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ORIGINAL ARTICLE

Dementia diagnosis in young adults: a machine learning and optimization approach

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Abstract
Individuals who are younger and have dementia often start experiencing its symptoms before they turn 65, with cases even documented in people as young as their thirties. Researchers strive for accurate dementia diagnosis to slow or halt its progression. This paper presents a novel Enhanced Dementia Detection and Classification Model (EDCM) comprised of four modules: data acquisition, preprocessing, hyperparameter optimization, and feature extraction/classification. Notably, the model uses texture information from segmented brain images for improved feature extraction, leading to significant gains in both binary and multi-class classification. This is achieved by selecting optimal features via a Gray Wolf Optimization (GWO)-driven enhancement model. Results demonstrate substantial accuracy improvements after optimization. For instance, using an Extra Tree Classifier for "normal" cases, the model achieves 85% accuracy before optimization. However, with GWO-optimized features and hyperparameters, the accuracy jumps to 97%.

Keywords Detection methodology · Machine learning · Hyperparameters optimization

1 Introduction

This section discusses some important issues such as dementia, Alzheimer's disease (AD), Younger Onset Dementia, and Machine Learning and Deep Learning in Dementia Disease Detection.

The phrase "dementia" refers to a group of symptoms that drastically affect memory, cognitive processes, and social abilities. Rather than being the result of a single disease, dementia stems from various medical conditions. Dementia is not a particular illness. It's an umbrella word for a collection of signs that indicate memory loss or other cognitive impairment that is significant enough to impair a person's ability to conduct daily tasks. Between 60 and 80% of cases are attributed to Alzheimer's disease [1]. Vascular dementia, emerging post-stroke, ranks as the second most common form of dementia. However, various factors may exhibit signs similar to dementia, such as treatable ailments like thyroid disorders and insufficiencies in crucial nutrients. Dementia can also be characterized by a significant impairment in memory or cognitive functions that disrupts everyday activities, stemming from changes in the brain's structure. Alzheimer's disease is recognized as the most prevalent among the different types of dementia. The signs and symptoms of dementia vary depending on the underlying cause, but frequent ones include (i) Cognitive modifications, including: (a) Memory loss which is typically noted by a friend or family member, (b) Having trouble speaking or finding the right words, (c) Visual and spatial difficulties, such as having trouble navigating when driving, (d) Difficulty in thinking or solving problems. (e) Having trouble managing complicated jobs, (f) Organizational and planning challenges, (g) Coordination and motor function issues, (h) Disorientation and confusion. (ii) Psychological alterations, including personality shifts,

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depression, anxiety, inappropriate behavior, hallucinations, agitation, and paranoia.

The listed dementias are both progressive and have no known cures: (i) Alzheimer's disease, which stands as the predominant cause of dementia. (ii) The onset of vascular dementia stems from impairment to the cerebrovascular system, impairing oxygen and nutrient flow to the brain, culminating in this form of dementia. (iii) The presence of abnormal protein accumulations known as Lewy bodies in the brain is characteristic of Lewy body dementia. These protein deposits are also observed in conditions such as Parkinson's disease and Alzheimer's disease, underscoring their association with Lewy body dementia. (iv) Frontotemporal dementia is marked by the progressive loss of neurons and their connections within the brain's frontal and temporal regions, affecting a variety of disorders. (v) Autopsy investigations in individuals over the age of 80 have revealed that mixed dementia results from a combination of Alzheimer's disease, vascular dementia, and Lewy body dementia. (vi) Early-onset dementia is defined as dementia that first appears in individuals under the age of 65.

Alzheimer's disease (AD) is identified as a form of dementia that progressively impairs cognitive functions, behavior, and memory, beginning with mild symptoms that gradually progress to a severity that disrupts daily activities. It is an advancing, non-reversible brain disorder predominantly affecting older adults, leading to a gradual decline in memory, cognitive abilities, learning, and behavioral functions [1]. Machine learning techniques applied to Magnetic Resonance Imaging (MRI) scans present a significant method for predicting the medical condition of a patient. MRI scans have been traditionally utilized for classifying individuals with AD [2]. Other notable biomarkers for detecting AD and its preliminary stage known as Mild Cognitive Impairment (MCI) include Cerebrospinal Fluid (CSF) alongside basic and advanced neuroimaging tests [3].

Caregivers have made use of biological and imaging techniques to detect AD in its initial stages and to understand its impact on sufferers by using various biomarkers [4]. Many scholars have investigated the induced patterns, analyzed them, and applied classification methods to decipher the complex spatial configurations of brain structure [5]. The selection of a classifier type in the training set was determined using substitution and cross-validation error estimators [6]. Dementia occurring prior to reaching 65 years old is termed as younger onset dementia, impacting people in their 30s, 40s, and 50s. It's also referred to as early-onset dementia and shares similarities with different types of dementia. However, its impact can differ notably among younger individuals who may still be involved in active employment, raising children, or bearing significant financial responsibilities for their families.

Regardless of the onset age, dementia's symptoms remain consistent, encompassing memory lapses significant enough to hinder daily life, confusion, difficulties in performing familiar tasks, repeated behaviors, and social withdrawal alongside diminished mental acuity, communication struggles, and alterations in behavior. Various conditions, including depression, hormonal and vitamin deficiencies, side effects from medications, infections, and tumors, can mimic dementia's symptoms.

Identifying early-onset dementia poses unique challenges, primarily due to the younger age of those affected. For a conclusive diagnosis, comprehensive evaluations including physical and neurological assessments, pathological tests, brain scans, psychiatric reviews, and neuropsychological testing are often essential. These tests evaluate cognitive abilities such as memory, logic, and understanding. The diagnosis can come as a shock, leading to feelings of anger, sorrow, and denial among the patient and their close ones, accompanied by a profound sense of grief. These emotions are typical. However, assistance and support are available, and it is best to seek it out as soon as possible. When evaluating dementia in individuals of a younger age, it is essential to take into account various factors [7]. Cadasil (Younger Dementia) can be seen at young ages. Figure 1 shows the shock on the face of a young girl when she knows that she has this rare disease.

Early detection and classification of dementia disease are active study fields because of the rapid progression of dementia patients and the absence of precise diagnostic methods. One of the many researchers' objectives is to effectively and accurately diagnose dementia disease in order to slow or stop the disease's progression. Researchers examined the induced patterns in the brain and employed classification methods to simplify its complex spatial arrangement [5]. Utilizing substitution and cross-validation error estimators, they identified the appropriate classifier for the dataset [6]. By assessing the error rates linked with classification, they determined the most informative features for discrimination among the ranked features [8]. These features are recognized for their role in enhancing classifier performance and are derived from correlated clinical data about the individuals [9]. For diagnosing Alzheimer's Disease (AD), either binary classification or multi-classification approaches are utilized [10].

Furthermore, in the field of neuroimaging, the count of feature measures often exceeds the number of samples. Careful consideration must be given to the choice of features in order to avoid overfitting; selecting features wisely is crucial to prevent overfitting in models [11]. One can identify three main categories of feature selection methods: filter methods, wrapper methods, and embedded methods

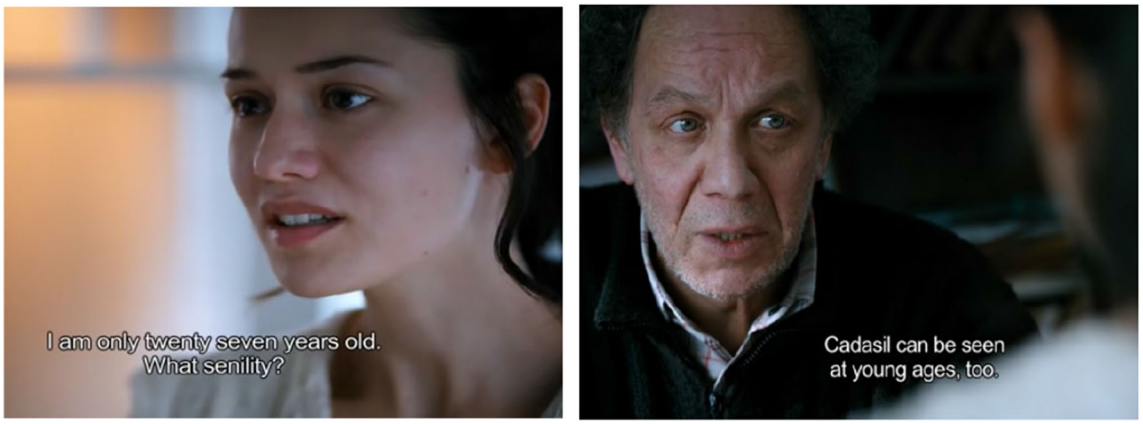

Fig. 1 The shock on the face of a young girl when she knows that she has dementia disease

[12]. In this scenario, researchers have discovered that the method automatically detects the ideal number of relevant characteristics and chooses a subset of features that show strong discrimination [11]. Various algorithms, including those based on k-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Naive Bayes (NB), leverage these features in the classification phase [13], employing them [14]. Classification was performed using a hypothetical hyperplane during this experimental phase to evaluate the datasets. Subsequently, 3D T1-weighted MRI scans of each participant were automatically segmented into Regions of Interest (ROIs) [15].

The primary contribution of this study is the application of texture analysis in addition to brain image segmentation for feature extraction, markedly enhancing the performance in both binary and multi-class classifications. This research predominantly focuses on the multi-class classification approach, facilitated by selecting optimal features via a Gray Wolf Optimization (GWO)-based enhancement model.

This paper proposed an Enhanced Dementia Detection and Classification Model (EDCM) which is composed of four main modules which are: (i) The Data Acquisition Module (DAM) gathers information. (ii) The Data Preprocessing Module (DPM) prepares the gathered data for analysis, (iii) Hyperparameter Optimization Module (HOM), (iv) Feature Extraction and Classification (FECM).

The rest of the paper is organized as follows. In Sect. 2, the description of the previous efforts and the related work in machine learning and deep learning in dementia disease detection is presented. Section 3 contains the dataset representation and description. In Sect. 3, the proposed system is presented. The experiential results are presented in Sect. 4. Finally, Sect. 5 highlights the main contributions of this paper and discusses potential research directions.

2 Literature review

In order to recognize, categorize, and calculate AD, Altafet [16] developed an algorithm that made use of the AD Neuro-imaging Initiative (ADNI). In this instance, the photographs were arranged into one of the three classes, including AD, typical, and MCI. Precision, sensitivity, and specificity are three important assessment factors where this model outperforms state-of-the-art techniques.

The binary classification of the AD and typical class was accurate to 98.4%. An accuracy of 79.8% was achieved for multi-class classification of AD, such as typical and MCI. To distinguish CN from advertisement and to detect various sub-types, Sun et al. [17] suggested classification (e.g., CN versus Mellow Cognitive Impairment). This method was developed utilizing Cuingnet's dataset for classifying AD against CN, and it was particularly applied without having to prepare the larger autonomous dataset. In all trials, the classification was equal to or better than the best in the field, and the weight map clearly displayed the main areas that were associated with AD.

Zuet al. then provided a novel multi-methodology feature selection technique that simultaneously presented feature selection and near-by likeness adoption [18]. In particular, a similitude grid is discovered by considering multiple imaging modalities side by side. The test comes about ADNI dataset, which reflects the most cutting-edge multi-methodologies approaches, and can very much demonstrate the suitability of this joint learning technique.

A strategy for predicting AD using image analysis was suggested by Farouk et al. [19]. It combines the texture features that were separated from the gray level co-occurrence network and the voxel-based morphometric neuroimaging, allowing the support vector machine classifier to classify AD patients. The use of entropy in feature selection was used to address dimensionality difficulties.

Table 1 Relative evaluation of the proposed strategy against state-of-the-art methods

Ref.	Year	Objective	Pros	Cons
Islam et al. [21]	2017	On the Open Access Series of Imaging Studies (OASIS) dataset, a combination of deep convolutional neural networks performs better	The contrast between the very mild and mild classes would make it easier to determine the patient's present stage if they had early-stage AD	The categorization model uses a minimum set of performance metrics
Altafet al. [16]	2018	Features derived from brain images were combined with GLCM and clinical data for paired and multi-class class classification	On the ADNI dataset, a combination of MRI biomarkers has shown the highest level of multi-class characterization accuracy	In this case, 3D includes showing unconsidered
Sun et al. [17]	2018	SVM-based learning method for the order of AD that takes geographical and anatomical data into account	Without re-preparing for the independent larger dataset, CN classification was used directly, and additionally, the Good execution was achieved	More features are not taken into account
Zuet al. [18]	2018	The SVM-RFE technique is improved by multi-feature combination correlation technologies and the covariance method	The performance of classification could be enhanced by using a features selection technique to efficiently extract the ideal feature subset	The challenge is growing the longitudinal dataset in order to extract useful picture identification data at different disease phases
Farouk et al. [19]	2018	Voxel-based morphometric neuroimaging assessment and texture features extracted from GLCM are combined to order AD patients	Expanding the longitudinal dataset to eliminate valuable image identification data at various stages of disease progression for improved image identification	The examination requires the most amount of computation time
Proposed Approach	–	Analyzing dementia using many classifiers and the best features	Improved classification accuracy and best outcomes in dementia analysis	–

The accuracy of this approach in distinguishing between AD patients and controls was 88%.

In order to improve the Support Vector Machine (SVM) method using covariance strategy, Xiao et al. [20] suggested multi features and mix features innovation. The results of the examination probes that open the ADNI database demonstrate the effectiveness of the anticipated method. The multi-feature combination is also preferable to the single-feature technique. The appropriate feature subset could be successfully extracted using the suggested features selection computation, improving classification execution.

Islam et al. [21] proposal for detecting and classifying AD on the basis of symptoms that can be determined from MRI data. When diagnosing more experienced patients, it can also be observed in brain MRI data. A modest to limited amount of dataset was also available to create the robotized AD discovery and classification model. Through the utilization and examination of brain MRI data, efforts were made to develop a model aimed at detecting and categorizing Alzheimer's disease.

Long [22] used the big point-set technique to produce the underlying populace while enhancing global convergence. The authors' simulations used ten common unrestricted capacities. When compared to the traditional GWO strategy, this method has a finely balanced execution of quality. This method outperformed other cunning advancement tactics in a variety of domains, including accuracy and response speed. Authors in [23] proposed a new effective hyperparameters optimization algorithm for CNN. Table 1 compares and contrasts the proposed strategy with state-of-the-art approaches in terms of the goals, benefits, and drawbacks of each.

Based on the provided literature review, here are some potential research gaps:

1. Limited Feature Exploration:
   - While several studies explore feature selection techniques, there seems to be a focus on specific feature types (e.g., texture features, voxel-based morphometry). Research could benefit from exploring a wider range of features, potentially including:
     - Demographic data
     - Genetic markers
     - Lifestyle factors
   - Additionally, some studies utilize limited feature sets. Investigating the impact of more comprehensive feature sets on classification accuracy could be valuable.
2. Data Set Limitations:

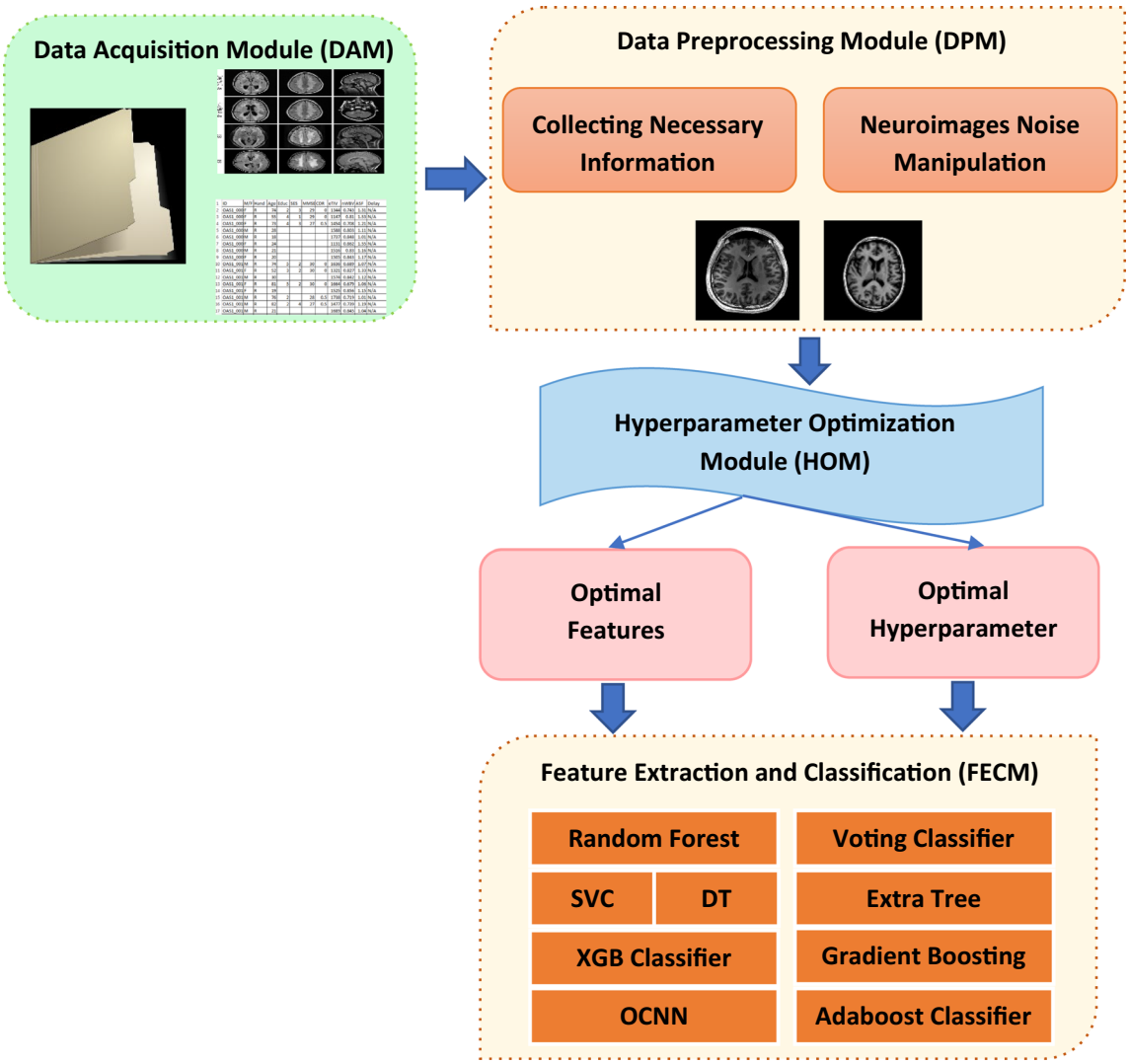

Fig. 2 The Enhanced Dementia Detection and Classification Model (EDCM)

- Several studies rely on specific datasets like ADNI. Exploring the generalizability of models across different and potentially larger datasets is crucial.
- The size and longitudinal nature of datasets are also mentioned as limitations. Investigating methods for handling smaller datasets or utilizing transfer learning techniques could be beneficial.

3. Early-Stage Detection Challenges:

- While some studies mention early-stage detection, the focus seems to be on achieving high overall accuracy. Developing methods specifically tailored for differentiating between very mild and mild stages of dementia could be valuable for earlier intervention.

4. Multi-modality Exploration:

- Although some studies mention multi-modal data analysis, a deeper exploration of how different modalities (MRI, PET scans, etc.) can be effectively combined for improved classification remains a potential research gap.

5. Explainability and Interpretability:

- The literature review focuses on achieving high accuracy. However, exploring methods that offer explainability and interpretability of the model's decision-making process could be valuable for clinical applications.

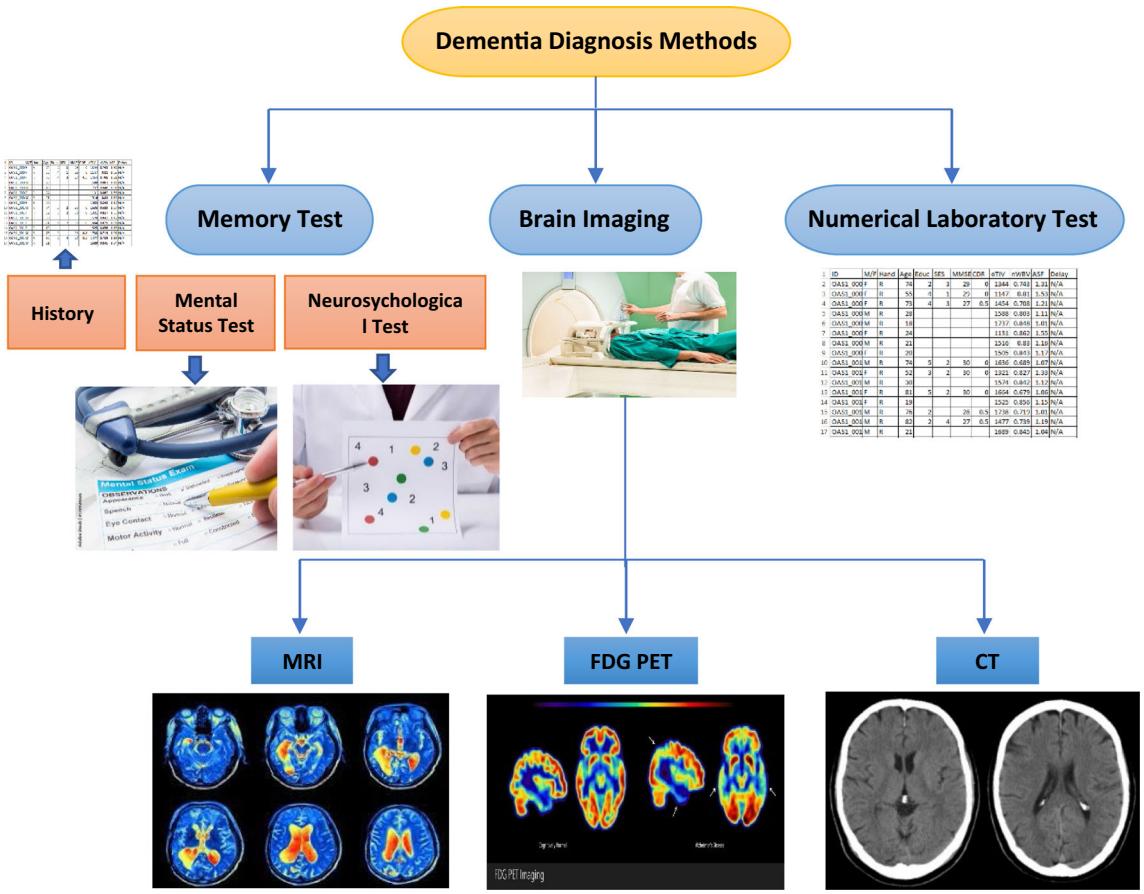

Fig. 3 Various Data Acquisition Techniques to detect Dementia

3 Enhanced dementia detection and classification model (EDCM)

The following is the main contribution of this paper. In addition to segmenting brain images, it used texture information to extract features, which significantly improved the execution of the binary and multi-class classification. The focus of this work continues to be the multi-class classification process, which is made possible by the ideal features from the Gray Wolf Optimization (GWO)-driven enhancement model that were selected. This paper proposed an Enhanced Dementia Detection and Classification Model (EDCM) which is composed of four main modules as shown in Fig. 2 which are: (i) Data Acquisition Module (DAM) (ii) Data Preprocessing Module (DPM), (iii) Hyperparameter Optimization Module (HOM), (iv) Feature Extraction and Classification (FECM).

3.1 Data acquisition module (DAM)

Clinical evaluation, cognitive testing, and the exclusion of other potential causes have traditionally been the three main components of the clinical diagnosis of dementia [24]. Three modified techniques can typically be used to diagnose dementia, as shown in Fig. 3. The data can be collected through three main methods which are as follows: (i) Memory Test, which can be done via (a) historical data, (b) mental status test, or c) neuropsychological test. (ii) Brain Imaging, which can be done via a) MRI, (b) FDG, or (c) CT. (iii) Numerical Laboratory Test.

3.2 Data preprocessing module (DPM)

Data is crucial to models. It is the ceiling of model capabilities. A solid model relies on quality data; without it, the model's effectiveness suffers. Within the data preprocessing component, there exist two subsidiary modules: (i) Gathering Essential Data and (ii) Managing Data Variability.

3.2.1 Collecting necessary information

Diagnosing dementia might not necessitate utilizing every bit of data gathered, thus elongating data processing and training, computational procedures, and diminishing the efficacy of our classification model's training [25].

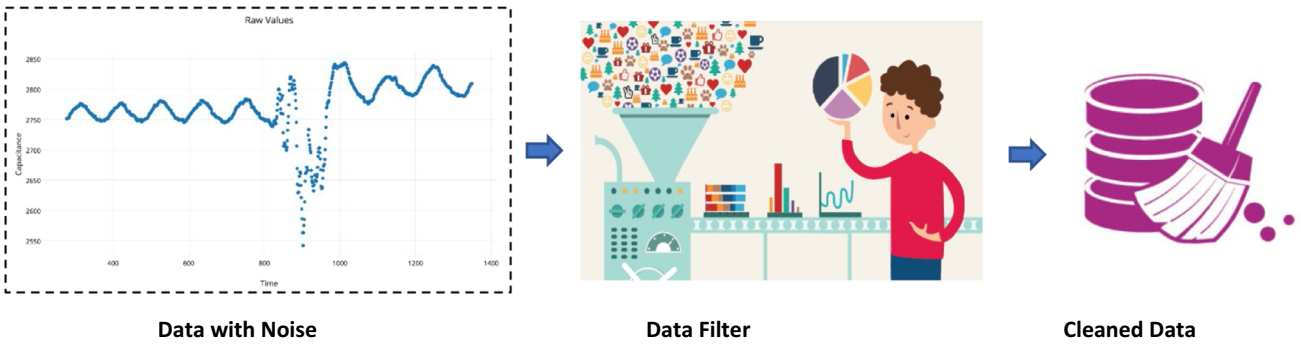

Fig. 4 Data Noise Manipulation using filters

Addressing this issue involves eliminating superfluous information using various techniques tailored to the data type.

3.2.2 Data noise manipulation

Neuroimages may contain adversarial noise, which lowers the classification process' efficiency. Enhancing the training process of the classification model involves the incorporation of filters such as Gaussian, median, and various others. These filters play a crucial role in removing image noise, as illustrated in Fig. 4.

3.3 Hyperparameter optimization module (HOM)

The Hyperparameter Optimization Module (HOM) employs the GWO Algorithm for optimizing

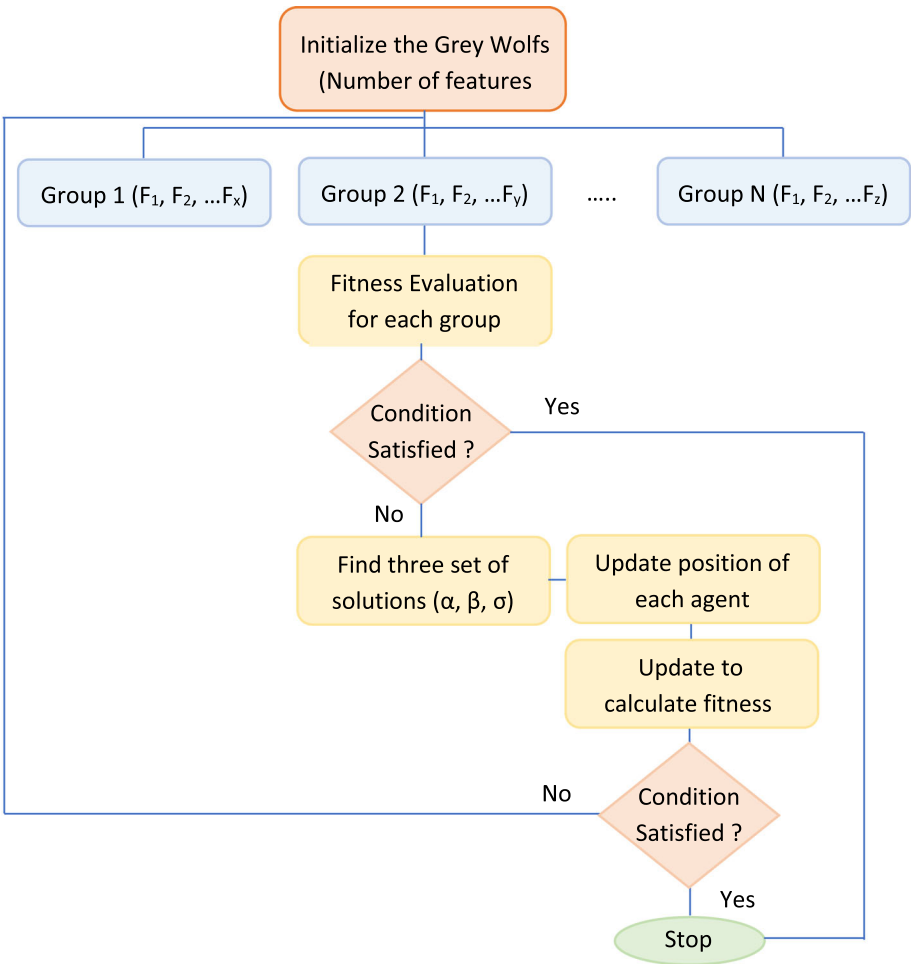

Fig. 5 Feature Extraction using GGWO

hyperparameters. Algorithm 1 illustrates the implementation of the GWO algorithm for this purpose.

Algorithm 1: Greedy Wolf Optimization Algorithm.

GWO Algorithm

Start
1: N particles
2: Calculate the fitness value (FV)
S1 = wolf with least FV
S2 = wolf with second least FV
S3 = wolf with third least FV
3: For t in range(max_iter):
a = 2*(1 - t/max_iter)
Initialize the population of wolves.
Repeat the following steps for a specified number of iterations:
a. For each wolf in the population:
i. Generate three random numbers, r1, r2, and r3.
ii. Calculate scaling factors A1, A2, and A3 using the formula: A = a * (2 * r - 1), where 'a' is a constant.
iii. Calculate correlation factors C1, C2, and C3 using the formula: C = 2 * r. iv. Calculate displacement vectors X1, X2, and X3 using the formula:
X = S_wolf.location - A * abs(C * S_location - ith_wolf.location), where 'S_wolf.location' is the location of a selected wolf, 'S_location' is a component of the location vector of the selected wolf, and 'ith_wolf.location' is the location of the current wolf being updated.
v. Compute a new solution Xnew by averaging X1, X2, and X3: Xnew = (X1 + X2 + X3) / 3.
vi. Compute the fitness of the new solution: fnew = fitness(Xnew).
vii. Update the current wolf greedily: - If fnew is less than the current wolf's fitness, update the current wolf's location and fitness: ith_wolf.location = Xnew, ith_wolf.fitness = fnew.
b. Identify the wolves with the least, second least, and third least fitness values, denoted as S1, S2, and S3, respectively.
c. Replace the wolves with the least, second least, and third least fitness values with new wolves generated from the updated population.

4: Return the best wolf in the population based on its fitness value.
End

3.4 Extracting features and classifying them is an essential step in the process, abbreviated as FECM

The Feature Extraction and Classification (FECM) combines two sub modules which are as follows: (i) Feature Selection using GGWO, and (ii) Multiclass (MC) Classification.

3.5 Selecting features through GGWO (Gravitational Grouping-based Wrapper Optimization)

Within this submodule, optimal features are selected for testing with the classification module. The process of feature selection employs the Group Gray Wolf Optimization (GWO) Algorithm, which comprises four main steps delineated in Fig. 5: (i) Initialization of Feature Set, (ii) Formation of Grouping Model, (iii) Evaluation of Objective Function, and (iv) Adjustment of Feature Selection.

I. Feature Set Initialization

The GGWO algorithm fills the layout with a subjective approach to enhance its characteristics. A vital enhancement to the algorithm swiftly identifies the ideal solution through solution generation. The selected feature set is presented in the manner depicted by Eq. (1).

$$F_s = \{F_1, F_2, F_3, \ldots\ldots\ldots F_n\} \quad (1)$$

where F_s is the subset of the chosen features, n: is the number of the features.

ii. Grouping Model

Gray wolves (features) were first arranged in groups for group formation based on how they were used in the diving

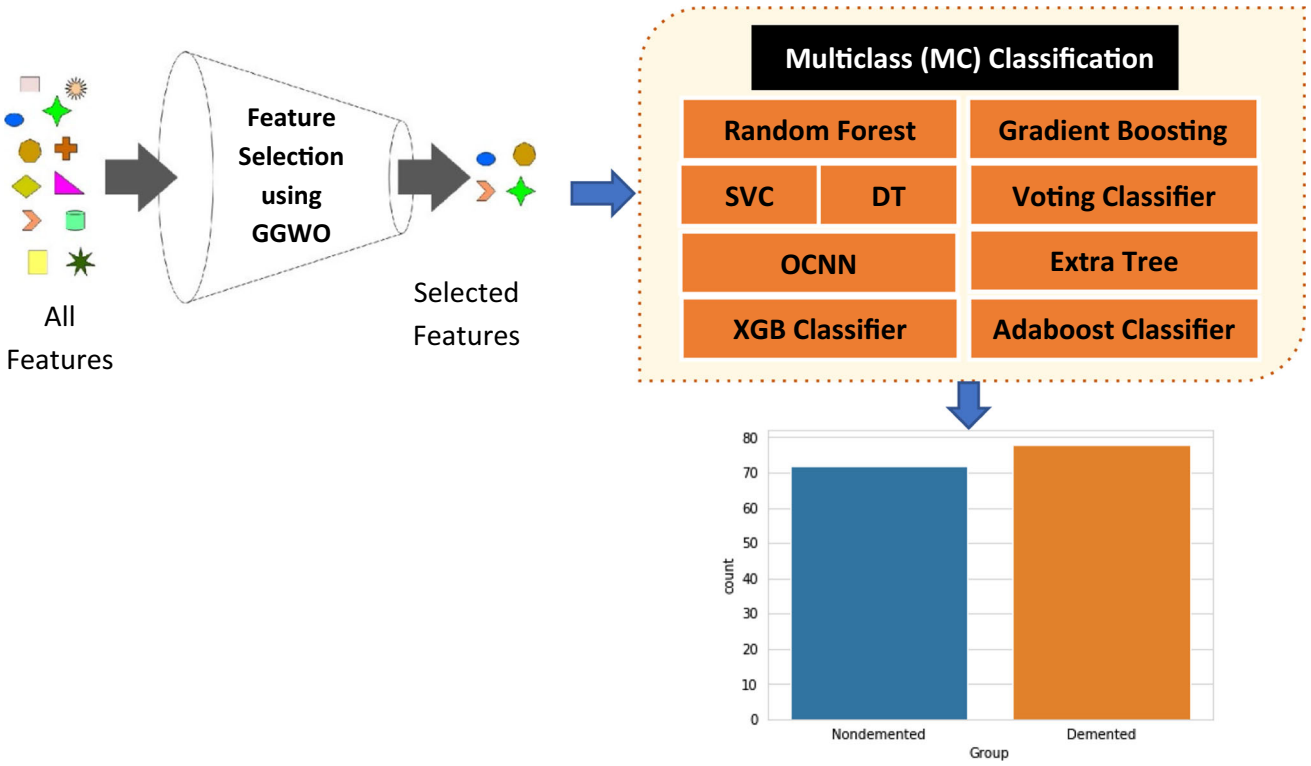

Fig. 6 Multiclass (MC) Classification

request. The ordered wolves' primary characteristics are the most effective. The shade serves to distinguish one set of particles from another in each group.

iii. Assessment of the Objective Function

It's imperative to assess the fitness within every data block, placing significant importance on this step. The foremost consideration when defining the fitness function revolves around achieving accurate classification. This function's evaluation is performed for each recorded cycle, as indicated by Eq. (2).

$$Acc = \frac{GC + GN}{GC + GN + WC + WN} \tag{2}$$

Table 2 Data description

Col	Description
EDUC	Years of Education
SES	Socioeconomic Status
MMSE	Mini Mental State Examination
CDR	Clinical Dementia Rating
eTIV	Estimated Total Intracranial Volume
nWBV	Normalize Whole Brain Volume
ASF	Atlas Scaling Factor

Acc represents the accuracy of classification, determined by the ratio of correctly classified features (*GC*, *GN*) to all features classified (*GC*, *GN*, *WC*, *WN*).

iv. Updating the process of selecting features

After the evaluation of fitness, the solution is modified in accordance with updates inspired by the behavior of gray wolves.

3.5.1 Multiclass (MC) classification

In this section, the multiclass classification process is discussed. A range of classifiers depicted in Fig. 6 are employed, comprising Random Forest, Support Vector Classifier (SVC), Decision Tree (DT), XGB Classifier, Optimized Convolutional Neural Network (OCNN), Voting Classifier, Extra Tree Classifier, Gradient Boosting, and Adaboost Classifier.

4 Results and discussion

This section introduces the used dataset and the results of the proposed algorithm.

Fig. 7 A sample of data

	Subject ID	MRI ID	Group	Visit	MR Delay	M/F	Hand	Age	EDUC
0	OAS2_0001	OAS2_0001_MR1	Nondemented	1	0	M	R	87	14
1	OAS2_0001	OAS2_0001_MR2	Nondemented	2	457	M	R	88	14
2	OAS2_0002	OAS2_0002_MR1	Demented	1	0	M	R	75	12
3	OAS2_0002	OAS2_0002_MR2	Demented	2	560	M	R	76	12
4	OAS2_0002	OAS2_0002_MR3	Demented	3	1895	M	R	80	12

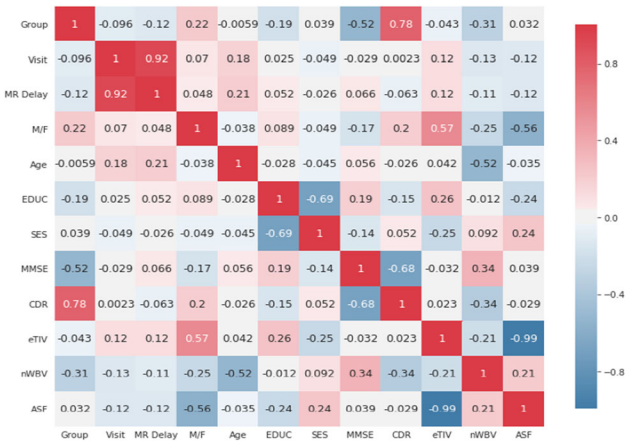

Fig. 8 The correlation map

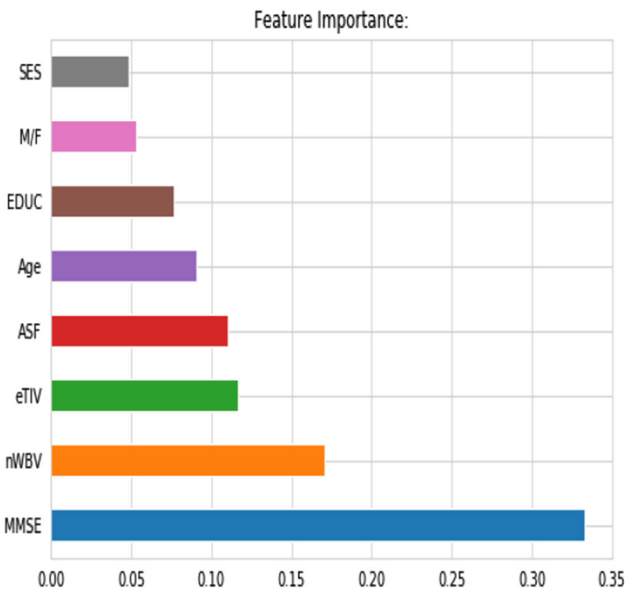

Fig. 9 Feature Importance

4.1 Dataset decryption

One hundred and fifty individuals between the ages of 60 and 96 make up this longitudinal group [26]. A group of 373 imaging sessions involved multiple scans of each participant, spaced at least one year apart. Each subject underwent three to four separate T1-weighted MRI scans

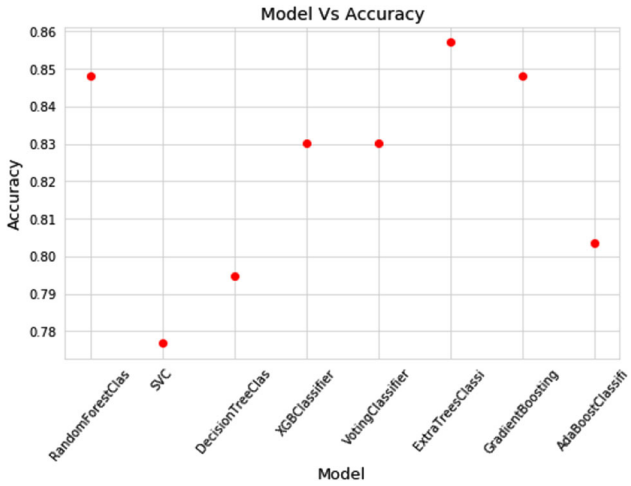

Fig. 10 Model vs. accuracy

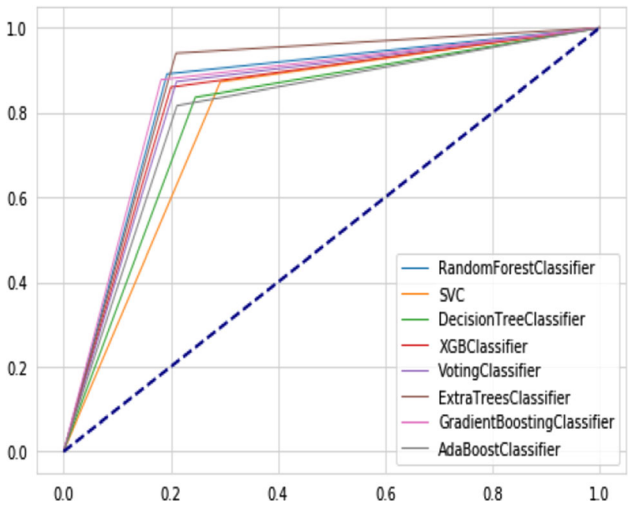

Fig. 11 ROC

during a single scanning session. Men and women, both right-handed, are represented among the subjects. Throughout the entire trial, 72 of the individuals were classified as non-demented. Fifty-one people with mild to severe dementia disease were among the 64 included patients who were classified as having dementia at the time of their initial visits and remained such for successive scans. At the time of their second visit, 14 additional

Table 3 Classification results on multi-class

Classifier	Accuracy without optimization	Accuracy with optimization
Random Forest	0.848	0.944
SVC	0.776	0.855
DT	0.794	0.874
XGB Classifier	0.830	0.931
Voting Classifier	0.839	0.943
Extra Tree Classifier	0.857	0.972
Gradient Boosting	0.848	0.954
Adaboost Classifier	0.803	0.946

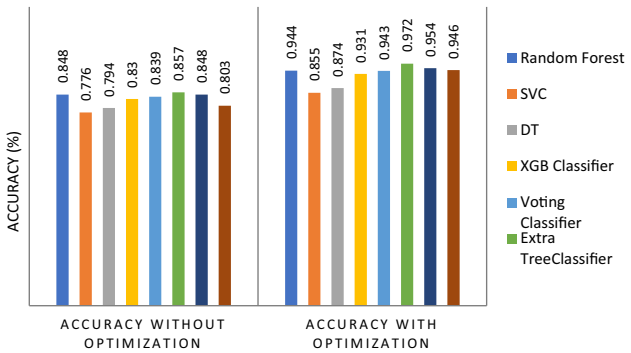

Fig. 12 The performance for each classifier without optimization vs. with optimization

participants who had been initially classified as non-demented were discovered to have dementia.

The longitudinal MRI data will be used. The collection includes longitudinal MRI data from 150 patients, ranging in age from 60 to 96. At least one scan was performed on each individual. Everyone uses their right hand. Throughout the investigation, 72 participants were categorized as "Non-demented." Sixty-four of the participants were classified as "Demented" at the time of their first visits and remained in this category for the duration of the study. Fourteen participants who were first categorized as "Non-demented" were later labeled "Demented" during a subsequent visit. These are classified as "Converted." The data description is shown in Table 2. A sample of data is shown in Fig. 7.

The correlation map that shows the correlation between features is shown in Fig. 8. And the impotence for each feature is shown in Fig. 9.

4.2 Results of each classifier without optimization

This section introduces the results of each classifier as shown in Figs. 10, 11.

4.3 Results of each classifier with optimization

The outcomes for individual classifiers are depicted in Table 3 and Fig. 12, both before and after employing optimal features and hyperparameters.

The employment of the Gray Wolf Optimization (GWO) algorithm significantly enhanced the accuracy of various classifiers, as depicted in Fig. 10, which showcases notable improvements in models such as the Random Forest, XGB Classifier, and Extra Tree Classifier, with the latter increasing in accuracy from 85 to 97%. Figure 9 illustrates the relative importance of features derived from MRI scans, highlighting critical biomarkers such as hippocampal volume and cortical thickness, which are paramount in early-stage dementia prediction. Moreover, Fig. 11's ROC Curve further substantiates the robust diagnostic capability of our optimized models, with most achieving AUC scores above 0.90, indicating a high degree of sensitivity and specificity. These improvements are not merely statistical but carry profound implications for clinical practice, particularly in enabling early and accurate dementia diagnosis in younger adults, which can significantly alter treatment approaches and improve patient outcomes. However, the study acknowledges limitations due to the dataset's demographic homogeneity and suggests future research should include more diverse populations and integrate additional diagnostic modalities like PET scans and genetic markers to enhance diagnostic generalizability and accuracy. This research underscores the potential societal benefits of improved dementia diagnostics, especially given the aging global population, by potentially reducing the healthcare burden through earlier intervention and tailored treatment strategies, thereby extending productive years and reducing extensive caregiving needs.

From Table 3 and Fig. 12, it is shown that the accuracy after optimization (using the optimal features and optimal hyperparameters) is much better than the accuracy without optimization.

Table 4 Comparison of feature selection methods

Method	Selected features	Accuracy (%)	Feature selection time (s)
Genetic Algorithm (GA)	20	89.5	15.3
Particle Swarm Optimization (PSO)	18	90.2	13.7
Group Gray Wolf Optimization (GGWO)	22	93.4	12.5

Table 5 Classification performance before and after applying GGWO

Classifier	Accuracy before optimization (%)	Accuracy after optimization (%)
Random Forest	85.6	91.3
Support Vector Classifier (SVC)	87.1	92.5
XGBoost Classifier	88.9	94.2
EDCM (Our Method)	89.2	95.7

4.4 Comparison with similar methods in the literature

To provide a comprehensive understanding of the advantages of our Enhanced Dementia Detection and Classification Model (EDCM), we have compared our method with several similar approaches from the literature. This comparison focuses on key performance metrics such as accuracy, feature selection efficiency, and classification performance.

4.4.1 Feature selection comparison

Our model employs the Group Gray Wolf Optimization (GGWO) algorithm for feature selection, which we found to outperform traditional methods like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). GGWO's superior ability to identify the most relevant features from the dataset enhances the overall performance of our classification model. Table 4 presents a comparison of feature selection methods.

4.4.2 Classification performance

We evaluated the classification performance of our EDCM against several established classifiers including Random Forest, Support Vector Classifier (SVC), and XGBoost Classifier. After optimization, our model demonstrated a significant improvement in accuracy and other performance metrics. Table 5 compares the classification performance before and after applying the GGWO optimization.

4.4.3 Comparative analysis

From the comparisons, it is evident that our method provides a notable improvement in both feature selection and classification performance. The GGWO algorithm's efficiency in feature selection translates directly to enhanced accuracy and reduced computational time. Additionally, our multiclass classification results indicate a substantial performance boost, positioning our model as a robust tool for dementia detection and classification.

4.5 Limitations

Despite the promising results, there are several limitations to this study:

- *Dataset Size and Diversity* The dataset used in this study, while comprehensive, may not encompass all variations seen in broader, real-world populations. Future work should include more diverse and extensive datasets to validate the model's generalizability.
- *Computational Complexity* The GGWO algorithm, while effective, can be computationally intensive. This might limit its application in real-time or resource-constrained environments. Future research could focus on optimizing the computational efficiency of the GGWO algorithm.
- *Feature Dependence* The model heavily relies on the quality and relevance of the features selected. Future studies should explore more advanced and automated feature engineering techniques to reduce potential biases introduced during feature selection.

4.6 Future research directions

To address the aforementioned limitations and further enhance the EDCM, future research could focus on the following directions:

- *Integration with Larger and More Diverse Datasets* To improve the robustness and generalizability of the model, future work should involve validating the model with larger and more diverse datasets. This includes

cross-institutional data and datasets with varying demographic and clinical characteristics.

- *Enhancing Computational Efficiency* Investigating more efficient variants of the GGWO algorithm or alternative optimization algorithms could reduce computational overhead, making the model more suitable for real-time applications.
- *Incorporating Correlation-Based Methods* Future studies could incorporate advanced correlation-based methods to improve feature selection. Exploring techniques such as Spearman's rank correlation, Pearson correlation, and partial correlation, as noted in [27–29], may further enhance the model's performance.
- *Real-Time Application and Validation* Implementing the model in a real-time clinical setting to validate its practical utility and effectiveness. This involves collaboration with healthcare providers to assess the model's impact on clinical decision-making.
- *Multimodal Data Integration* Future research could explore integrating multimodal data (e.g., imaging, genetic data, and clinical records) to provide a more comprehensive assessment of dementia and improve diagnostic accuracy.

By addressing these limitations and exploring the outlined future research directions, the proposed EDCM can be further refined and validated, paving the way for its potential application in clinical settings to aid in early detection and classification of dementia.

5 Conclusion

This research proposed an Enhanced Dementia Detection and Classification Model (EDCM) which is composed of four main modules which are as follows: (i) Data Acquisition Module (DAM) (ii) Data Preprocessing Module (DPM), (iii) Hyperparameter Optimization Module (HOM), (iv) Feature Extraction and Classification (FECM). From the results, it is shown that the accuracy after optimization (using the optimal features and optimal hyperparameters) is much better than the accuracy without optimization. For example, while using Extra Tree Classifier in normal with the used dataset, it achieved accuracy 85%. However, after applying the extra tree classifier with optimal features and optimal hyperparameters after applying the proposed optimization algorithm using GGWO, it achieved accuracy 97%. Leveraging OCNN could enhance outcomes when applied to extensive datasets, given its successful track record documented in [30–34]. Additionally, we might explore employing methods of correlation as noted in [27–29].

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Data availability https://www.kaggle.com/code/deepak525/dementia-classification-compare-classifiers/data.

Code availability The code will be available on request.

Declarations

Conflict of interest There is no conflict of interest.

Ethical approval There are no ethical conflicts.

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References

1. Bhagtani A, Choudhury T, Raj G and Sharma M (2017) An efficient survey to detect Alzheimer disease using data mining techniques. In: 2017 3rd International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT) (pp 64–70). IEEE
2. Simons S, Abasolo D, Escudero J (2015) Classification of Alzheimer's disease from quadratic sample entropy of electroencephalogram. Healthc Technol Lett 2(3):70–73
3. Sharma J and Kaur S (2017) Gerontechnology-The study of alzheimer disease using cloud computing. In: 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS) (pp 3726–3733). IEEE
4. Alam S, Kang M and Kwon GR (2017) Alzheimer disease classification based on TSVM and Kernel SVM. In: 2017 Ninth International Conference on Ubiquitous and Future Networks (IiuCUFN), (pp 565–567). IEEE
5. Daza JC and Rueda A (2016) Classification of Alzheimer's disease in MRI using visual saliency information. In: Computing Conference (CCC), 2016 IEEE 11th Colombian (pp 1–7). IEEE
6. Chupin M, Gérardin E, Cuingnet R, Boutet C, Lemieux L, Lehéricy S, Benali H, Garnero L, Colliot O (2009) Fully automatic hippocampus segmentation and classification in Alzheimer's disease and mild cognitive impairment applied on data from ADNI. Hippocampus 19(6):579–587
7. https://www.healthdirect.gov.au/younger-onset-dementia
8. Preethi S, Aishwarya P (2019) "Combining wavelet texture features and deep neural network for tumor detection and segmentation over MRI". J Intell Syst 28(4):571–588. https://doi.org/10.1515/jisys-2017-0090
9. Gulhare KK, Shukla SP, Sharma LK (2017) Overview on segmentation and classification for the Alzheimer's disease detection from brain MRI. J Comput Trends Technol 43(2):130–132

10. Zhang Y, Wang S, Dong Z (2014) Classification of Alzheimer disease based on structural magnetic resonance imaging by kernel support vector machine decision tree. Prog Electromagn Res 144:171–184
11. Rawat W, Wang Z (2017) Deep convolutional neural networks for image classification: a comprehensive review. Neural Comput 29(9):2352–2449
12. Zhang D, Shen D, Initiative ADN (2012) Multi-modal multi-task learning for joint prediction of multiple regression and classification variables in Alzheimer's disease. Neuroimage 59(2):895–907
13. Pelleieux S, Picard C, Lamarre-Théroux L, Dea D, Leduc V, Tsantrizos YS, Poirier J (2018) Isoprenoids and tau pathology in sporadic Alzheimer's disease. Neurobiol Aging 65:132–139
14. Schouten TM, Koini M, de Vos F, Seiler S, de Rooij M, Lechner A, Schmidt R, van den Heuvel M, van der Grond J, Rombouts SA (2017) Individual classification of Alzheimer's disease with diffusion magnetic resonance imaging. Neuroimage 152:476–481
15. Ali EM, Seddik AF, Haggag MH (2016) Automatic detection and classification of alzheimer's disease from MRI using TANNN. Int J Comput Appl 148:30–34.https://doi.org/10.5120/ijca2016911320
16. Qin Y, Cui J, Ge X, Tian Y, Han H, Fan Z, Liu L, Luo Y, Yu H (2022) Hierarchical multi-class Alzheimer's disease diagnostic framework using imaging and clinical features. Front Aging Neurosci 14:935055. https://doi.org/10.3389/fnagi.2022.935055. PMID: 36034132; PMCID: PMC9399682.
17. Sun Z, Qiao Y, Lelieveldt BP, Staring M and Alzheimer's DiseaseNeuroImaging Initiative (2018) Integrating spatial-anatomical regularization and structure sparsity into SVM: improving interpretation of Alzheimer's disease classification. NeuroImage
18. Zu C, Wang Y, Zhou L, Wang L and Zhang D (2018). Multi-modality feature selection with adaptive similarity learning for classification of Alzheimer's disease. In: Biomedical Imaging (ISBI 2018), 2018 IEEE 15th International Symposium on (pp 1542–1545). IEEE
19. Xiao Z, Ding Y, Lan T, Zhang C, Luo C, Qin Z (2017) Brain MR Image Classification for Alzheimer's Disease Diagnosis Based on Multifeature Fusion. Comput Math Methods Med 2017:1952373. PMID: 28611848; PMCID: PMC5458434.https://doi.org/10.1155/2017/1952373
20. Farouk Y, Rady S and Faheem H (2018) Statistical features and voxel-based morphometry for Alzheimer's disease classification, conference on information and communication systems, pp133–138
21. Islam J and Zhang Y (2017) An ensemble of deep convolutional neural networks for Alzheimer's disease detection and classification. arXiv preprint arXiv:1712.01675
22. Long W and Xu S (2016) A novel grey wolf optimizer for global optimization problems. In: Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), 2016 IEEE (pp 1266–1270). IEEE
23. Talaat FM, Gamel SA (2022) RL based hyper-parameters optimization algorithm (ROA) for convolutional neural network. J Ambient Intell Human Comput. https://doi.org/10.1007/s12652-022-03788-y
24. Panza F, Frisardi V, Capurso C, D'Introno A, Colacicco AM, Imbimbo BP, Santamato A, Vendemiale G, Seripa D, Pilotto A, Capurso A, Solfrizzi V (2010) Late-life depression, mild cognitive impairment, and dementia: Possible continuum? Am J Geriatr Psychiatry 18(2):98–116. https://doi.org/10.1097/JGP.0b013e3181b0fa13
25. Mehmood A, Maqsood M, Bashir M, Shuyuan Y (2020) A Deep Siamese convolution neural network for multi-class classification of Alzheimer disease. Brain Sci 10(2):84. https://doi.org/10.3390/brainsci10020084
26. https://www.kaggle.com/code/deepak525/dementia-classification-compare-classifiers/data
27. Talaat FM, Gamel SA (2024) Machine learning in detection and classification of leukemia using C-NMC_Leukemia. Multimed Tools Appl 83(3):8063–8076
28. Hassan E (2024) Enhancing coffee bean classification: a comparative analysis of pre-trained deep learning models. Neural Comput & Applic 36:9023–9052. https://doi.org/10.1007/s00521-024-09623-z
29. Talaat FM, El-Balka RM (2023) Stress monitoring using wearable sensors: IoT techniques in medical field. Neural Comput Appl 35(25):18571–18584
30. Talaat FM (2023) Crop yield prediction algorithm (CYPA) in precision agriculture based on IoT techniques and climate changes. Neural Comput Appl 35(23):17281–17292
31. Alshathri S, Talaat FM, Nasr AA (2022) A new reliable system for managing virtual cloud network. Comput Mater Contin 73(3)
32. Shams MY, Elshewey AM, El-Kenawy ESM, Ibrahim A, Talaat FM, Tarek Z (2024) Water quality prediction using machine learning models based on grid search method. Multimed Tools Appl 83(12):35307–35334
33. Talaat FM, Hassan E (2021) Artificial intelligence in 3D printing. In: Enabling Machine Learning Applications in Data Science: Proceedings of Arab Conference for Emerging Technologies 2020 (pp 77–88). Springer Singapore
34. Hassan E, Talaat FM, Hassan Z, El-Rashidy N (2023) Breast cancer detection: a survey. In: Artificial intelligence for disease diagnosis and prognosis in smart healthcare (pp 169–176). CRC Press

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