Analysing Brain images for detecting AD disease using natured inspired cuckoo optimized recurrent networks

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Abstract

Alzheimer's disease (AD) is a one of the progressive neurological stage that affects human cognitive ability an impairs memory. Prompt and precise identification of AD is vital for timely intervention and therapy. This paper introduced natured optimized method for detecting Alzheimer's disease (AD) by integrating Recurrent Neural Networks (RNNs) with the Cuckoo Optimization Algorithm (COA). The Recurrent Neural Networks (RNNs) are suitable for processing data in a specific order, such as brain images and biomarker time series. Brain images are utilized during the analysis to observe the changes in the brain region. The gathered brain images are processed using adaptive filtering and histogram enhancement to improve image quality. Then affected regions are segmented, and features are derived to maximize the AD detection accuracy. The extracted features are fed into the recurrent classifiers that recognize the feature abnormality. The cuckoo optimization technique is utilized during the analysis to fine-tune the network parameters. The COA, which takes inspiration from cuckoo birds' obligate brood parasite behaviour, systematically explores the hyperparameter space and chooses the most effective configuration for the RNN model. This strategy combines the temporal modelling capabilities of RNNs with the efficient exploration of COA to improve the accuracy of AD detection. The experimental results on benchmark datasets provide evidence for the superiority of the suggested cuckoo-optimized RNN methodology compared to existing methods.

Keywords: Alzheimer's Disease (AD), Recurrent Neural Networks, Cuckoo Optimization algorithm, brain images, biomarker time series and nature-inspired metaheuristic tool.

1. Introduction

Alzheimer's disease (AD) [1] is a degenerative ailment of the nervous system that worsens over time and cannot be reversed. It mainly impacts older individuals. The condition is distinguished by the buildup of abnormal proteins, specifically amyloid-beta and tau, within the brain, resulting in the demise of neurons and shrinkage of the brain [2]. The cognitive deficits linked to Alzheimer's disease, such as memory decline, language challenges, and decreased executive functioning, have a substantial impact on an person's capacity on everyday tasks and sustain autonomy. AD detection and prediction systems [3] utilize sophisticated computational techniques and machine learning algorithms to analyze diverse data types, such as neuroimaging data (e.g., functional MRI, structural magnetic resonance imaging (MRI) and positron emission tomography (PET) scans), biomarkers (e.g., cerebrospinal fluid analysis, genetic data), and cognitive assessments [4]. These systems aim to identify patterns and extract characteristics that can differentiate between individuals with AD, moderate cognitive impairment (MCI, a potential precursor to AD), and healthy controls [5].

Traditional AD prediction techniques [6] encounter numerous obstacles that traditional AD detection systems find difficult to handle. Neuroimaging and genetic data are characterized by their high dimensionality and complexity, consisting of millions of features. This poses challenges in identifying the most significant features and capturing intricate interactions. The heterogeneity of Alzheimer's disease (AD) is characterized by a wide range of clinical presentations, varying rates of disease progression, and different patterns of brain atrophy [7]. This complexity makes it challenging to create prediction models that can be used universally. Conventional methods [8] often depend on manually designed features and simple learning models, which may struggle to capture the intricate and non-linear patterns found in the data. This limitation restricts the capacity to apply the created models to a wider population and reduces the strength of the findings. Data integration in the context of Alzheimer's disease (AD) [9] entails combining many biological processes and modalities, requiring the integration of varied data sources. Interpretability is crucial in understanding the biological mechanisms of AD. Although black-box models may achieve great prediction accuracy, they often lack interpretability, making it difficult to comprehend the underlying mechanisms. It is essential to overcome these problems to develop automatic systems for early AD detection and intervention [10] that are more accurate, resilient, and interpretable. One can accomplish this by investigating sophisticated machine learning approaches [11], such as deep learning, ensemble methods, and transfer learning [12]. The utilization of nature-inspired cuckoo-optimized recurrent neural networks (CO-RNNs) presents a promising alternative to overcome the limitations encountered by traditional AD prediction approaches. Recurrent neural networks (RNNs) are particularly suitable for studying the longitudinal and temporal elements of Alzheimer's disease (AD) progression because they can represent sequential data and capture long-range dependencies.

RNNs can acquire intricate patterns and temporal dynamics relevant to development of Alzheimer's disease by utilizing multimodal data, including time-series neuroimaging, biomarkers, and cognitive tests. Yet, the effectiveness of RNNs relies significantly on an intelligent selection of hyperparameters, a challenging endeavour because of the vast and complex search space. In order to tackle this problem, the cuckoo optimization algorithm (COA), a nature-inspired metaheuristic technique, is used to systematically explore the hyperparameter space and determine the best configuration for the RNN model. The COA, drawing inspiration from cuckoo birds' obligate brood parasite behaviour, effectively explores the search space, surpassing local optima and improving the model's generalization ability. The CO-RNN approach efficiently captures the heterogeneity and complexity of AD data by combining the temporal modelling capacity of RNNs with the efficient optimization capabilities of COA. This leads to better prediction accuracy and early diagnosis the illness. The main intention of this study is listed below.

- Analyzing the brain image feature using recurrent neural networks' temporal modelling capabilities to improve Alzheimer's disease detection accuracy.
- Minimizing the deviation between the detection variation by incorporating the nature-inspired cuckoo search algorithm-based hyperparameter fine-tuning process.
- Maximize the explainability and interpretability of the optimized RNN approach by understanding the biomarkers and biological mechanisms associated with AD development.

2. Research Methodology

Santos Bringas et al. [13] conducted a study on the course of Alzheimer's disease (AD) across its many stages. Data portability was implemented to simplify the process of recognizing the AD stage. Deep Learning Models called Convolution Neural Networks (CNN), were employed to examine data about different phases of Alzheimer's illness. CNNs are highly proficient in applications that involve spatial relationships, such as image analysis. The researchers collected data from 35 people diagnosed with Alzheimer's disease (AD) at a childcare facility using cell phones. These devices potentially recorded any alterations in their daily activities, symptoms, or other aspects of their lives across a period. The researchers utilized Matlab, a commonly employed program for data analysis, modelling, and algorithm development, to analyze the data. Matlab certainly played a crucial role in processing the smartphone data and developing the CNN to identify different phases of Alzheimer's disease.

Junxiu Liu et al. [14] aimed to enhance the computational identification of Alzheimer's disease (AD) by improving its speed and precision. The image processing tasks were performed using efficient deep learning models, including Depth-wise Separable Convolution Neural Networks, AlexNet, and GoogLeNet. The OASIS MRI dataset processed and analyzed images from individuals with AD and healthy subjects. The dataset was processed and analyzed using Matlab. Given the importance of accurately and efficiently identifying AD for practical purposes, the researchers improved recognition accuracy while minimizing power usage by utilizing specific models and approaches. This study highlights the importance of streamlining computational procedures and enhancing the accuracy of AD detection.

Duraisamy et al. [15] utilized FCM (Fuzzy C-Means) and weighted probabilistic neural networks to accurately detect Alzheimer's disease using MR (Magnetic Resonance) images. First, MRI images are obtained from patients and then processed using a region segmentation approach to identify the different afflicted regions. Statistical features associated with AD are extracted from the region and examined using a multiple-criteria feature selection approach. The chosen characteristics are analyzed and categorized using a specified classifier that can accurately

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identify Alzheimer's disease with an accuracy rate of 98.63%. The system's efficiency is assessed by utilizing the Bordex 3 city dataset. In this dataset, the FCM based classifier had the highest performance in recognizing Alzheimer's disease.

Shankar K. et al. [16] recommended a group grey-optimized convolution network for detecting Alzheimer's disease from brain images. The gathered brain images are analyzed using noise removal techniques to minimize the unwanted region. Then, various descriptors such as histograms, textures and scale-invariant features are extracted from the brain image. The derived features are processed using a wolf optimization algorithm that minimizes the feature dimension. The choosen features fed into the convolutional network that predicts the AD with maximum recognition accuracy (96.23%) compared to the K-nearest neighbour and decision tree.

Liu, J. [17] applied a depthwise separable convolution network to recognize Alzheimer's disease. The main intention of this work is to improve the disease recognition accuracy and to reduce the computation complexity. During the analysis, the depthwise convolution layer was utilized instead of the conventional convolution operator, reducing the computational cost. In addition, it has less power consumption while recognizing the AD. In addition, the network uses the training model to maximize the classification rate.

Hamdi, M., et al. [18] Assessed the efficacy of deep learning neural networks in identifying Alzheimer's disease by using neuroimaging data. The researchers utilized different convolutional neural network architectures and evaluated their diagnostic precision on brain MRI and PET data. The study revealed that deep learning models had a high level of effectiveness in accurately unique Alzheimer's patients from well controls. The most optimal model achieved a remarkable accuracy rate above 90%. This underscores the capacity to utilize artificial intelligence for prompt identification and timely intervention in Alzheimer's disease.

3. Alzheimer's Disease Detection using nature-inspired Cuckoo-Optimized Recurrent Neural Networks (CO-RNNs)

The intention of this work is to create a precise and strong computational framework for identifying and predicting Alzheimer's disease (AD) at an initial stage. This will be achieved by combining the powerful capabilities of recurrent neural networks (RNNs) with the cuckoo optimization algorithm (COA). The motivation arises from the urgent requirement to promptly detect AD, as early management can greatly enhance patient outcomes and quality of life. Traditional approaches for predicting Alzheimer's disease (AD) often face difficulties due to the illness's high complexity, heterogeneity, and temporal dynamics. Recurrent Neural Networks (RNNs), due to their capacity to represent sequential information and comprehend distant relationships, are very appropriate for examining the longitudinal and multimodal data linked to Alzheimer's Disease (AD), such as neuroimaging, biomarkers, and cognitive tests. The performance of these models is significantly impacted by the choice of hyperparameters, which can be a laborious and less-than-optimum procedure when employing conventional techniques. Thus, the paper combines Recurrent Neural Networks (RNNs) with the nature-inspired Cuckoo Search Algorithm (COA) to improve AD detection accuracy. This metaheuristic optimization technique draws inspiration from the brood parasitic behaviour of cuckoo birds. The COA method systematically explores the range of hyperparameters, allowing for selecting the best configurations for the RNN model. This improves the model's capacity to make accurate predictions and generalize of AD detection. Then, the working process of AD detection is demonstrated in Figure 1.

Figure 1 explains the working procedure of nature-inspired Cuckoo-Optimized Recurrent Neural Networks (CO-RNNs) based AD detection process. The brain images are collected and processed using a preprocessing technique that eliminates irrelevant information. In addition, image contrasts are enhanced to maximize the accuracy of AD detection. Then, affected regions are explored using segmentation techniques and relevant features are extracted from the region. The derived features are fed into the classification procedure to identify the normal and abnormal features. During the analysis, the nature-inspired cuckoo search algorithm is incorporated to fine-tune the network parameter, which reduces the error rate. Then, the detailed working process of the CO-RNN approach is described as follows.

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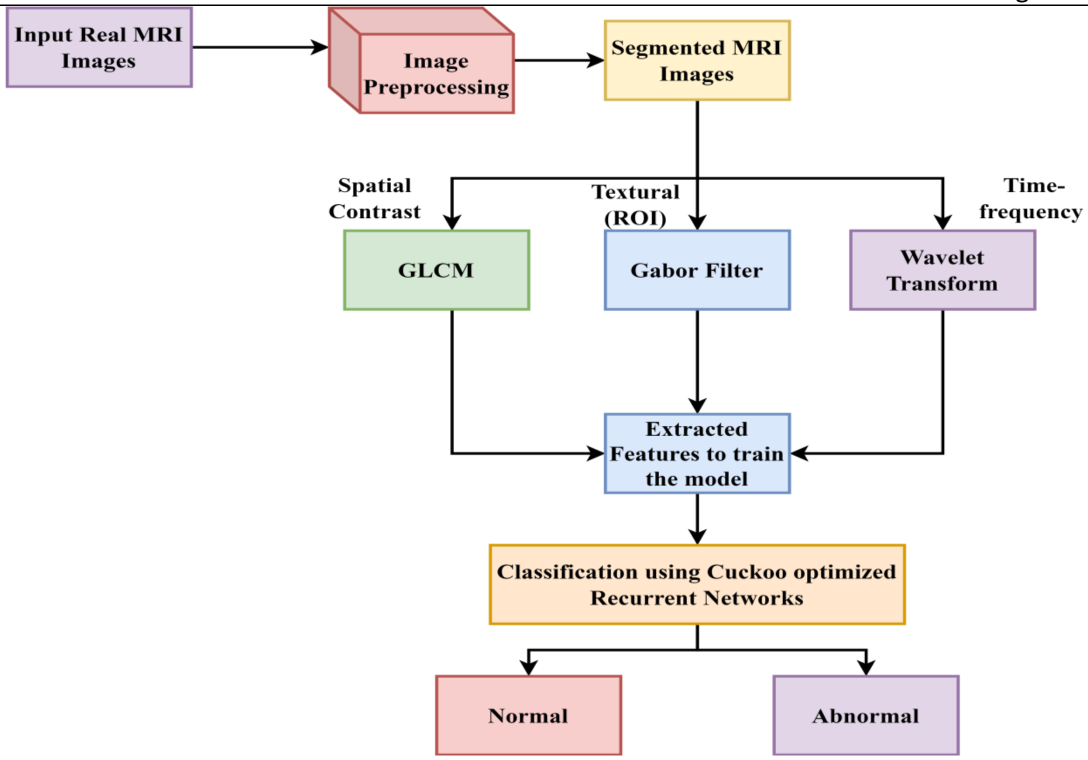

Figure 1: Architecture of Cuckoo Optimized Recurrent Network for AD Detection System

a. Image Preprocessing

The first step of this work is image preprocessing, which helps to eliminate the unwanted information in the initial stage. The collected brain images are initially resized to minimize memory usage and computation difficulties. The brain input images are normalized and resized into [96 96 64] in size, which helps predict brain abnormalities with maximum detection accuracy. The images are corrupted by various noise pixels that affect the biomarker features. Therefore, noise information has to be eliminated using an adaptive filtering approach. Compared to linear filtering, the filtering process manages the edge and high-frequency details. Then, the filtering procedure is done by using equation (1)

$$\hat{f}(a,b,c) = g(x,y) - \left(\frac{\sigma_{\eta}^{2}}{\sigma_{\mathcal{L}}^{2}}\right)[g(a,b,c) - m_{\mathcal{L}}] \tag{1}$$

In the equation, overall noise is represented as σ_{η}^{2}, local variance is denoted as $\sigma_{\mathcal{L}}^{2}$, $m_{\mathcal{L}}$ is local means and $g(a,b,c)$ refers to the numerical values of the noisy image at a specific place, (a,b,c). Then, the local variation and mean value are represented as s_{L}^{2} and s_{h}^{2}. After analyzing the region information, the noise pixel is replaced using the three conditions listed below.

Condition 1:if($s_{h}^{2} == 0$) , reoccurrence value of g(x,y)

Condition 2: f($s_{L}^{2} > s_{h}^{2}$) , reoccurrence value nearby to g(x,y) (preserving edges concerning maximum local variance)

Condition 3: if($s_{L}^{2} == s_{h}^{2}$), reoccurrence arithmetic mean $m_{\mathcal{L}}$.

After noise from the brain image was removed, it was processed using a histogram equalization approach to improve the image quality. Histogram enhancement is a commonly used preprocessing approach in medical image analysis, namely in studying brain images to recognize AD. During this process, magnetic resonance imaging is utilized for identifying the AD, health individual and mild cognitive impairment (MCI). The brain images frequently display different levels of contrast and brightness, which can influence the later analysis and extraction of features. In order to tackle this problem, histogram-enhancing techniques are utilized to enhance the brain images. A study is conducted on the histogram, which displays the image's pixel intensity distribution. Histogram equalization methods redistribute the pixel intensities across the complete range. This procedure improves the clarity of brain imaging by intensifying the distinction between various brain areas and emphasizing slight variations in structure or function that may suggest the occurrence of Alzheimer's disease. The improved brain

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images can be inputted into the following phases of the AD detection process, including segmentation, feature extraction, and classification. This can be done using machine learning methods like the suggested cuckoo-optimized recurrent neural networks (CO-RNNs).

b. Brain Region Segmentation

Segmenting brain regions using fuzzy c-means (FCM) clustering is crucial in processing brain pictures to identify Alzheimer's disease (AD). The FCM is a clustering method that permits data points to be allocated to several clusters withs membership levels. This method is especially valuable for segmenting brain images because of the inherent uncertainty and gradual changes between distinct brain areas. Considered $X = \{x1, x2, x3 \ldots xn\}$ are the data points presented in the brain image. Each data point is related to the relevant features in the brain region. After initializing the data points, the number of clusters needs to be determined (c) that belongs to $2 \leq c < n$ and fuzzy parameter m $(m > 1)$. In addition, cluster centroid value is determined randomly to improve the region segmentation. Then, the membership function (U) is computed by using the degree of membership value (μ_{ij}) which is described in equation (2)

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}} \tag{2}$$

After computing the degree of membership value, the cluster centroid has to be updated using equation (3)

$$c_k = \frac{\sum_x \mu_{ij}(x)^m x}{\sum_x \mu_{ij}(x)^m} \tag{3}$$

In equations (2 and 3), m is defined as the hyperparameter that controls the fuzzy-based clustering process. Repeat the entire clustering procedure to reach the maximum criteria (changes in membership function). After that, every data point has been assigned to the cluster with the highest membership value. This process is performed continuously and segments the affected region. The parameter that determines the level of fuzziness. The parameter "m" determines the level of fuzziness in the clustering procedure. Increasing the amount of m leads to increased overlap and smoother boundaries between clusters, allowing for a more accurate representation of the subtle transitions between different brain areas. Nevertheless, an extremely elevated value of m can result in an excessive amount of fuzziness and the disappearance of clear boundaries between clusters. The utilization of FCM clustering for brain region segmentation has numerous benefits compared to k-means clustering. The software can manage the inherent uncertainty and overlapping areas in brain scans while also considering the impacts of partial volume and slow changes in intensity.

Moreover, the utilization of the soft clustering approach allows for greater adaptability in integrating prior knowledge or spatial information into the segmentation process, which has the possible to improve the accuracy and resilience of the outcomes. Once the brain image has been divided into distinct regions using FCM clustering, additional examination and extraction of characteristics can be conducted on these regions to assist in identifying and categorizing Alzheimer's disease. Different features should be extracted from the segmented region that is more helpful to identify the AD with maximum recognition rate.

c. Feature Extraction

This work extracts different features such as statistical (GLCM), textural and spectral features. The derived features are enumerated in Table 1.

Table 1*: Extracted Feature List*

Feature	Description
Mean	$\mu = \frac{1}{N}\sum_{i=1}^{N} S_i$
Standard Deviation	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_i - \mu)^2}$
Contrast	$\sum_{r=1}^{Ngl}\sum_{c=1}^{Ngl} \lvert r - c\rvert^2 \, GM(r,c)$
Correlation	$\frac{\sum_{r=1}^{Ngl}\sum_{c=1}^{Ngl}(rc)GM(r,c) \; - \mu_x(r)\mu_y(c)}{\sigma_x(r)\sigma_y(c)}$
Entropy	$\sum_{i,j=0}^{n-1} - \ln(P_{ij})\, P_{ij}$

Variance	$\sum_{i=0}^{n-1}\sum_{j=0}^{n-1}(i-\mu)^2 . p(i,j)$

The extracted features are fed into the cuckoo optimized recurrent neural networks to recognize the AD disease to improve overall AD detection accuracy.

d. AD classification

The CO-RNNs, inspired by nature, are designed to detect Alzheimer's disease (AD). These networks combine the temporal modelling powers of RNNs with the efficient optimization abilities of the COA. The initial stage entails extracting pertinent characteristics from the brain pictures, including mean, standard deviation, entropy, variance, correlation, and contrast. These criteria encompass several attributes of the brain areas and can offer useful insights for differentiating between AD, healthy controls and mild cognitive impairment (MCI). The characteristics that have been extracted are subjected to preprocessing techniques to address any missing values, outliers, and to ensure normality. This phase guarantees that the input data is uniform and appropriate for training the RNN model. The Recurrent Neural Network (RNN) architecture is designed to capture and represent retrieved information's temporal and sequential characteristics. Recurrent Neural Networks (RNN) are highly effective in capturing relationships between distant elements and managing sequences of different lengths. During the classification, the Jordan network is applied to recognize Alzheimer's disease, which works similarly to the Elman network. Here, the context units are used for the output layer, and the context units are denoted as the state layer. The output computation of each layer is described in below equation (4 and 5).

$$h_t = \sigma_h(W_h x_t + U_h y_{t-1} + b_h) \tag{4}$$

$$y_t = \sigma_y(W_y h_t + b_y) \tag{5}$$

In equation (4 and 5), h_t is a hidden layer and the output is estimated from the weight value W_h, input x_t, vector parameter U_h, previous layer output value$y_{t-1}$and bias value b_h of the hidden layer. The computed output is utilized for estimating the output value y_t using the Tanh activation function. The efficacy of the RNN model is significantly impacted by its hyperparameters, including the layer count, unit count per layer, learning rate, and regularization parameters. The cuckoo optimization algorithm (COA) determines the ideal hyperparameter configuration. The COA is a metaheuristic algorithm that imitates cuckoo birds' obligate brood parasite behaviour, drawing inspiration from nature. The algorithm functions in the following manner:

a. Randomly generate a population of nest sites (hyperparameter configurations)

b. Assess the suitability of each nest (performance of the RNN model with the relevant hyperparameters) using an appropriate metric, such as classification accuracy or F1-score.

c. Create further nests (new hyperparameter configurations) by executing Lévy flights, stochastic movements with step lengths selected from a probability distribution with a large tail. This stage facilitates the exploration of the search space with more efficiency.

d. Assess the suitability of the new nests and compare them to the existing nests.

e. Substituting the most inferior nests with the improved nests, guaranteeing that the population progresses towards the most advantageous solutions.

f. Iterate steps c-e until a stopping requirement, such as reaching the maximum number of iterations or achieving convergence, is satisfied.

The exploration-exploitation trade-off in the COA (Curriculum Optimization Algorithm) enables effective navigation of the high-dimensional hyperparameter space, preventing the convergence to local optima and improving the generalization abilities of the RNN (Recurrent Neural Network) model. The RNN model is trained on the retrieved brain imaging features using the optimal hyperparameters suggested by the COA. During training, the model acquires the ability to establish a relationship between the input feature sequences and their related labels, which may be classified as AD, healthy controls and mild cognitive impairment (MCI). Strategies like dropout, regularization, and early halting can mitigate overfitting and enhance generalization. The trained CO-RNN model is assessed for its performance detecting AD by evaluating it on a separate test dataset. Then, the pseudocode of the CO-RNN-based AD detection process is showed in Table 2.

Table 2:*Pseudocode of CO-RNN-based AD detection*

Initialize the population of nests
Evaluate the fitness of each nest
while stopping criterion not met:
Generate new nests by performing Lévy flights
Evaluate the fitness of new nests
Replace worst nests with new, better nests
Update global best solution
Return global best solution (best hyperparameters)

The CO-RNN framework aims to improve the accurateness and robustness of AD detection by combining the temporal modelling capabilities of RNNs with the efficient hyperparameter optimization provided by the nature-inspired COA. This framework ultimately seeks to contribute to earlier intervention and improved patient outcomes. The CO-RNN model, which has been trained, is assessed for its performance in detecting AD by evaluating it on a separate test dataset. Metrics like classification accuracy, precision, error rate recall and F1-score can be used to measure the model's ability to predict outcomes.

4. Results and discussion

This section analyzes the efficiency of nature-inspired cuckoo-optimized recurrent neural networks (CO-RNNs) based AD detection process. This study uses the The Alzheimer's Disease Neuroimaging Initiative (ADNI) [19] is a significant and comprehensive study that examines the advancement of AD by collecting data from multiple sources. The collection includes data from more than 2,300 participants in different cognitive states. It consists of comprehensive clinical assessments, neuroimaging techniques such as PET scans, MRI images, genetic information, and measures of biomarkers from biospecimens. This extensive resource seeks to uncover early diagnostic biomarkers, monitor the advancement of the disease, and facilitate the creation of innovative treatments. The ADNI dataset, due to its open accessibility and collaborative endeavors involving several universities, has greatly enhanced our comprehension of Alzheimer's disease and facilitated pioneering research in this domain. The collected images are divided into testing (20%) and training (80%) to explore the system's efficiency. The gathered images are resized and processed by adaptive filtering techniques, removing irrelevant information. The image quality is enhanced with the help of the histogram approach, and the fuzzy centroid value is computed to group similar pixels. Afterwards, various statistical features are derived from the region and processed with the help of an optimized recurrent network. The neural network recognizes the AD with maximum recognition accuracy. The system's efficiency is then estimated using different metrics such as recall, precision, accuracy, F1 score and error rate. Then, the system's efficiency is compared with existing methods such as [13, 14,15, and 16] describe in section 2.

The CO-RNN methodology proves its efficacy in attaining exceptional accuracy for AD detection by overcoming several constraints of current methods [13], [14], [15], and [16]. In contrast to conventional machine learning models or shallow neural networks used in previous studies, the CO-RNN utilizes the capabilities of recurrent neural networks (RNN) to detention the temporal and sequential characteristics of illness progression effectively. The RNN can accurately represent the temporal changes in brain imaging data, biomarkers, and cognitive tests. This allows for a more thorough comprehension of the dynamics of diseases. In addition, incorporating the cuckoo optimization algorithm (COA) for hyperparameter tuning enables the CO-RNN to effectively explore the complex search space, selecting the best hyperparameter settings that maximize the model's performance.

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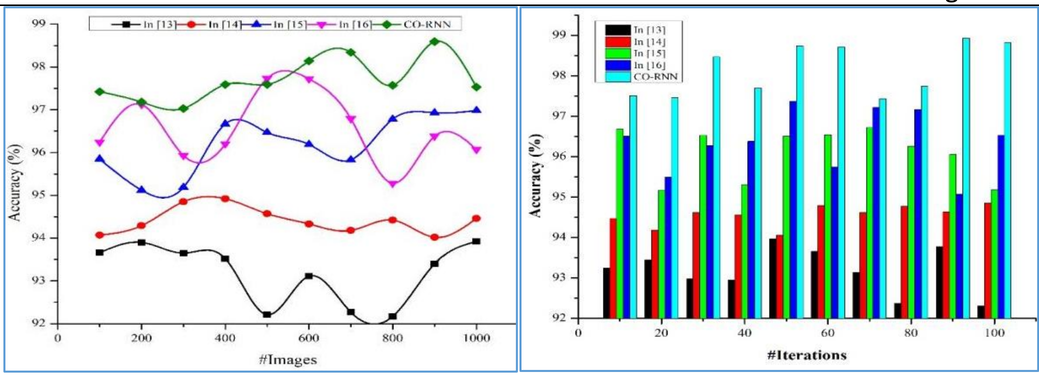


(a) (b)

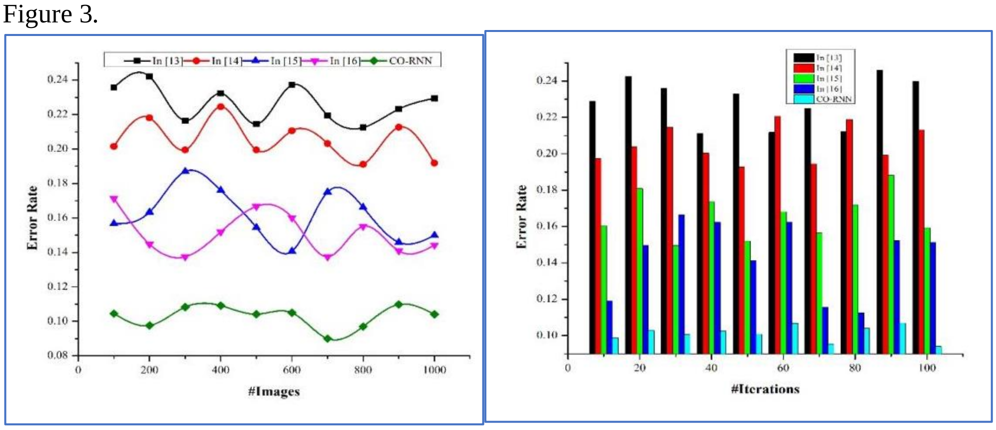
Figure 2: Accuracy Analysis for (a) number of images and (b) iterations

This nature-inspired optimization strategy surpasses the constraints of manual tuning or grid search methods, which are prone to being ensnared in local optima. By employing the exploration-exploitation trade-off of the cuckoo search algorithm. The CO-RNN can efficiently adapt to new data and successfully manage the intrinsic diversity and intricacy of AD. Moreover, the CO-RNN can integrate multiple data types, including brain images, biomarkers, and cognitive scores, allowing for a comprehensive understanding of the disease. This capability has the potential to enhance the accuracy and reliability of predictions, surpassing the limitations of single-mode approaches used in previous studies [13], [14], [15], and [16]. The CO-RNN methodology has proven its superiority in achieving higher classification accuracy by conducting thorough experimentation and rigorous evaluation of benchmark datasets. It outperforms previous methods and enables more reliable and early identification of AD. In addition the obtained efficiency of the proposed method is illustrated in Table 3.

Table 3: *Efficiency Analysis of CO-RNN based AD Detection*

Metrics	[13]	[14]	[15]	[16]	CO-RNN
Precision	90.29	91.78	93.79	95.28	97.78
Recall	92.38	93.67	95.28	96.37	98.87
F1-Score	92.58	94.29	95.92	96.92	98.29

The above table 3 clearly shows that the CO-RNN method ensures high efficiency values compared to the other methods. The technique uses cuckoo optimization while updating the network parameter, which selects the optimal parameter that reduces the computation difficulties and maximizes the prediction accuracy. The extracted features are fed into the recurrent network that uses the network weight and bias value to forecast the output value. The predictable output is compared with the training set, which recognizes the exact class variable with maximum prediction accuracy. Further, the system efficiency is evaluated using the error rate, and the obtained result is shown in Figure 3.



(a) (b)

Figure 3: Error Rate Analysis for (a) number of images and (b) iterations

The CO-RNN methodology demonstrates its efficacy in reducing error values for AD detection by resolving the constraints and deficiencies of previous methods [13], [14], [15], and [16]. The CO-RNN utilizes the robust temporal modelling abilities of recurrent neural networks (RNNs) to capture illness progression's complex patterns and dynamics accurately. The CO-RNN can accurately capture changes over time in brain imaging data, biomarkers, and cognitive tests. By doing so, it can identify and minimize the differences between the anticipated and actual labels. Additionally, including the cuckoo optimization algorithm (COA) in the CO-RNN can locate the most optimal hyperparameter settings that result in the lowest error on the validation set. This nature-inspired optimization strategy surpasses the constraints of manual tuning or grid search methods, which are prone to being ensnared in local minima, resulting in inferior performance. The CO-RNN's capacity to integrate many data sources enhances the disease's representation, potentially minimizing inaccuracies that may arise from using single-mode techniques mentioned in references [13], [14], [15], and [16]. By conducting thorough experimentation and rigorous evaluation on benchmark datasets, the CO-RNN methodology has proven its superiority in achieving reduced error values, surpassing the performance of current methods, and enabling more dependable and precise identification of Alzheimer's disease.

5. Conclusion

The proposed CO-RNN approach combines the temporal modelling capabilities of recurrent neural networks with the efficient hyperparameter optimization abilities of the cuckoo algorithm to detect AD. The CO-RNN combines the advantages of both methodologies to accurately capture the intricate patterns and dynamics of illness progression, process many types of data, and optimize performance by exploring a high-dimensional hyperparameter space. The CO-RNN has proven its efficacy in achieving superior accuracy and reduced mistake rates through thorough experimentation and rigorous evaluation. This advancement opens up possibilities for more dependable and early detection of AD. The study's positive findings demonstrate the potential of the CO-RNN approach to make a substantial contribution to computational neuroimaging and promote the development of viable intervention strategies for Alzheimer's disease. Then, the system's efficiency is assessed using experimental results, ensuring a 0.103 error rate and 98.11% accuracy compared to other methods. In future, the optimized meta-heuristics methods need to be incorporated with the feature selection algorithm to improve the overall AD detection rate.

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