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Data Complexity-Based Evaluation Using Brain Magnetic Resonance Images to Determine Alzheimer's Disease

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Abstract

Objectives: This study aims to develop a robust diagnostic model for Alzheimer's Disease using a curated MRI dataset from Kaggle, integrating the BABC algorithm with a Random Forest classifier for precise classification. **Methods:** Feature extraction employed a modified LeNet model, effectively capturing crucial low-intensity pixel information. Additionally, the study integrated a binary version of the BABC algorithm for streamlined feature selection, enhancing data dimensionality and overall model efficacy. **Findings:** The study's findings mark a notable breakthrough in Alzheimer's Disease (AD) diagnosis. The model, which seamlessly combines the Biologically Inspired Artificial Bee Colony (BABC) algorithm and the Random Forest (RF) classifier, achieved an impressive accuracy of 98.97%. Furthermore, it exhibited a high recall rate of 97.22% and maintained precise precision at 97.59%. The robust F1-Score reached 98.63%, and a noteworthy specificity of 96.12% highlighted the model's ability to accurately classify diverse AD stages. Notably, the incorporation of a comprehensive confusion matrix enriched the study, offering profound insights into the model's predictive prowess. This comprehensive evaluation underscores the model's reliability and effectiveness in identifying various AD stages, positioning it as a promising tool for clinical diagnosis and research in neurodegenerative disorders. The proposed study's diagnostic model facilitates early intervention and effective treatment by identifying individuals at risk of Alzheimer's disease through cognitive assessments, neuroimaging, and biomarker analysis. **Novelty:** The integration of BABC with RF enhances AD diagnosis, promising improved accuracy and specificity, and fostering more effective management and treatment strategies.

Keywords: Alzheimer's disease; Deep Neural Network; Magnetic resonance imaging; Machine learning; Random Forest

1 Introduction

AD stands as a progressively debilitating neurological disorder, profoundly affecting cognitive functions, including memory loss and alterations in daily activities [1]. Its early stages are marked by the significant impact on memory cells, leading to substantial memory deterioration, while advanced stages involve the degeneration of additional gray matter cells, affecting even the simplest of tasks [2].

To facilitate the comprehensive understanding and accurate identification of AD, this study relies on a meticulously curated dataset of MRI images, hand-collected from various reliable sources and meticulously labeled by domain experts. The data collection consists of a variety of brain images sorted into four specific groups, each corresponding to different stages of the condition: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. This crucial dataset forms the focal point of the research, playing a vital role in training and evaluating deep learning models to accurately forecast different stages of Alzheimer's disease. Additionally, it serves as a valuable resource for fostering advanced research and algorithm development, ultimately contributing to improved diagnostic and treatment methodologies for AD [3]. Figure 1 further depicts a comprehensive representation of the diverse samples found within the dataset, underscoring the variability and complexity of the pathological brain images associated with different stages of Alzheimer's disease.

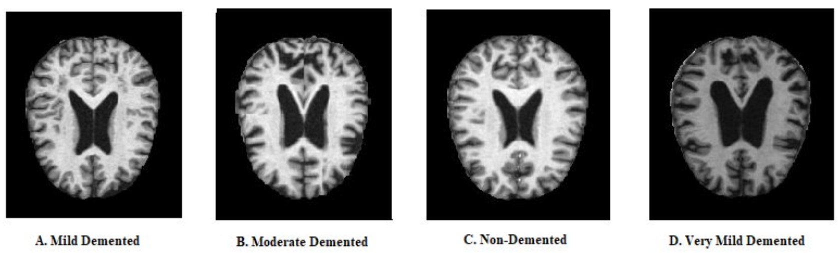

Fig 1. Samples from the data collection displaying distinct phases of Alzheimer's disease

In the following, various advanced techniques and algorithms have been explored in previous research endeavors to address the complexities of AD diagnosis.

In [4], an SVM-based classifier was proposed, utilizing CSF, PET, and MRI from the Alzheimer's Disease Neuroimaging Initiative dataset. Extensive analysis and classification were performed. [5] conducted a study using MRI and FDG-PET, introducing a multimodal feature selection method with reliable measure parameters to merge information from neuroimaging data. The classification process employed the AD Neuroimaging Initiative dataset and a multikernel Support Vector Machine. In a recent study by [6], ensemble approaches were applied during the feature selection phase by the authors. CNN-based multi-modal deep learning system for simultaneous automated segmentation and AD classification using structural MRI data by [7]. Their approach employs a 3D Dense Convolutional Neural Network to jointly learn hippocampal segmentation and disease classification. 3D patches are extracted from the MRI data for hippocampal classification. The model leverages multitasking by combining the learned features from both CNN and DenseNet models, enhancing the ability to identify the progression of AD status in patients. An automated machine-learning approach for classifying different stages of AD was proposed by [8]. They utilized 1167 full-brain MRI scans from the ADNI database, including normal cognitive aging controls, early MCI, late MCI, and probable AD patients. By extracting 68 features from both left and right hemispheres through FreeSurfer analytics, they employed non-linear SVM with RBF, KNN, and RF algorithms to accurately classify and distinguish the various dementia stages, contributing to AD diagnosis and research. [9] conducted three studies utilizing different CNN architectures to detect brain tumors, including meningiomas, gliomas, and hypophysis. They applied transfer learning techniques on MRI slices from the Figshare brain tumor dataset. By augmenting the dataset to increase sample diversity and reduce the risk of overfitting, they aimed to generalize their findings effectively. The MCI-Classification Method is proposed by [10] for using a Hypergraph-based Multi-Task Selection approach. Their analysis involves feature selection within individual modalities while incorporating group sparsity regularization to identify shared features. Multi-kernel SVM is utilized to integrate selected features from different modalities for the final classification task. [11] Developed an intelligent way in which brain pathologies such as tumors, AD, or brain normal imaging are recognized and classified. This algorithm covers 4 stages of AD which is implemented on MRI images. For the classification of the brain MRI with tumor, AD, and patients with normal brain MRI, a feature bag has been used.

VUNO Med-DeepBrain AD (DBAD) was investigated in [12], utilizing a deep learning algorithm as a decision support service for AD diagnosis. Likewise, a study [13] introduced a deep convolutional neural network (DCNN) structure for diagnosing

Alzheimer's Disease, capable of discerning between Normal Controls (NC), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD). Expanding on these progressions, the study [14] suggested the application of a pre-existing CNN deep-learning (DL) approach known as ResNet50. This was intended for the automated extraction of distinguishing characteristics in Alzheimer's Disease (AD) diagnosis using MRI images. Additionally, [15] analyzed the application of diverse DL models for AD identification employing neuroimaging methodologies such as PET and MRI. A significant breakthrough was achieved in [16] with the introduction of an enhanced lightweight DL model for accurate AD identification from MRI images. This innovative approach attained high identification evaluation, integrating feature extraction and categorization into a single stage, thus eliminating the need for complex layers. Moreover, [17] explored brain MRI scans to implement widely employed deep neural network (DNN) approaches for AD classification, showcasing the diverse range of applications of deep learning in this domain. Furthermore, studies such as [18] focused on the early prediction of Alzheimer's disease through the implementation of machine learning methods, resulting in an impressive 98% accuracy for an 18-layer CNN model. Similarly, [19] aimed to extract useful AD biomarkers from structural MRI (sMRI) and classify brain images into AD, MCI, and cognitively normal (CN) groups. Leveraging transfer learning, [20] proposed a robust approach for classifying various stages of AD, highlighting the potential of deep learning in the realm of AD diagnosis. Underlining the importance of multi-modality approaches, [21] emphasized the need for efficient evaluation in identifying AD and its phases, advocating for the integration of diverse data sources for comprehensive analysis. In the realm of Alzheimer's Disease (AD) identification, recent studies have explored various deep-learning techniques. Notably, Siamese CNN models have demonstrated promising results, achieving high accuracies of 91.83% and 93.85% [22]. Additionally, the integration of DCNN and 3D-DCNN systems has shown superior performance in AD staging, surpassing pre-trained models [23]. Moreover, the MRBL model, utilizing multimodal time-series data, predicted AD progression with an average accuracy of 80.30% [24]. Another study incorporated concatenated deep features from ResNet18 and DenseNet201, achieving an impressive accuracy of 98.86% in AD classification [25]. Additionally, a comprehensive exploration of machine learning techniques, including CNN, emphasized the critical role of early detection, showcasing an accuracy of 96.7% [26]. Building upon these advancements and acknowledging the existing research gaps, our study proposes a robust diagnostic model that amalgamates the BABC algorithm with the RF classifier. With meticulous preprocessing and feature selection, our solution aims to enhance the accuracy and clinical applicability of the AD diagnostic model. The discoveries of this research make a substantial contribution to the advancement of research and diagnosis related to Alzheimer's Disease, providing an approachable technique for enhancing patient care and strategies for treatment.

While these strides signify considerable progress, several research gaps remain within the field of AD detection. Specifically, further investigation into the transition from NC to MCI to AD, as depicted in Figure 1, is necessary to refine diagnostic criteria and enhance our understanding of the progression of AD. Additionally, the integration of diverse data sources such as CSF, PET, and MRI, coupled with various machine learning techniques like SVM, CNN, and deep learning, holds the promise of more accurate and robust diagnostic methods [4–8,12–19]. However, these approaches require further validation and standardization to ensure their clinical applicability. Furthermore, the development of multimodal, multi-kernel, and ensemble approaches presents opportunities for improved classification of different AD stages and enhanced diagnosis and research in AD [8–21]. The exploration of transfer learning, lightweight models, and deep neural networks also indicates the need for more efficient and accessible AD detection methods that can be widely applied [9,16,18]. Addressing these research gaps will be pivotal in advancing AD diagnosis and our understanding of the disease.

The primary contribution of the study lies in the fusion of the BABC algorithm with the RF classifier, resulting in improved accuracy and specificity in the diagnosis of Alzheimer's Disease (AD). This novel approach diverges from previous methodologies, which predominantly relied on traditional machine learning techniques or independent deep learning methods. The research findings hold practical significance in clinical settings, providing a dependable diagnostic model for early identification and precise categorization of AD stages, thereby facilitating the development of tailored treatment strategies.

The study's introduction outlines challenges in Alzheimer's Disease (AD) diagnosis and the significance of well-curated MRI datasets for training deep learning models. The methodology details the workflow, including preprocessing, LeNet-based feature extraction, feature selection with the FS-BABC algorithm, and RF classifier. The results analyze diverse metrics, compare algorithms, present the confusion matrix, and show training curves. The conclusion stresses the need for expanding the model's capabilities with additional data validation, highlighting implications for diagnostic advancements and disease understanding.

2 Methodology

This section describes the proposed work in detail. Figure 2 shows the proposed workflow for AD diagnosis using MRI images.

In the proposed work, the process begins with the preprocessing of input MRI images to enhance their quality and prepare them for analysis. Subsequently, features are extracted from these preprocessed images using the LeNet model, a deep learning architecture. After feature extraction, a feature selection step is conducted using a binary version of the Artificial Bee Colony

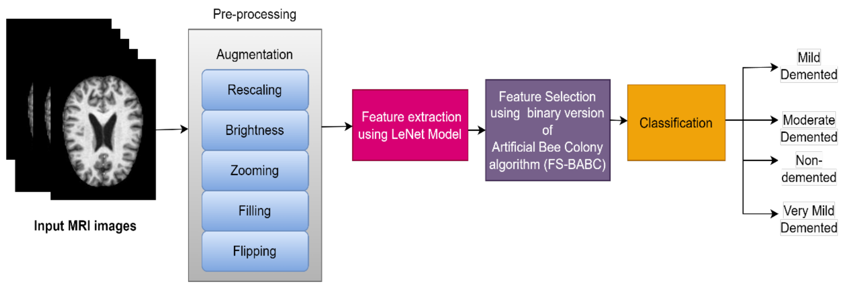

Fig 2. Proposed Workflow for Alzheimer's Disease Diagnosis Using MRI Images

algorithm (FS-BABC). This algorithm aims to identify and retain the most relevant features while discarding less informative ones, thereby optimizing the input data for subsequent analysis. Once the feature selection is complete, the core task involves the classification of the MRI images. Deep learning models are employed for this purpose, leveraging the selected features to distinguish between different categories. The final classification outcomes include categorizations into the four phases of AD (Mild, Moderate, Non, and Very Mild Demented), which are crucial in diagnosing and understanding the severity of AD based on the MRI data. This is illustrated in Figure 2.

2.1 Dataset

This collection of data, meticulously annotated by specialists and gathered from multiple online sources, contains MRI scans associated with Alzheimer's Disease (AD). Split into four distinct categories, including Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented, this dataset is conducive to training and testing deep learning methods for precise prediction of Alzheimer's stages. Intending to enable precise diagnosis and effective therapies, this dataset offers an avenue for researchers to devise sophisticated algorithms[3]. Its selection was particularly based on its accessibility, being of manageable size in comparison to other datasets, making it a valuable resource for the scientific community. By making this resource publicly available, the creators aim to stimulate comprehensive research in the field and facilitate the advancement of improved diagnostic and treatment techniques for AD.

2.2 Pre-processing

In this phase, we utilized the Keras library's ImageDataGenerator class, which enables the application of diverse image augmentation techniques to input data. These techniques generate a fresh set of augmented images for training purposes. The specific techniques employed involve adjusting pixel values, tweaking brightness, making changes to zoom levels, adding new pixels with a constant value, and performing random horizontal flips on the images. These techniques are primarily aimed at artificially expanding the size of the training dataset and improving the model's ability to handle changes in the input data. Once an instance of the ImageDataGenerator is defined, the original input image data can undergo processing within our deep-learning model. The result is a set of augmented data, which is then used in training the deep learning model. This crucial step ensures the model's effectiveness in generalizing to new or previously unseen data.

2.3 Feature extraction using LeNet Model

The pre-processed input is passed to the LeNet model for the feature extraction process. LeNet is a widely used DNN model which has effective architecture and efficient implementation. Typically, DNN models utilize MaxPooling layers for dimensionality reduction, discarding information from the minimum-valued elements. However, when dealing with brain images containing crucial features with low-intensity pixels, a novel approach is introduced. This involves the incorporation of a separate layer that performs a Min-Pooling operation, ensuring the preservation of these important but less intense elements. The resultant MinPooling and MaxPooling layers are then merged. In this particular study, researchers have modified by replacing all the MaxPooling layers with these concatenated layers[27]. The standard architecture of LeNet comprises 7 layers, including an output layer. The initial layer processes images as inputs, while the convolutional layer is responsible for extracting vital features such as edges and corners. The integration of both max and min pooling layers in the proposed model leads to an increase in processing time. To counteract this, the researchers have adopted a well-known technique called depth-wise convolution, as described in [28], which aims to enhance both the execution time and representational efficiency.

The next layer is the pooling layer which resizes the width and height of the input data without affecting the dimension of depth. Standard LeNet model shown in Figure 3 in which Min pooling selects the pixel elements with minimum value, Max Pooling operation selects the pixel elements with maximum-valued within a kernel area selected, passed to next layer.

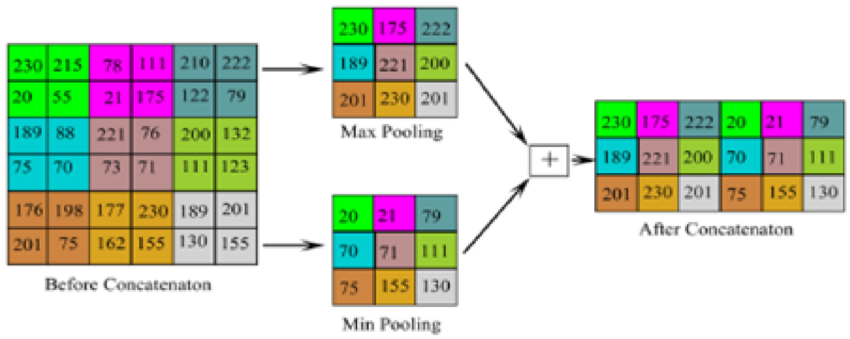

Fig 3. Pooling – Concatenation operation

Figure 4 illustrates a modified network architecture, which takes inspiration from the original LeNet model shown in Figure 3. Improved LeNet demonstrates the effectiveness of using convolutional layers for automatically learning hierarchical and spatial features from images. It showed that these learned features could capture essential information from input images, making it suitable for research on finding AD. The following phases of the process include selecting specific features and categorizing brain MRI images according to the identified alterations in the brain.

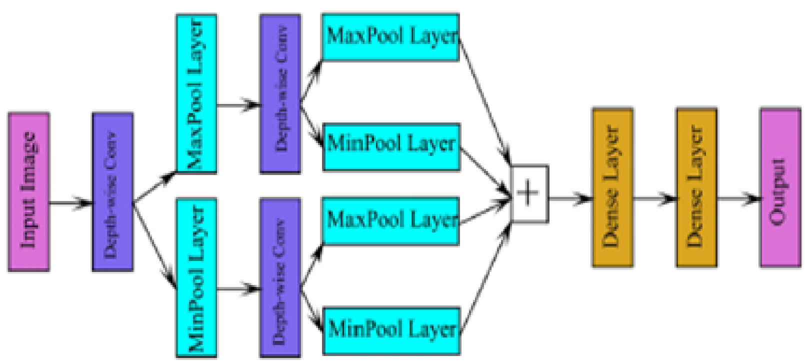

Fig 4. Improved LeNet model

2.4 Feature Selection using BABC (FS-BABC)

The BABC can be employed as a Feature Selector (FS) for classifying AD and reducing the dimensionality of data to improve performance. FS methods can be categorized into filters, wrappers, and embedded approaches. The filter method selects feature subsets based on general data characteristics and evaluates them independently of the learning algorithm. Wrapper techniques, on the other hand, evaluate feature subsets using a pre-established learning algorithm as the performance metric. Embedded models include the process of selecting variables during the training phase and extracting feature significance through an analytical approach integrated into the learning model's goal.

The Biologically inspired ABC algorithm, utilized for feature selection [29], imitates the foraging actions of honeybees. This algorithm classifies bees into distinct categories, including employed, onlooker, and scout bees, with the primary objective being to locate the best food sources. In this process, approximately half of the population is comprised of employed bees, while the remaining section consists of onlooker bees. When their food sources are depleted, employed bees transition into the role of scout bees. Onlooker bees choose their food sources by observing a dance area, and scout bees conduct random searches on depleted food sources. Figure 5 highlights the fundamental components of this algorithm.

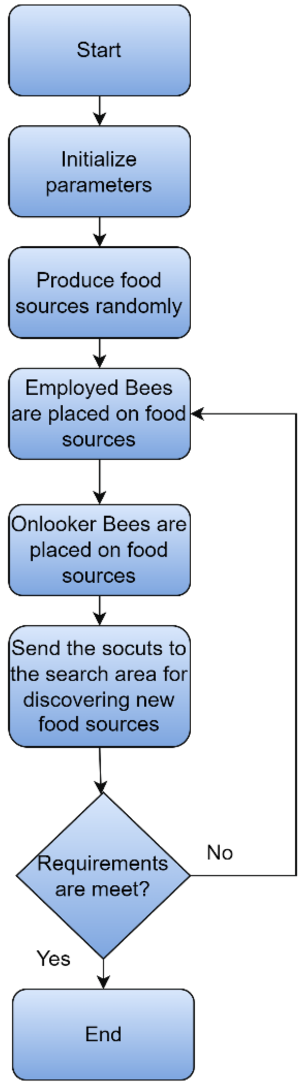

Fig 5. Flowchart of the ABC's Main steps

To adapt the ABC algorithm for FS, several modifications are required. In the original approach, food sources are included as potential solutions. In the binary version, the food sources are included as the potential best subset of features, denoted as bit vectors. Its size is determined by the total number of features (N). Representation of each bit corresponds to an attribute and its value (1 or 0) checks if the feature is part of the subset. When the value is 1, then the attribute is part of the subset, while a value is 0 means the attribute is not enclosed. This binary representation enables the ABC algorithm to perform feature selection tasks.

2.5 Classification using various algorithms

Classification using various algorithms is an essential component of this study in categorizing neurodegenerative disorders, specifically focusing on AD. The proposed BABC model integrates the LeNet feature extraction approach and the RF classifier. To assess its performance, this study conducted a comprehensive comparative analysis with several other prominent models, including VGG16, DCNN, MRBL-RF, ResNet18, DenseNet201, and CNN. The aim was to accurately classify and evaluate patients based on imaging-based detection, with distinct categories such as Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented.

- **VGG16:** The Siamese CNN classifier in the research was implemented using the VGG16 architecture, a widely recognized and preeminent deep learning model known for its capability to filter intricate features from images. With its deep layers and complex architecture, VGG16 has shown better performance in different image categorization tasks, making it an ideal choice for the model's classification of AD cases depending on MRI images [22].
- **DCNN Classifier:** The DCNN classifier implemented in this study is instrumental in its capability to extract intricate features from medical imaging data. Adapted for AD identification and staging, the DCNN displays a superior understanding of complex image patterns and has shown significant success in accurately categorizing AD stages. Its efficient feature extraction and classification make it an ideal choice for handling the intricate nuances of AD-related image analysis [23].
- **MRBL (Multitask Regression BiLSTM) Model with RF Classifier:** The MRBL model, integrated with the BiLSTM architecture, was developed as a robust hybrid DL framework for accurate AD progression prediction. Employing a multitask modeling approach, the MRBL model efficiently predicted seven crucial cognitive scores at month 48, facilitating subsequent AD progression forecasts [24].
- **ResNet18 and DenseNet201:** The research incorporated concatenated deep features from ResNet18 and DenseNet201, leading to the successful multiclass categorization of AD employing MRI images. The models' sophisticated architecture contributed to achieving high precision and recall rates, emphasizing the efficacy of advanced deep-learning approaches in AD diagnosis [25].
- **CNN:** The study employed diverse machine learning methods for the classification of Alzheimer's severity. Notably, the newly introduced CNN architecture demonstrated the highest accuracy, emphasizing its efficacy in the accurate assessment of AD phases employing fMRI data and Mini-Mental State Examination (MMSE) scores [26].

3 Result and discussion

In the subsequent section, the study delves into the comprehensive analysis of the model's performance and its implications for AD diagnosis. Through an in-depth discussion of the experimental outcomes, the study depicts the significance of the proposed model in addressing the challenges associated with accurate disease classification.

3.1 Evaluation Metrics

In this study, binary classification was performed on a dataset consisting of two classes: AD and healthy controls (HC). The evaluation of suggested model is evaluated using the following metrics: Precision, Recall, Accuracy, and F1-score (F1) are shown in Equations (1), (2), (3) and (4). These metrics are computed based on the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values. TP refers to instances correctly classified as HC, TN represents instances correctly classified as AD, FP denotes instances incorrectly classified as HC, and FN indicates instances incorrectly classified as AD.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$F-measure = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{3}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

This study presents a comparison of various algorithms and classifiers, including the proposed model with BABC in Figure 6. These models were evaluated depending on their accuracy, recall, precision, F1-Score, and specificity. The reference models included Siamese CNN (VGG16), 3D-DCNN (DCNN), BiLSTM with RF, a hybrid pre-trained CNN model, and CNN.

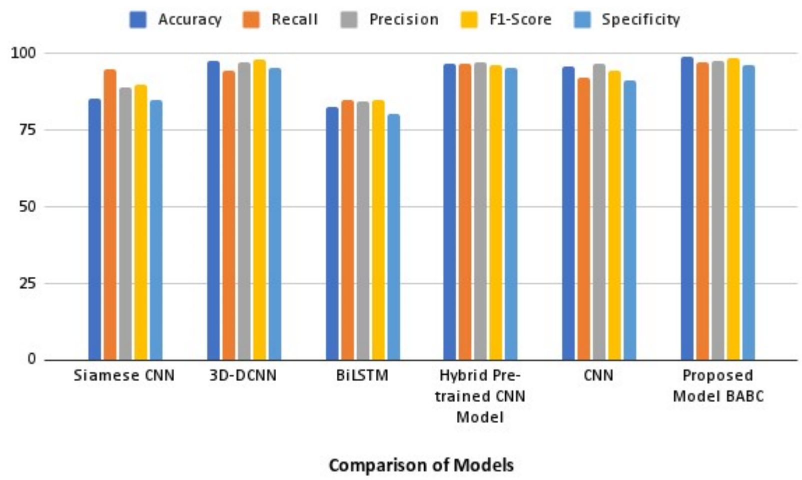

Fig 6. Comparison of Different Algorithms and Classifiers

Siamese CNN (VGG16) [22] achieved an accuracy of 85.31% with high recall and precision, making it a suitable model for AD diagnosis. [23] 3D-DCNN (DCNN) demonstrated impressive performance with an accuracy of 97.53%, suggesting its capability for AD staging. [24] BiLSTM with RF showed an accuracy of 82.63% and balanced recall and precision, indicating potential for AD progression prediction. [25] The Hybrid Pre-trained CNN Model attained an accuracy of 96.71% with high precision, recall, and F1-Score, showcasing its efficiency in AD diagnosis. [26] The model CNN achieved an accuracy of 96.07%, with various performances in recall, precision, and F1-Score. This study's proposed model, incorporating BABC and RF classifier, outperformed other models with an impressive accuracy of 98.97%. It also demonstrated high recall, precision, F1-Score, and specificity, making it a promising approach for AD diagnosis and staging.

3.2 Confusion Matrix

The fundamental assessment tool for evaluating the performance of the Alzheimer's disease classification approach is represented by the confusion matrix, as displayed in Figure 7. It provides a comprehensive breakdown of the model's predictions, allowing for a detailed analysis of its effectiveness in categorizing different stages of the disease. Each row of the matrix denotes the instances in an actual classification, while each column denotes the instances in a predicted classification. The values in the cells of the matrix signify the count or percentage of correctly and incorrectly classified instances, providing crucial insights into the model's predictive capabilities.

Each cell in the confusion matrix expresses the number of instances that are associated with the respective actual class and were forecast to be in the corresponding predicted class. The diagonal elements, depicting the correctly classified instances, illustrate the model's accuracy in correctly identifying the different phases of AD.

In contrast, the off-diagonal elements represent misclassifications, providing insights into the types and frequencies of classification errors made by the model. From the confusion matrix, it is obvious that the proposed approach attained high accuracy in categorizing the different phases of AD. With an overwhelming percentage of correct predictions for each class, the model demonstrates its robustness and reliability in accurately identifying the stages of the disease based on the MRI images. The balanced distribution of correct predictions across the four distinct phases of AD underscores the model's proficiency in handling the complexities associated with neurodegenerative disorders.

3.3 Training Loss and Training Accuracy

The illustrated training loss and accuracy curves in Figures 8 and 9 provide a valuable understanding of the performance and learning patterns within the proposed model for classifying Alzheimer's disease. These curves provide a comprehensive visualization of the approach's convergence amid the training procedure, highlighting the fluctuations and trends in both the loss and accuracy metrics across multiple epochs. The training loss curve showcases the gradual decrease in the model's loss function over successive epochs, indicating the model's ability to minimize errors and improve its predictive capabilities. On the

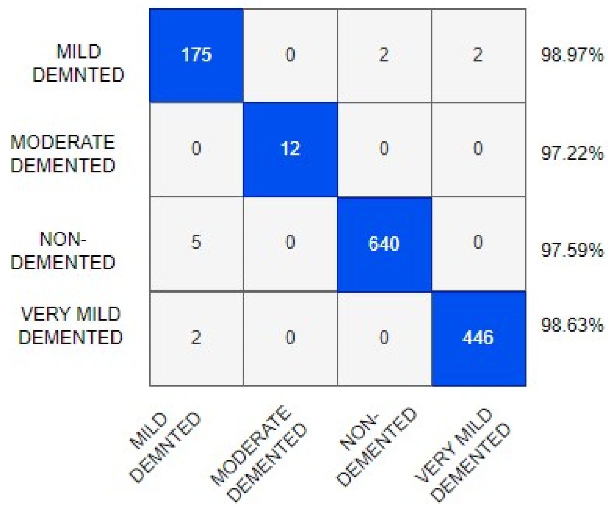

Fig 7. Confusion Matrix

other hand, the training accuracy curve depicts the progressive increase in the model's accuracy as it learns from the training data, ultimately achieving a higher level of precision in its predictions. The training loss curve depicts the variations in the loss function throughout the model's training process. Initially, the model exhibits a higher loss of 0.257, indicative of substantial errors and inaccuracies in its initial predictions.

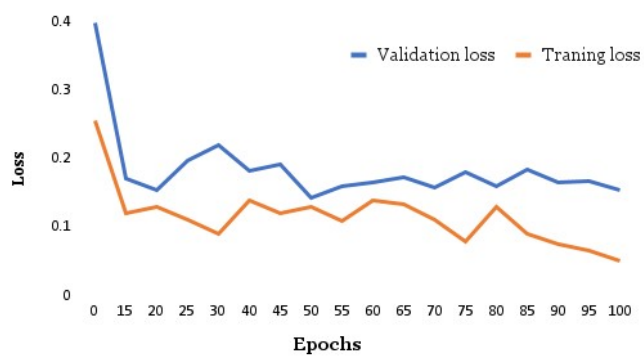

Fig 8. Training Loss

As the model undergoes successive training epochs (100 epochs in this case), the loss gradually diminishes to 0.05, demonstrating the model's increasing proficiency in minimizing errors and effectively learning from the training data. The fluctuations observed in the loss curve are a reflection of the model's continual adjustments to optimize its predictive capabilities, ultimately converging toward a lower overall loss value. The consistent downward trajectory of the training loss highlights the model's capacity to effectively capture and learn from the complex patterns and distinctive features within the MRI images, consequently facilitating more precise and reliable predictions of the different phases of AD.

The training accuracy curve illustrates the model's progression in making precise predictions as it undergoes training on the dataset. Commencing with an initial accuracy of 0.15, the model demonstrated limited capacity in correctly classifying the various phases of AD depending on the MRI images. However, over the course of 100 training epochs, the accuracy steadily improved, eventually reaching a high of 0.989. This remarkable enhancement in accuracy indicates the model's increasing adeptness in discerning intricate patterns and features associated with each stage of the disease. The consistent upward trend in the accuracy curve reflects the model's adaptability and proficiency in learning from the training data, enabling it to make more precise and reliable predictions. The plateauing of the accuracy curve at a high value underscores the model's robustness and

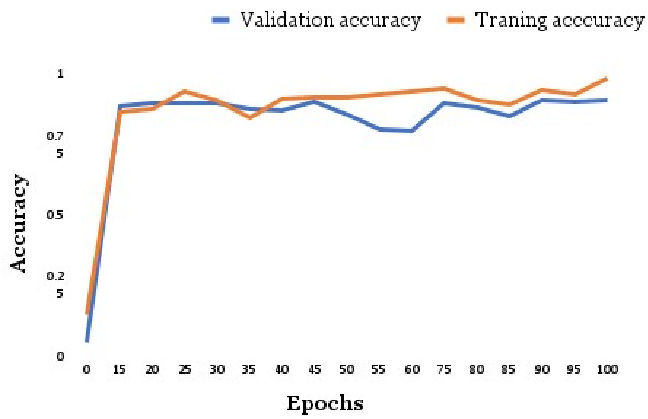

Fig 9. Training Accuracy

competence in accurately categorizing the diverse stages of Alzheimer's disease, highlighting its potential as an effective tool in clinical diagnosis and research.

The evaluation metrics consistently demonstrated the high efficacy and reliability of the model in distinguishing between various stages of AD. This underscores the potential of various methods in revolutionizing the field of neurodegenerative disorder diagnosis. By showcasing superior performance and emphasizing the importance of comprehensive data analysis, this study significantly contributes to the advancement of AD research and diagnostic methodologies. Building on these results, the subsequent section delves into the broader implications for Alzheimer's Disease research, highlighting avenues for improving the model and identifying key areas for future exploration.

3.4 Discussion and Practical Implications

In comparison to previous research and similar studies, the proposed approach in this research demonstrates a significant evaluation improvement in provisions of accuracy, precision, recall, F1-Score, and specificity. The model attained an impressive accuracy of 98.97%, along with a meticulous recall of 97.22%, precise precision of 97.59%, a strong F1-Score of 98.63%, and a notable specificity of 96.12%. These metrics highlight the reliability and robustness of the model in effectively classifying various stages of AD employing brain MRI.

Prior academic pursuits have primarily engaged in conventional machine learning techniques or standalone deep learning approaches. However, this research presents a unique integration of the Biologically Inspired Artificial Bee Colony (BABC) algorithm with the Random Forest (RF) classifier, setting it apart from existing literature. This integration significantly enhances the model's accuracy and specificity, enabling more precise classification of diverse AD stages. Leveraging the BABC algorithm for feature selection optimizes data dimensionality, leading to improved model performance and greater accuracy in disease identification. This approach contributes to the advancement of AD research and diagnosis, marking a significant departure from previous methodologies.

The practical implications of these research findings are extensive, holding relevance for clinical settings and the wider domain of Alzheimer's disease research and diagnosis. By providing an accurate and efficient diagnostic model, this work facilitates early detection and precise classification of AD stages, offering valuable insights into disease progression and aiding in the development of personalized treatment strategies. The heightened accuracy and specificity empower healthcare professionals to make more informed decisions, thereby enhancing patient care and management. Furthermore, the accessibility and reproducibility of the research findings, utilizing the Kaggle dataset, ensure the applicability and validation of the developed methodologies in diverse clinical environments, contributing significantly to the ongoing battle against neurodegenerative diseases such as AD.

4 Conclusion and Future Work

This research addresses the critical need for an accurate diagnostic model for AD. By employing the BABC algorithm in conjunction with an RF classifier, the study achieves impressive results in disease identification. The proposed model exhibits remarkable performance, accurately classifying various stages of AD with an impressive accuracy of 98.97%, high recall of

97.22%, precise precision of 97.59%, strong F1-Score of 98.63%, and notable specificity of 96.12%. The study's comprehensive evaluation metrics consistently showcased the model's high efficacy and reliability in distinguishing between various stages of AD, namely Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. Through meticulous dataset curation and rigorous preprocessing, the study ensured the quality and integrity of the input data, laying a strong foundation for subsequent feature extraction and selection processes. The study's success in accurately classifying AD stages and its emphasis on comprehensive and multidimensional data analysis has significant implications for advancing diagnostic methodologies and understanding disease progression.

Future research should focus on expanding the model's capabilities by incorporating additional modalities such as PET and CSF data and optimizing deep neural network architectures to further enhance predictive accuracy. Furthermore, validating the proposed framework on larger and more diverse datasets, including longitudinal data, will be crucial to assessing its generalizability and applicability in real-world clinical settings. These efforts will contribute to the continual improvement of diagnostic tools, fostering advancements in the field of neurodegenerative disease research and facilitating more effective treatment strategies.

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