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Metaheuristic-enhanced Deep Learning Model for Accurate Alzheimer's Disease Diagnosis from MRI Imaging

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Abstract: Alzheimer’s Disease (AD) is the neuro-degenerative dementia, where the precise and early recognition of AD is vital for timely treatment to reduce mortality rate. A new automated model is implemented in this work for early

discovery of AD in the Magnetic Resonance Imaging (MRI) brain scans. Initially, the input brain scans are taken from the Alzheimer's disease Neuroimaging Initiative (ADNI) database. Further, the acquired raw brain scans are visually improved by employing the binary normalization technique. The denoised brain scans are fed to the pre-trained Convolutional Neural Network (CNN) named GoogleNet for feature extraction. Next, the extracted richer feature values are fed to the Long Short Term Memory (LSTM) network for classifying the brain scan as Normal Control (NC), Mild Cognitive Impairment (MCI) and AD. In this manuscript, a Honey Badger Optimization Algorithm (HBOA) technique is incorporated with the LSTM networks for hyper-parameters optimization, where this procedure helps in diminishing the LSTM network's complexity and computational time. The experimental results conducted on the ADNI database underscore the HBOA-based LSTM network's effectiveness, showcasing a remarkable mean classification accuracy of 97.83% in multi-class classification. Moreover, the sensitivity of HBOA based LSTM for AD/NC is 96.73% which is high when compared to the existing methodologies such as SVM with radial basis kernel function and NCSINs. This performance surpasses that of other comparative models for AD detection, emphasizing the superior capabilities and potential of the proposed method in the early detection.

Index Terms: Binary Normalization Technique, Convolutional Neural Network, Honey Badger Optimization Algorithm, Long Short Term Memory Network, Magnetic Resonance Imaging.

1. Introduction

Life expectancy is rising, which is causing a shift in global demographics towards an older population. Although people are living longer, not everyone can age healthily [1]. Alzheimer's disease [AD], an escalating and irreversible neurodegenerative disorder that is associated with ageing in humans, stands as a formidable challenge within the domain of global health.AD has a substantial adverse impact on the overall well-being for individuals who are affected as well as their caregivers. With ageing comes a rising prevalence of AD, affects 10% of people over the age of 65 [2]. The state is affected by multiple risk factors, encompassing ageing, genetics, head trauma, vascular disorders, infections, and environmental variables. It represents the utmost prevalent cause of dementia in the elderly, a condition characterized by a decline in thinking and independence in daily tasks [3] characterized by the gradual deterioration of cognitive functions, such as memory loss and impaired reasoning, and changes in behaviour. A rise in low-grade chronic inflammation (also known as "inflammaging") with advancing age is linked to a possible link to AD's neurodegenerative process.

AD is a pathology that results in brain cell degradation. A primary indicator of AD is moderate cognitive impairment (MCI), characterised by subtle disparities in brain alterations across the intermediate stages [4]. It is distinguished by two most significant neuropathological characteristics such as elevated levels of hyper-phosphorylated tau (p-tau), which aggregates intracellularly as neurofibrillary tangles (NFTs), and amyloid-β (Aβ) [5,6], which forms extracellular senile plaques [7], observed in the brain tissues of AD patients. The clinical spectrum of AD is demonstrated by three instances. One is genetically determined Alzheimer's disease, as per the ongoing global endeavours of the Alzheimer Prevention Initiative and the Dominantly Inherited Alzheimer Network, along with the clinical trials that go along with them. The second illustrates a language variation of Alzheimer's disease that typically manifests at a younger age (less than 70 years of age), highlighting the challenge of diagnosing Alzheimer's in people whose memory issues are not the primary symptom. The final one is a typical amnestic variety that is more frequently observed among individuals aged 70 years and older. It illustrates the increasing number of older individuals experiencing dementia and AD; these people are frequently living alone and becoming more and more reliant on others for care [8].

To address the escalating challenge of AD, primary research objectives include enhancing early detection, improving classification accuracy, and developing personalized treatment strategies. AI-driven image processing offers greater sensitivity and less user intervention than traditional methods, which could not be sensitive enough for early-stage detection. Furthermore, AI enables thorough data integration, fusing MRI data with clinical, genetic, and demographic data to provide a more comprehensive picture. However, the technology is limited by things like resource-intensive needs, potential biases in training data, interpretability challenges, and ethical considerations.

A substantial portion of the elderly population worldwide faces the challenges posed by AD, an incapacitating neurological condition without a known cure. The timely identification of AD is essential for providing effective care and overall patient well-being, particularly during the initial stages, empowering individuals to implement preventive measures before irreversible brain damage occurs [4,9]. Despite extensive research efforts, a definitive cure remains elusive, emphasizing the urgent need for advancements in early detection, classification, and personalized treatment strategies to mitigate the profound societal impact of this debilitating disease. Actions designed to tackle several risk factors in the nondemented elderly population, inclusive of middle-aged individuals, may potentially prevent or postpone the onset of Alzheimer's disease, as the disease is thought to begin decades before clinical symptoms manifest [6].

Navigating the complexities of AD and other neurodegenerative conditions necessitates a multidisciplinary approach. This holistic strategy incorporates targeted ultrasound, deep brain stimulation, stem cell therapy, gene therapy, medication, life style changes, and cutting-edge imaging technologies such as image processing Artificial Intelligence (AI) and Magnetic Resonance Imaging MRI. This comprehensive approach holds tremendous promise for advancing our ability

to treat, prevent, or decelerate the progression of these challenging neurological disorders [1]. In addressing this challenge, the integration of state-of-the-art technologies, including image processing AI and MRI, plays a pivotal role in both diagnosing and predicting AD. Leveraging advanced image processing algorithms enhances the accuracy of brain imaging, facilitating the identification of subtle changes indicative of early-stage AD. Concurrently, MRI technology offers detailed structural and functional information, contributing to a thorough comprehension of the progression of the disease. The synergistic utilization of image processing techniques AI and MRI not only facilitates precise diagnosis but also enables the prediction of potential risks, allowing for proactive interventions before significant cognitive decline occurs.

In the realm of AD detection and classification using medical imaging, the integration of Artificial Intelligence (AI) comprises a diverse array of techniques, prominently featuring Machine Learning (ML) and Deep Learning (DL). These methodologies have undergone substantial evolution, ushering in a transformative era in analysing MRI data and significantly impacting diagnostic capabilities [10]. Machine Learning, a subset of AI, is defined by the development of algorithms empowering systems to learn patterns from data [11,12]. Situated within a multidisciplinary framework, ML mimics human learning processes, aiming to endow machines with the ability to gain additional knowledge or skills, restructure pre-existing knowledge frameworks, and iteratively enhance their effectiveness. In the context of AD, ML has proven instrumental in identifying MRI biomarkers associated with the disease [9]. Through training on extensive datasets of MRI scans, ML algorithms discern subtle patterns indicative of AD, thereby facilitating more precise and nuanced diagnostic outcomes.

The advent of Deep Learning marks a technological leap in computer-aided diagnostics, characterized by minimal reliance on image pre-processing. Distinct from traditional ML methods, deep learning seamlessly integrates optimal data representations from unprocessed images without necessitating manual feature selection. Convolutional Neural Networks (CNNs), a specific type of DL inspired by the human brain's structure, particularly excel in image analysis tasks [13,14]. The historical application of CNNs dates back to 1995, where they were employed for lung nodule detection in chest x-rays [12]. When applied to MRI data, DL algorithms automatically acquire hierarchical representations of features, providing a profound understanding of complex structural and functional alterations in the brain linked to AD. This depth of analysis proves advantageous for capturing intricate details that may pose challenges for traditional methods. The role of AI in the classification of AD involves training models to distinguish between different disease stages based on MRI features. Supervised learning techniques, such as SVM or Random Forests [11,15], facilitate the categorization of MRI scans into classes such as healthy, MCI, or AD. These models leverage labelled training data to make predictions on new, unseen data. Complementary to supervised methods, unsupervised learning techniques, including clustering algorithms [13], hold value in grouping MRI scans based on inherent similarities. This approach is particularly beneficial in instances where the complete spectrum of AD manifestations is not well-defined or when exploring novel patterns in the data.

The utilization of AI in AD detection and classification extends beyond the realm of image analysis. Techniques such as Natural Language Processing (NLP) [11] serve to examine and extract information from clinical notes and medical literature, offering additional context for diagnostic models. Furthermore, the integration of multi-modal information, wherein MRI data is combined with genetic, clinical, or demographic data, enhances the overall accuracy and reliability of AD classification models. Additionally, AI contributes significantly to the development of predictive models that forecast AD progression based on longitudinal MRI data. Reinforcement learning techniques may optimize treatment strategies by accounting for the dynamic nature of the disease over time. Notwithstanding these advancements, the responsible deployment of AI in clinical settings demands examination of ethical issues, interpretability of complex models, and potential biases in training data.The integration of AI, encompassing Machine Learning (ML) and Deep Learning (DL), with MRI technology is crucial in this regard. Using cutting-edge image processing methods improves brain imaging precision and makes it easier to spot minute alterations that point to early-stage AD. Because they provide enhanced sensitivity, automatic feature extraction, and thorough data analysis, machine learning and deep learning techniques present notable improvements over classical approaches.AI is being used for more than only picture analysis; it is also being used for multi-modal data integration and predictive modelling. NLP techniques, for instance, can be used to analyse clinical notes in addition to MRI data, and reinforcement learning can be used to optimise treatment plans based on longitudinal MRI data. Nevertheless, in order to guarantee the efficient and fair application of these technologies, issues like ethical questions, the interpretability of complicated models, and potential biases in training data must be resolved.

In conclusion, the amalgamation of AI, ML, and DL with MRI represents a watershed moment in AD diagnosis, providing heightened precision, early detection capabilities, and a deeper comprehension of the illness. The transformative influence of these technologies extends beyond image analysis, encompassing comprehensive data integration and predictive modelling, thereby shaping a promising future for advancements in neurodegenerative disease diagnosis and treatment.

The paper is summarized as follows: In section 2, the recent work done by different authors related to the proposed algorithm has been discussed. Section 3 signifies the methodology of the proposed approach. Section 4 provides the experimental outcomes of the proposed approach. Eventually, the conclusion and future work are presented in section 5.

2. Related Works

Some of the recent developments in the related field are discussed here. An enhanced LeNet DNN model was put

forth by Hazarika et al. [16] for the purpose of classifying AD patients using MRI data. Based on the features that were retrieved, the authors used supervised learning methodology to classify the MRIs as cognitively normal (CN), AD, or MCI. The study aimed to evaluate the performance of the proposed model with other widely used DNN models and show how well it works for AD classification based on brain MRIs. The enhanced LeNet model achieved an overall accuracy of 94.63 %, according to the study. Potential drawbacks considering the content of the paper include the requirement for additional validation of the improved LeNet model on more extensive and varied datasets in order to evaluate generalizability. Furthermore, more research is necessary to comprehend the impact of the additional Min-Pooling layer on categorization.

Neffati, et al.[17] integrated Downsized Kernel based Principal Component Analysis (DKPCA) and Support-Vector-Machine (SVM) for effective AD. In this literature study, the DKPCA methodology normalizes the extracted features for ensuring better classification. The normalized features were given to the SVM for classification but it supports only binary class classification. Basheera. S and Ram M.S.S.[18] and Janghel R R and Rathore Y K.[19] implemented Convolutional Neural Network (CNN) for AD with an inclusion of independent component analysis. However, the CNN model was computationally costly, where it requires higher end systems for data processing. Mehmood et al.[20] implemented Siamese CNNs model for categorizing the dementia stages. The Siamese CNN model needs large quantity of augmented data for obtaining a higher classification score.

A DL-based paradigm for the binary categorization of AD using cross-sectional T1-weighted sMRI brain images was proposed by Tufail et al. [21]. In order to obtain various features from local brain images, the authors construct 2D-CNNs. These features are then combined to produce the final classification for Alzheimer's disease detection. For their 2D CNNs, they used three distinct architectures: Xception, Inception version 3, and a specially designed CNN made with separable convolutional layers. The authors employ many performance criteria to assess the efficacy of the suggested models, one of which is accuracy, which was determined to be 0.911 ± 0.014. The shortcomings of the suggested model include difficulties in understanding learnt features for practical applications, performance bias resulting from unequal data, possible problems with data leakage, and the need to investigate other imaging modalities and network designs for a more thorough examination.

A deep learning technique for the early diagnosis of AD using brain MRI data was presented by Faisal et al. [22]. The authors classified MRI pictures into AD, MCI, and CN groups using CNNs. Because there are fewer parameters in the suggested strategy, there is less computational complexity. The accuracy rate attained by the model was 90.75. The model's drawback is that it necessitates laborious and computationally demanding data preprocessing. It is difficult to integrate high-dimensional, multimodal, large-scale data from sophisticated neuroimaging. Overfitting and generalisation are possible problems when the model is applied to different populations or datasets.

Ebrahimi et al [23] demonstrated the application CNNs for the detection of AD on MRI images. The study contrasts multiple deep models and configurations, encompassing both 2D and 3D CNNs and RNNs. The methodology used in this research involves pre-processing the MRI images for detection, registration, and intensity normalization. The type of classification used in this research is binary classification of AD patients from healthy subjects. The outcomes show that, with 96.88% accuracy, the 3D voxel-based approach with transfer learning performs better than the other approaches. Relying on transferring learning from 2D to 3D CNNs may pose challenges in capturing all relevant features. Integrating the feature extraction step in 2D CNNs with the classification step in RNNs for sequence-based decisions is complex. Ambiguity in multi-view approaches could create challenges in making final decisions due to conflicting information from different views.

Shojaei.S et al.[24] focussed on developing the Occlusion Map method in conjunction with a genetic algorithm and backpropagation-based explainability techniques. A 3D-CNN model was trained to detect AD and Cognitive Normal (CN). The network attained 87% accuracy in 5-fold cross-validation in line with similar studies. R. Divya, and R. Shantha Selva Kumari [25] integrated both logistic regression and genetic algorithms for selecting optimal features from the ADNI database. The chosen optimal features were given to the SVM classifier with radial basis kernel function for image classification as AD, MCI and NC. The evaluation metrics like accuracy, sensitivity, and specificity confirmed that the presented model has obtained superior classification results, but it supports only binary classification. J. Feng et al.[26] implemented Non-subsampled Contourlet Sub-band based Individual Networks (NCSINs) for ADs classification. The computational time of NCSIN was higher, while processing larger ADNI databases.

The E2AD2C architecture, developed by Hadeer A. Helaly [27], is a DL framework intended for the multi-classification of AD. It is built on CNNs. Their methodology delineated two unique ways. The first approach used a combination of 2D and 3D convolution techniques to process structural brain images in both 2D and 3D from the ADNI dataset. Using the VGG19 model, the second approach used transfer learning. Accuracy rates of 95.17% and 93.61% were achieved for 2D and 3D model. Furthermore, accuracy of the VGG19 model for classifying AD stages across several classes was 97%. The model needs to address uncertainties in accurately highlighting relevant features before segmentation

A deep sequence-based model for diagnosing AD using MRI images was proposed by Ebrahimi et al. [28]. The MRI pictures are pre-processed, a pretrained 2D CNN is used to extract features from MRI image slices, and an RNN is fed the features' extraction order. In order to identify AD, binary classification is the method used in this investigation. With an accuracy of 91.78%, the suggested TCN model achieved the best classification performance. When integrating a sequence-based network with separately collected features, ambiguities in sequence-based categorization occur. It is difficult to maintain the spatial dependency between adjacent image slices when 2D MRI slices rather than full 3D MRI

scans are used as the input. Voxel preselection strategies are necessary to address the high computing burden and feature dimensionality that voxel-based algorithms encounter.

SegNet is used in a DL-based segmentation technique that Buvaneswari et al. [29] devised to identify AD. ResNet-101 is then used to precisely diagnose AD and dementia diseases based on relevant features of SMRi brain components. The accuracy of the suggested approach was 95%. The precision of brain area segmentation in the model is dependent on the calibre and resolution of structural MRI data. In order to evaluate the model's resilience and applicability to different clinical contexts, more testing and validation on a more extensive and varied dataset are required.

Herzog NJ [30] proposed computational algorithm to classify MRI data from ADNI 3 from DL structures. For the detection of dementia, an eight-layered CNN and transfer learning from pretrained CNNs on ImageNet were utilised. A variety of configurations using KNN, Softmax, SVM or linear discriminant classification layers were tested. The accuracy of the proposed approach was 90.12% for MCI and 86.40% for EMCI. They focussed only on binary classification. The existing researches has faced different issues during the AD classification. The classification by deep learning approach suffers when underlying patterns are not obtained due to insufficient hyperparameters. Additionally, it leads to affect the capacity for generalizing the unobserved information. The issue of overfitting is caused, when the classifier learns the training data instead of generalizing it. Therefore, the motivation behind this research is to overcome the aforementioned issues for a better classification of AD.

For addressing the above-mentioned issues and improving the classification efficiency, a novel hyper-parameter optimized HBOA based LSTM network is introduced in this research manuscript to achieve better AD classification. The main contributions are listed below.

- The HBOA based hyperparameter optimization is developed for LSTM for learning and understanding the temporal patterns related with the disease. Accordingly, the LSTM avoids the overfitting by ensuring an appropriate balance among generalization capacity and model complexity. The HBOA with effective searching the hyperparameter space helps to discover optimal hyperparameters. Further, the HBOA's global search enables an exploration of diverse range of solutions and avoiding the local optima issue to obtain optimum hyperparameters.
- The LSTM has the capacity of extracting the long-term dependencies in the sequential information obtained from GoogleNet features which used to perform an effective classification over the clinical information.
- In this research, the GoogleNet has the ability for learning the hierarchical features that includes both low level details and high level semantics of brain and information related to the AD. These incorporation of features in LSTM helps to utilize the extracted depictions in various levels of abstraction for effective classification.

3. Materials and Methods

In AD disease detection, the proposed framework includes four steps: database description: ADNI dataset, image denoising: normalization, feature extraction: GoogleNet and Image classification: HBOA based LSTM network. The block-diagram of the proposed system is shown in Fig 1.

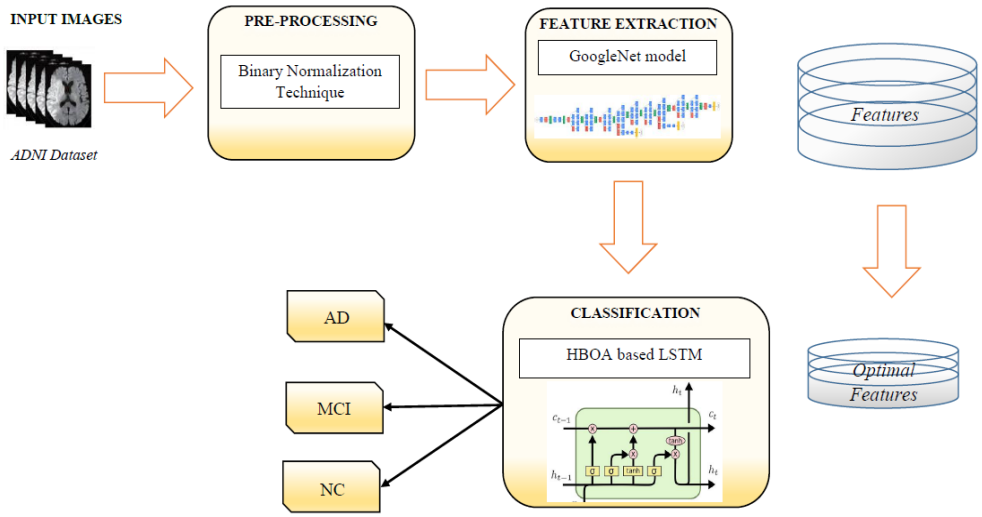

Fig.1. Block diagram of the proposed approach

3.1. Dataset Description

In this study, the proposed hyper-parameter optimized HBOA based LSTM effectiveness is tested on the ADNI database. In this study, around 171 AD records, 347 NCs records and 558 MCI records are acquired from the ADNI database. In the acquired records, 27 MCI subject's records are transformed into AD records, and the vital statistics of

the ADNI database is depicted in table 1. The ADNI database includes positive biomarkers of subjects after each 36, 24, 28, 12 and 6 months from the standards. The main motivation of using the ADNI database is to analyse whether organic marker, MRI, and clinical analysis are integrated for encompassing MCI improvements, and early detection of AD (Aqeel et al. [31]; Basaia et al. [32]; Zhou et al. [33]. The ADNI samples are depicted in Fig. 2. Database available link: https://adni.loni.usc.edu/data-samples/access-data/. The ADNI datasets are utilised because they offer an extensive compilation of MRI images and clinical information particularly associated with the disease. A well selected, extensive collection of photos, ranging from healthy controls to varying degrees of cognitive impairment, is provided by ADNI. In order to ensure that the model can generalise successfully across various patient circumstances and imaging changes, this diversity is essential for both training and evaluating the model.

Table 1. Demographic information of the ADNI database

Disease states	Gender	MMSE score	Records
AD	90 female/81 male	22.05 ± 4.31	171
MCI	284 female/274 male	27.68 ± 1.98	558
NCs	210 female/137 male	29.04 ± 1.27	347

* MMSE-Mini Mental State Examination

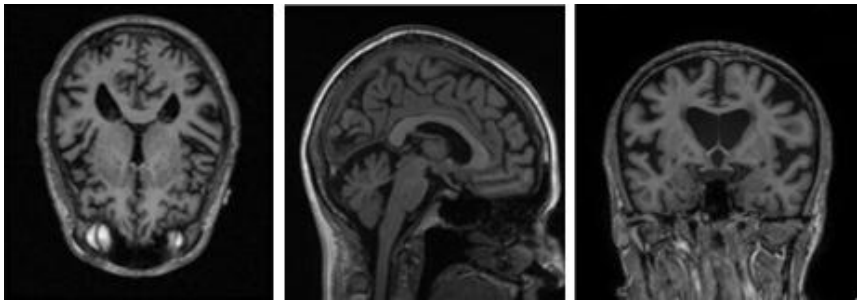

Fig.2. Sample ADNI database images

3.2. Model Selection

The selection criteria for the models used in this research are given as follows:

- Pre-processing using Normalization: It is utilized for standardizing the intensities of pixel over different scans and imaging protocols that helps to reduce the inconsistency and enhances the capacity of extracting significant features.
- Feature extraction using GoogleNet: The GoogleNet has the ability for learning the hierarchical features includes both the low level details and high level semantics of brain and data related to the AD.
- Classification using LSTM: LSTM is effective in obtaining the long-term dependencies in the sequential data that helps to analyse the appropriate information from GoogleNet features. Accordingly, the features from GoogleNet provides the representations in various levels of abstraction which enhances the classification.
- Hyperparameter optimization using HBOA: The HBOA is choosen because of its efficiency in foraging the hyperparameter space during the discovery of hyperparameters. Moreover, an exploration of diverse range of solutions and avoiding the issue of local optima are used to obtain optimum hyperparameters with an effective convergence.

3.3. Preprocessing

Further, the brain images attained from ADNI are fed to the image denoising step and it is carried out by applying linear normalization technique. Normalization is used to ensure all input has reliable scale and distribution that is important for training. In MRI images, the normalization is used to standardize intensities of pixel over various scans and imaging protocols which minimizes the inconsistency and improving the model capacity for obtaining meaningful features. The linear normalization technique alters the range of brain image pixel values in order to eliminate the noises from the brain images. Additionally, the linear image normalization technique calibrates the dissimilar pixel intensity value into normal distribution that makes better image visualization. The general mathematical expression of linear normalization is denoted in (1) (Bianconi et al. [34])

$$IM_N = (IM - Min) + \frac{newMax - newMin}{Max - Min} + newMin \quad (1)$$

Where, IM_N indicates normalized brain images, IM states acquired brain images, $newMax - newMin$ indicates distributed maximum and minimum pixel intensity value, Max represents maximum pixel intensity value with the range of 255 and Min states minimum pixel intensity value with the range of 0. The sample normalized brain images IM_N are specified in Fig.3. Normalization process simplifies the feature extraction by ensuring that an observed depiction is invariant to alteration in the intensity levels. Therefore, the normalization helps to extract expressive and discriminative features using the GoogleNet that used to concentrate the structural and textural patterns instead of intensity values.

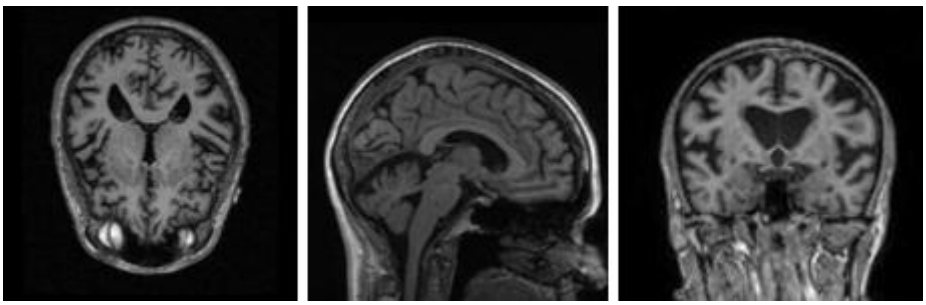

Fig.3. Sample normalized brain images

3.4. Feature Extraction

In the next step, the richer features are extracted from the normalized brain images IM_N by implementing a pre-trained CNN model named GoogleNet. Usually, the traditional CNNs are ineffective in feature extraction, where a larger amount of feature values exhibits complex variations. Therefore, the pre-trained CNN model: GoogleNet is utilized for extracting richer-feature values from the normalized brain imagesIM_N. The GoogleNet helps to extract the hierarchical representations of features which obtained both the low level image information and high-level semantic information of AD. Therefore, this GoogleNet is supported to obtain the spatial hierarchies in MRI images, discovering the features in various scales and resolutions. The GoogleNet is an inception module, where the calculations are carried-out utilizing dissimilar kernel types in an individual layer. The conventional CNN model's use a single kernel type in a layer, and the commonly utilized kernels in the GoogleNet are 7×7, 5×5, 3×3, and 1×1. The results of these kernels are integrated to generate the final output value [35]. Because of its exceptional capacity to effectively capture hierarchical aspects, GoogleNet is favoured in this effort. Its inception modules enable it to efficiently extract both high-level and low-level characteristics from MRI images by utilising different kernel sizes and depths. This capacity is essential for understanding the intricate patterns linked to Alzheimer's disease. In addition, despite its depth, GoogleNet is made to be computationally economical, requiring fewer parameters and less processing power than other deep networks of a comparable complexity.

The GoogleNet model extracts 1024 richer features from the normalized brain images IM_N. In addition, the GoogleNet model performs different operations for managing a larger number of parameters which arises while utilizing numerous layers and kernels in the network. In this manuscript, two 3×3 convolutional kernels are utilized for processing the high dimensional features. In the developed system, the GoogleNet model is effective in light-weighted feature extraction networks. The assumed parameters of the GoogleNet model are stated as follows: minimum batch size is 16, validation frequency is 20, maximum epochs is 50, initial-learning rate is 0.01 and solver name is stochastic gradient descent with momentum.

3.5. Classification

The extracted 1024 richer feature values of GoogleNet are given to the proposed hyper-parameter optimized HBOA based LSTM network for image classification like AD, NC, and MCI. LSTM network is appropriate in capturing the long-term dependencies that helps for analysing the clinical information. The GoogleNet has the capacity to learn the hierarchical features which obtained both low level details and high level semantics of brain and information related to the AD. The incorporation of these GoogleNet features into the LSTM helps to integrate and use the extracted depictions in various levels of abstraction that used to enhance the classification. In this research manuscript, the HBOA is proposed for hyper-parameter optimization in the LSTM network. The hyper-parameters selected by the HBOA are represented as follows: gradient threshold is 1.00, execution environment is auto, optimizer is Adam, minimum batch size is 27, L2 regularization is 0 to 0.1, maximum epochs is 5 to 100, learning rate is 0.001 to 0.01, and gradient decay factor is 0 to 1. Generally, the LSTM network resembles recurrent neural network, where it consists of recurrent-hidden layer, input layer, and output layer. The LSTM network has multiplicative cells, and it consists of multiplicative and temporal units. The temporal and multiplicative units control the input data (extracted features) in memory-blocks. The cell memory state consistently causes error, so the forget gate f_t is added to the inner cell values. If the data is outdated in the memory blocks, and it is replaced by a carousel weight W. The LSTM network consists of three important gates: input gate i_t, output gate O_t, and forget gate f_t. The LSTM network's input is denoted as $x = x_1, x_2. \ldots . x_T$, and the output is represented as $y = y_1, y_2, . \ldots y_T$, where, T is represented as classification time period. The mathematical representations of the input i_t, forget f_t, cell C_t, and output O_t are depicted in (2-5) [36].

$$i_t = \Theta(W_{ix}x_t + W_{\Im}m_{t-1} + W_{ic}C_{t-1} + b_i) \quad (2)$$

$$f_t = \Theta\left(W_{fx}Xt + W_{fm}m_{t-1} + W_{fc}C_{t-1} + b_f\right) \quad (3)$$

$$C_t = f_t \Phi C_{t-1} + i_t \Phi g(WcxXt + W_{cm}m_{t-1} + b_c) \quad (4)$$

$$O_t = \Theta(W_{ax}Xt + W_{om}m_{t-1} + W_{oc}C_t + b_o) \quad (5)$$

Where, $y_t = W_{ym}m_t + b_y$, and $m_t = O_t \Phi h(C_t)$. In addition to this, Θ (.) represents sigmoid function, Φ denotes scalar vector products, W indicates weight matrix, c_{t,m_t} states activation-vector, and b specifies bias vector. The sigmoid function is mathematically stated in (6).

$$\Theta(X) = \frac{1}{1-e^x} \quad (6)$$

The sigmoid operation operates in the ranges of [-2, 2] and [-3, 3] are mathematically stated in (7) and (8). For medical image classification, the LSTM network uses truncated back-propagation and recurrent learning. The output memory cells return with reliable error carousels, when the square error aggregation reaches the reduced error in the memory.

$$C(X) = \frac{2}{1-e^x} - 2 \quad (7)$$

$$H(X) = \frac{4}{1-e^x} - 3 \quad (8)$$

On the other hand, the HBOA mimics the behavior of honey badgers for catching prey. In this manuscript, the HBOA technique is implemented for optimizing the hyper-parameters in the LSTM network which used to reduce the computational time.

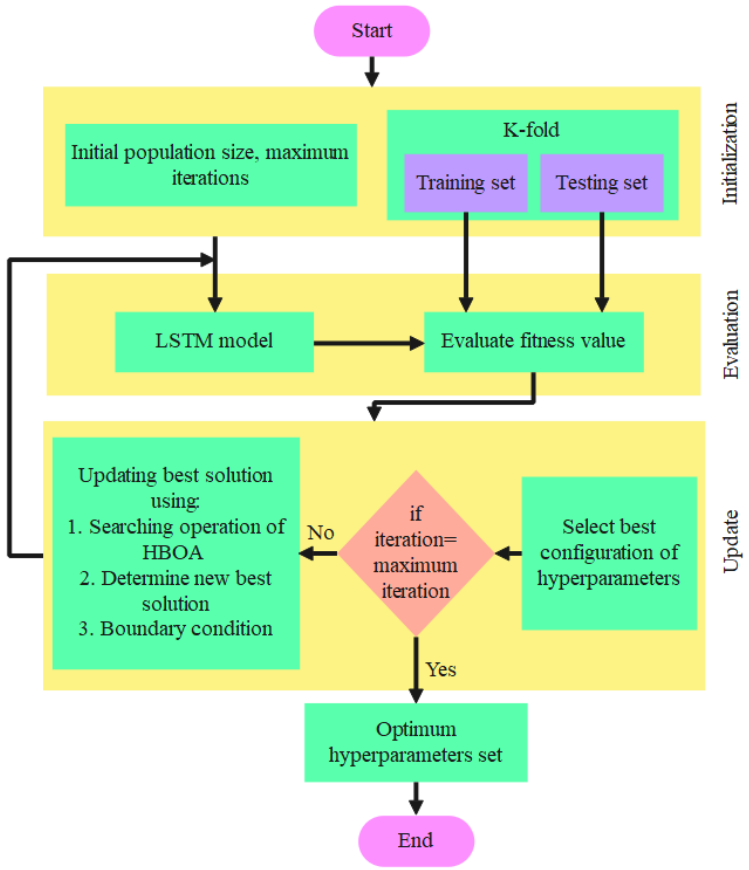

Fig.4. Architecture of HBOA based hyperparameter optimization for LSTM

The architecture of HBOA based hyperparameter optimization for LSTM is shown in Fig.4. Due to efficiency in searching the hyperparameter space, the HBOA is used for discovering optimal hyperparameters. The exploration of diverse range of solutions and avoiding the issue of local optima helps to obtain optimum hyperparameters. The LSTM with optimum hyperparameters helps to enhance the classification and generalization. Further, the tuning over hyperparameters helps to obtain a balancing among LSTM's complexity and generalization capacity which leads to mitigate overfitting issue. The HBOA technique consists of two major phases such as honey and digging. The honey badger follows the honey bird to determine the beehive in the honey phase, and the prey is identified on the basis of honey badger's smelling in the digging phase. Firstly, the agents are initialized based on (9) [37].

$$Z_i = LB_i + r_1 \times (UB_i - LB_i), i = 1,2,3,..N \tag{9}$$

Where, UB and LB represents upper and lower boundaries and r_1 states a random number that ranges between zeros to one. In addition to this, a density factor α is utilized to balance the exploitation (honey) and the exploration (digging) searches. The density factor α is indicated in (10).

$$\alpha = E \times exp^{(-\frac{iter}{M_{iter}})} \tag{10}$$

Where, $iter$ represents iteration number, M_{iter} represents maximum number of iterations, and $E > 1$ denotes a constant value. Further, the solutions are updated utilizing the digging phase operators and it is carried-out utilizing cardioid movements formula, which is represented in (11).

$$Z^{new} = Z_k + A \times \beta \times In \times Z_k + A \times \alpha \times d^i \times r_3 \times |cos(2\pi r_4) \times [1 - cos(2\pi r_5)]| \tag{11}$$

Where, Z^{new} indicates new value of Z_k and Z_i that represents the best solution determined so far. The term $r_3, r_4, r_5, and\ r_6$ indicates random number, β specifies constant value, and A is used for controlling the search direction and it is mathematically defined in (12).

$$A = \begin{cases} 1, & If\ (r_6 \leq 0.5), \\ -1, & Else \end{cases} \tag{12}$$

Where, In represents smell intensity of the prey, and distance between the prey and the honey badger is determined using (13) and (14). In addition, the solutions are updated by using the operators of the honey phase, and this procedure is performed using (15).

$$In_i = r_2 \times \frac{S}{4\pi d_i^2} \tag{13}$$

Where,

$$S = (Z^i - Z^{i+1})^2, d_i = Z_k - Z_i \tag{14}$$

$$Z^{new} = Z_k + A \times r_7 \times \alpha \times d_i \tag{15}$$

Where, $r_2\ and\ r_7$ states a random number. In HBOA, the hyper parameters are selected based on $Fit(Z_i)$ and it is mathematically stated in equation (16). It is assumed as an optimization issue which aims in minimizing the classification error as well as selecting the optimum hyperparameters of LSTM for better computational efficiency.

$$Fit(Z_i) = \eta \times \frac{|Z_i|}{d} + \Re \times \big(1 - \gamma_E(D)\big), \Re + \eta = 1 \tag{16}$$

Where, the coefficients $\Re$ and η are used to balance the number of hyper-parameters by using $\gamma_E(D)$ dependency degree which is stated in (17). The factor d indicates the number of possible hyper-parameters. The positive region $POS_C(D)$ is specified in (18).

$$\gamma_C(D) = \frac{|POS_C(D)|}{|U|} \tag{17}$$

$$POS_C(D) = U\overline{K}(Z), Z\epsilon\frac{U}{D} \tag{18}$$

Where, lower approximation is indicated as $\overline{K}(Z)$, and the term $\gamma_E(D)$ aims in calculating the approximating power of hyper-parameters. The assumed parameter of the HBOA technique is denoted as follows: population size is 30,

maximum iteration is 100, dimension is 4, β is 1, α is 1, and random numbers range is 0.6.

4. Results

In medical image classification, the proposed HBOA based LSTM network is designed based on a Matlab R2020b. The proposed HBOA-based LSTM model was evaluated on a PC with an Intel Core i5 processor and 16 GB of RAM, running Windows 10. It required 45.2 seconds of computational time for training on the ADNI dataset and showed efficient performance with reduced testing times compared to other methods. This efficient use of hardware and time underscores the model's practical feasibility. The HBOA based LSTM network efficiency is analysed utilizing five different performance measures like precision, sensitivity, F1-score, specificity and accuracy, which are mathematically denoted in (19-23). In addition, the performance measure: precision is defined as the proportion of total number of the classified positive samples to the correctly classified positive samples. The F1-score is stated as a harmonic mean of the precision and recall values and the performance measure: accuracy is determined as the proportion of the total amount of samples to the amount of correct classification.

$$Precision = \frac{TP}{TP+FP} \times 100 \tag{19}$$

$$F1 - score = \frac{2TP}{FP+2TP+FN} \times 100 \tag{20}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{21}$$

The term FN, FP, TN and TP states false negative, false positive, true negative, and true positive. The performance measure: specificity analyses the HBOA based LSTM capacity in classifying the TN of each class. The performance measure: sensitivity analyses the HBOA based LSTM capacity in classifying the TP of each class.

$$Specificity = \frac{TN}{TN+FP} \times 100 \tag{22}$$

$$Sensitivity = \frac{TP}{TP+FN} \times 100 \tag{23}$$

Table 2. Simulation results by varying the classification techniques

Axial plane					
Classifiers	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**F1-score (%)**	**Precision (%)**
Random forest	96.41	95.59	94.	94.83	94.08
KNN	93.60	94.67	93.92	93.76	92.86
Decision tree	68.26	69.74	69.07	69.29	68.85
MSVM	82.75	83.13	82.53	82.50	81.88
RNN	94.09	93.06	93.95	93.40	93.75
GRU	95.31	95.21	94.30	95.40	95.60
LSTM	**97.23**	**97.12**	**98.22**	**96.34**	**95.57**
Coronal plane					
Random forest	97.76	96.01	97.60	95.08	94.16
KNN	92.03	90.86	91.95	92.03	93.22
Decision tree	70.68	69.27	71	69.11	68.95
MSVM	80.93	79.37	80.68	79.88	80.38
RNN	95.75	94.33	95.02	94.73	95.15
GRU	96.01	96.82	95.95	96.47	96.13
LSTM	**98.19**	**97.55**	**96.91**	**96.92**	**96.31**
Sagittal plane					
Random forest	95.40	94.24	93.32	94.58	94.92
KNN	94.15	95.75	93.01	94.74	93.74
Decision tree	73.45	74.86	72.55	73.12	71.47
MSVM	84.96	86.99	84.10	84.45	82.05
RNN	92.61	92.75	92.22	92.84	92.93
GRU	94.93	94.39	94.35	94.45	94.51
LSTM	**98.09**	**97.69**	**95.82**	**97.32**	**96.95**

4.1. Quantitative Analysis

In this section, the experimental examination is carried-out by varying the classification techniques such as LSTM, Multi-SVM (MSVM), decision tree, random forest, KNN, Recurrent Neural Network (RNN) and Gated Recurrent Unit (GRU). The simulation result is individually taken for three planes such as axial, coronal and sagittal. By inspecting table 2, the LSTM network with HBOA technique has achieved maximum results in all three planes. Particularly, in the axial-plane, the HBOA based LSTM network obtained 95.57% of precision, 97.12% of sensitivity, 96.34% of F1-score, 98.22% of specificity, and 97.23% of classification accuracy. Correspondingly, in the coronal plane, the HBOA based LSTM network achieved 96.31% of precision, 97.55% of sensitivity, 96.92% of F1-score, 96.91% of specificity, and 98.19% of classification accuracy.

In the Sagittal plane, the developed HBOA based LSTM network has achieved 96.95% of precision, 97.69% of sensitivity, 97.32% of F1-score, 95.82% of specificity, and 98.09% of accuracy. Whereas, the obtained simulation outcomes of the HBOA based LSTM network are better than the comparative classifiers like MSVM, decision tree, KNN, random forest, RNN and GRU. In addition, the k=5 fold cross validation (80:20% training and testing) results are stated in table 2.

Related to other cross-fold validations, k=5 fold cross validation attained better results and it helps in reducing the proposed HBOA based LSTM network's bias and variance. Graphical representation of the simulation results by varying the classification techniques is represented in Fig. 5.

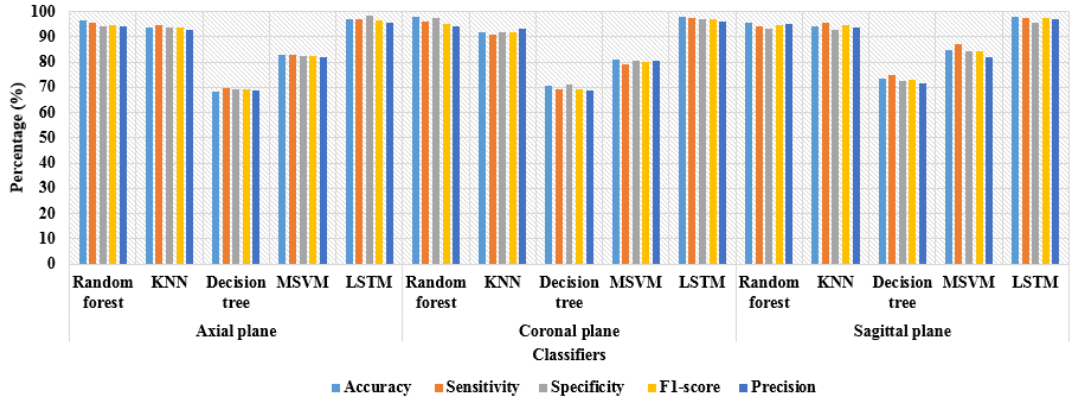

Fig.5. Graphical representation of the simulation results by varying the classification techniques

This analysis reported that the HBOA with LSTM has better performance when compared to the Random forest, KNN, Decision tree and MSVM. Here, the LSTM has the capacity of obtaining the long-term dependencies in the sequential information that makes it efficient to evaluate the clinical information from ADNI dataset. Next, the optimal hyperparameters from the HBOA utilized in LSTM efficiently learn and understand the temporal patterns related with the disease. Therefore, the optimization of hyperparameters using HBOA is used to avoid the overfitting by discovering an appropriate balance among its generalization capacity and model complexity.

Similarly, the validation accuracy is additionally examined using table 3 for offering the understanding of how well the classifier generalizes to the unknown information and it is considered as an important measure to evaluate its performance and effectiveness. This evaluation depicts that LSTM outperforms well than the Random forest, KNN, Decision tree, MSVM, RNN and GRU. The LSTM with higher validation accuracy represents that it performs the reliable classification.

Table 3. Analysis of validation accuracy

Axial Plane		**Coronal Plane**		**Sagittal Plane**	
Classifiers	**Accuracy (%)**	**Classifiers**	**Accuracy (%)**	**Classifiers**	**Accuracy (%)**
Random forest	94.08	Random forest	94.16	Random forest	94.92
KNN	92.86	KNN	93.22	KNN	93.74
Decision tree	68.85	Decision tree	68.95	Decision tree	71.47
MSVM	81.88	MSVM	80.38	MSVM	82.05
RNN	90.86	RNN	89.01	RNN	91.5
GRU	93.07	GRU	92.88	GRU	93.18
LSTM	95.57	LSTM	96.31	LSTM	96.95

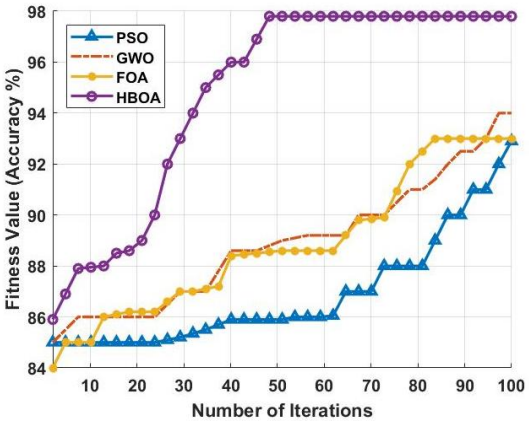

Fig.6. Convergence analysis

The convergence analysis of HBOA shown in Fig. 6 is evaluated using with different optimization approaches such as Firefly Optimization Algorithm (FOA), Grey Wolf Optimization (GWO), and PSO. This graph denotes that the HBOA achieved better convergence than the FOA, GWO and PSO. The efficiency of foraging in hyperparameter space, exploration of diverse range of solutions and avoiding the issue of local optima helps to enhance the convergence of the HBOA. Additionally, the simulation results obtained by varying the hyper-parameter optimization techniques is indicated in table 4. By investigating table 4, the HBOA with LSTM has better classification in all three planes. The achieved simulation outcome is effective related to other optimizers: FOA, GWO, and PSO. As represented earlier, the hyper-parameter optimization aids in decreasing the computational time of the model.

Table 4. Simulation results by varying the optimization techniques

Axial plane					
Optimizers	**Accuracy**	**Sensitivity (%)**	**Specificity (%)**	**F1-score (%)**	**Precision (%)**
PSO	93.57	92.28	94.01	91.18	90.12
GWO	94.44	93.43	94.22	93.27	93.10
FOA	92.85	91.51	93.08	90.39	89.30
HBOA	97.23	97.12	98.22	96.34	95.57
Coronal plane					
PSO	94.32	92.50	95.93	93.92	95.38
GWO	94.95	91.77	96.83	93.52	95.35
FOA	95.28	94.60	90.44	94.51	94.43
HBOA	98.19	97.55	96.91	96.92	96.31
Sagittal plane					
PSO	92.78	93.54	92.92	94.48	95.43
GWO	94.09	92.54	93.35	91.78	91.03
FOA	93.53	90.83	91.64	93.30	95.92
HBOA	98.09	97.69	95.82	97.32	96.95

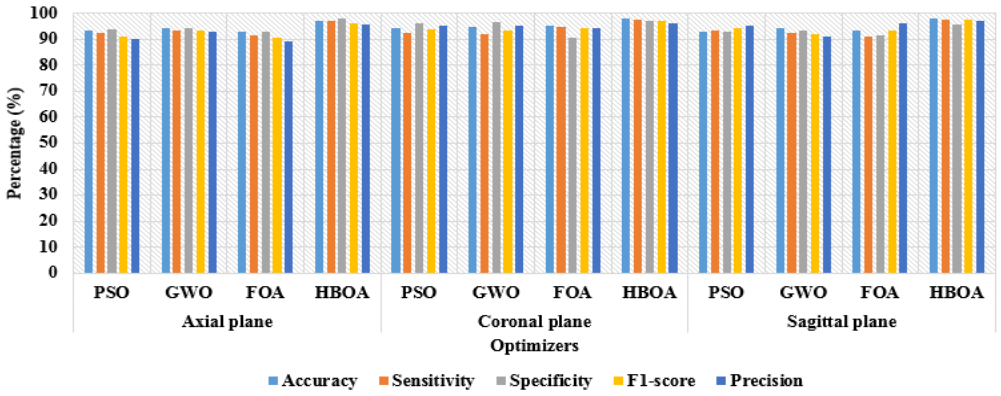

Fig.7. Graphical representation of the simulation results by varying the optimization techniques

The HBOA based LSTM network consumes 45.2 seconds of computational time on the ADNI database, which is better than remaining classification and optimization. On the other hand, the LSTM consumes the computational time of 2.09 minutes, when it faces the issue of overfitting during the classification. The graphical presentation of the simulation result by varying the optimization techniques is represented in Fig.7. The parameters considered for PSO: social factor is 2, inertia weight is 0.9, threshold is 0.5, dimension is four, cognitive factor is 2 and maximum iteration is 100. The parameters considered for GWO and FOA are: population size is 30, dimension is 4, threshold is 0.5 and maximum-iteration is 100.

Table 5. Analysis of K-fold validation

Axial plane					
Classifiers	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**	**F1-score (%)**	**Precision (%)**
2.00	90.01	91.92	90.50	91.47	91.02
3.00	94.96	91.41	93.94	93.12	94.89
5.00	97.23	97.12	98.22	96.34	95.57
7.00	95.75	93.72	94.63	93.77	93.83
9.00	92.64	90.28	91.29	91.33	92.39
Coronal plane					
2.00	94.10	95.72	94.98	94.86	94.02
3.00	96.12	94.41	95.69	95.17	95.93
5.00	98.19	97.55	96.91	96.92	96.31
7.00	95.88	93.17	92.36	93.82	94.48
9.00	93.46	94.85	92.19	94.42	93.99
Sagittal plane					
2.00	95.79	93.25	94.98	93.44	93.63
3.00	96.96	94.93	95.77	94.53	94.14
5.00	98.09	97.69	95.82	97.32	96.95
7.00	95.33	93.54	94.84	95.09	96.70
9.00	94.19	92.75	95.91	94.51	96.34

Further, the K-fold validation is provided in the table 5 that helps to understand how well the HBOA based LSTM is generalized by evaluating it on various subsets of the data. An effective classification over various folds represents the robust generalization of HBOA based LSTM. The T-test is performed for HBOA based LSTM and it returns the P value as 0.034 which results it is statistically significant.

4.2. Comparative Analysis

The proposed HBOA based LSTM efficacy is compared with two existing models developed by Divya, R., & Shantha Selva Kumari, R[25] and Feng J et al[26]. Divya R & Shantha Selva Kumari R[25] have combined logistic regression and genetic algorithms for choosing optimum features. Among different classification techniques, the SVM with radial basis kernel function achieved a higher accuracy of 91.41%, 89.39% and 96.82% for binary classification of AD/MCI, MCI/NC and AD/NC on ADNI database. Then, Feng J et al.[20] implemented NCSINs for effective AD classification, and the experimental results indicates that the developed NCSINs model achieved 90.03%, 84.64%, and 94.21% of classification accuracy for binary classification of AD/MCI, MCI/NC and AD/NC on ADNI database. Naz S et al.[38] used ImageNet model with freeze features for binary classification and it achieved accuracy of 99.27%, 97.06% and 98.89% for binary classification of AD/MCI, MCI/NC and AD/NC on ADNI database.

Related to the existing models, the proposed HBOA based LSTM model has achieved significant classification results in terms of specificity, sensitivity and accuracy, and it is stated in table 6. On the other hand, the developed HBOA based LSTM model has also reduced the computational time and complexity to linear. These are the main issues discussed in the related works section. The accuracies of various methods, as reported by different researchers, were compared and analysed in Fig. 8. This comparative study highlights the effectiveness of the proposed HBOA-LSTM method. Several other methods also demonstrated notable performance, such as those by Alshammari et al [46] and Hazarika et al [20]. The results suggest that combining optimization algorithms with advanced neural network architectures can significantly enhance accuracy. Lower-performing methods indicate areas where further research and improvement could be beneficial. Among the published studies, the proposed method called HBOA-LSTM achieved the highest accuracy of 97.83, indicating its efficacy in the given field of research.

Table 6. Comparative results

Model	Classes	Accuracy (%)	Sensitivity (%)	Specificity (%)
SVM with radial basis kernel function [25]	AD/MCI	91.41	69.55	98.11
	MCI/NC	89.39	95.18	80.07
	AD/NC	96.82	92.83	98.79
NCSINs [26]	AD/MCI	90.03	91	89.50
	MCI/NC	84.64	89.71	77.45
	AD/NC	94.21	96.58	92.44
ImageNet[38]	AD/MCI	99.27	-	-
	MCI/NC	97.06	-	-
	AD/NC	98.89	-	-
HBOA based LSTM	AD/MCI	98.10	97.20	98.19
	MCI/NC	96.09	97.88	96.40
	AD/NC	97.19	96.73	98.99

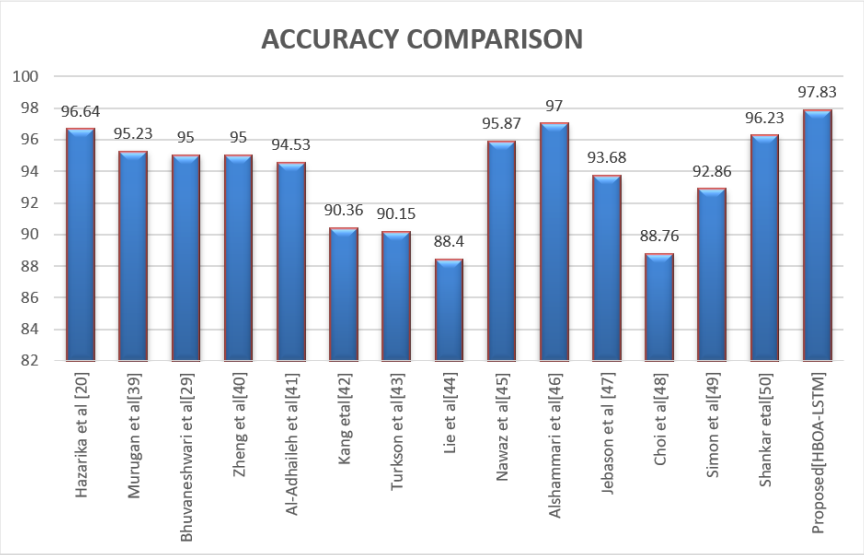

Fig.8. Graphical representation of the accuracy comparison between proposed and existing methods

5. Discussions

This study introduces and evaluates a novel model for identifying medical images, employing an HBOA (Honey Badger Optimisation Algorithm) based LSTM (Long Short-Term Memory) network. The aim is to diagnose neurodegenerative disorders using three imaging planes: axial, coronal, and sagittal. The research comprises quantitative analysis, a comparison with existing models, and an investigation of hyper-parameter optimisation strategies. The HBOA-based LSTM network's performance is extensively evaluated against various classifiers, including LSTM, Multi-SVM (MSVM), decision tree, random forest, and KNN. Assessment is done across three imaging planes using precision, sensitivity, F1-score, specificity, and accuracy as key metrics.

The utilization of a k=5 fold cross-validation approach further strengthens the robustness of the HBOA-based LSTM network, reducing bias and variance. Additionally, the study investigates hyper-parameter optimisation by contrasting the HBOA with LSTM with other optimizers, such as Particle Swarm Optimisation (PSO), Grey Wolf Optimisation (GWO), and Firefly Optimisation Algorithm (FOA). Results indicate that the HBOA with LSTM outperforms others, achieving superior classification metrics in a reduced computational time of 45.2 seconds on the ADNI database. A comparison of accuracies reported by various researchers, shown in Fig. 8, reinforces the superiority of the proposed HBOA-LSTM method. With the highest accuracy of 97.83%, the model outperforms others, demonstrating effectiveness in medical image classification.

The HBOA-based LSTM model demonstrates notable strengths, including high classification accuracy of 97.83% and efficient performance due to the use of GoogleNet for feature extraction. This combination enables quick processing and efficient handling of complicated brain imaging data. By utilising HBOA to optimise hyperparameters, the model becomes more predictive and less prone to overfitting, increasing its ability to accurately identify Alzheimer's disease in a variety of imaging planes. Its dependence on the ADNI dataset, however, might make it less applicable to different populations or datasets, which could have an impact on generalisability. Furthermore, the computational demands and complexity of the model may make it difficult to implement in real-world scenarios when resources are limited, calling

for additional optimisation for wider application.

The proposed model's superior performance across metrics and imaging planes, combined with efficient hyper-parameter optimization, positions it as a promising approach in the field. The study contributes to medical image classification advancements and offers valuable insights for researchers and practitioners in related domains.

6. Conclusions

In this paper, a HBOA based LSTM is introduced for AD detection. The proposed framework includes four phases like image collection, image denoising, feature extraction and classification. After collecting the MRI brain scans from the ADNI, the image denoising is performed by applying a binary normalization technique that helps in improving the collected brain image visualization. The pre-trained CNN model: GoogleNet is developed for extracting deep feature vectors from the visually improved brain images. Lastly, a HBOA based LSTM is introduced for brain image classification as NC, MCI, and ADs. The performance measures: precision, sensitivity, f1-score, specificity and accuracy demonstrated the efficiency of the developed HBOA based LSTM in AD detection. The extensive-experimental investigation indicated that the HBOA based LSTM has attained mean classification accuracy of 97.83%, sensitivity of 97.45%, specificity of 96.98%, F1-score of 96.86%, and precision of 96.27% in multi-class classification. Related to the existing models: SVM with radial basis kernel function and NCSIN, the HBOA based LSTM network attained high classification results in binary class classification. In future work, a novel modified deep learning model is included with the proposed framework to further enhance AD detection.

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Data availability

The datasets analysed for current study are freely available in the ADNI online data repository.

Compliance with Ethical Standards: Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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