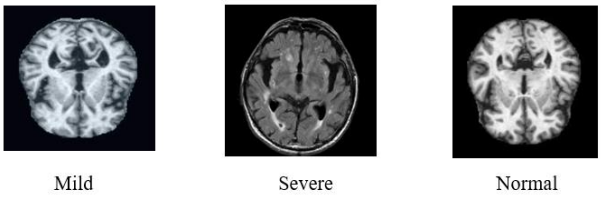

Figure 6: Sample MRI brain images taken from the dataset

Figure 6 illustrates the sample MRI brain image which are taken from the chosen datasets. The proposed AD-HCBL classifiers the AD into three categories, namely: Normal, Mild, and Severe. These are the input samples on which the proposed classification framework is trained and also tested. The images reflected in the dataset reflect the structural changes relating to various phases of impairment of the nervous system.

5. CONCLUSION

In this research, a novel AD-HCBL is proposed for accurate and automated AD detection using MRI Images. The proposed AD-HCBL integrates a ResNet 50 + GLCM for extracting the features from the MRI scan image. These extracted features are then refined with the FSRO to pick the most relevant features, which gives a good exploitation versus exploration balance and also minimises the redundancy. A BiLSTM classifier is then utilised to learn the dependency among the selected features and accurately classify the MRI images into Normal, Mild, and Severe stages of AD. The proposed method is applied to two datasets with Python, i.e., on the AD Multiclass Dataset and the ADNI data. The AD multiclass dataset achieves an AY of

98.23%, a PN of 98.56%, and a RL of 98.01%, and the ADNI dataset achieves an AY of 97.58%, a RL of 97.51% and a PN of 97.22%. For future research, the proposed AD-HCBL can be expanded with the concept of adaptive learning and multimodal medical data to increase the robustness and real-time clinical applicability.

CONFLICTS OF INTEREST

The author proclaims that there are no conflicting interests to disclose in this study.

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