International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(2) 2026 pp. 203-214
https://doi.org/10.70917/ijcisim-2026-2411
Article

Hybrid Optimization-Based Machine Learning Framework for Predicting Mild Cognitive Impairment Progression

Lavanya M S[1],Vanishri Arun*[2],Mayura Tapkire[3], C.K.Vanamala[4], Padma M T[5],Manjunath Naganna[6],Vinutha Prakash[7]

[1,2*,7]JSS Science and Technology University, Mysuru, Karnataka, India
[6]Vidya Vikas Institute of Engineering & Technology,Mysuru, Karnataka, India
[3,4,5]The National Institute of Engineering, Mysuru, Karnataka, India
[*]**Corresponding Author:** Vanishri Arun*

Abstract: — Mild Cognitive Impairment (MCI) is a transitional state from normal aging to dementia. Early detection of its progression is critical for clinical intervention and patient care in a timely manner. In this study, a hybrid machine learning approach to predict the progression from MCI to dementia using OASIS dataset. The proposed methodology combines Recursive Feature Elimination (RFE), Particle Swarm Optimization (PSO), Sequential Model-Based Optimization (SMBO) and Gradient Boosting Classifier (GBC) to improve prediction performance and model robustness. Preprocessing techniques were utilized to rectify missing values, remove superfluous features and execute category encoding. RFE was utilized to discern the most relevant clinical and neuroimaging attributes associated with dementia progression, while PSO was applied to refine feature subsets and enhance model efficiency. The hyperparameter optimization of the GBC was accomplished using Optuna-based SMBO to determine the optimal parameter configuration. The optimized framework effectively found complex nonlinear relationships among cognitive, demographic and brain imaging factors. The experimental results demonstrated that the proposed model achieved a classification accuracy of 96%, showcasing good precision, recall and F1-score in distinguishing stable MCI from MCI that advanced to dementia.The model demonstrated reliable predictive performance with robust ROC-AUC and Precision-Recall AUC scores. SHAP-based interpretability analysis revealed that age, normalized whole-brain volume, Clinical Dementia Rating (CDR), Mini-Mental State Examination (MMSE)were the most significant predictors of dementia conversion. The combination of PSO with RFE and SMBO improved feature optimization and model generalization. The proposed method is an effective decision-support tool for early evaluation of dementia risk and personalized clinical care for neurodegenerative diseases.

Keywords: — Dementia, Gradient Boosting Classifier (GBC), Mild Cognitive Impairment (MCI), OASIS, Optuna, Particle Swarm Optimization (PSO), Recursive Feature Elimination (RFE), Sequential Model-Based Optimization (SMBO).

1. Introduction

Individuals with MCI experience a decline in cognitive abilities beyond that of the general population as a whole, yet they are not completely unable to carry out their daily tasks on their own. A big challenge in contemporary healthcare is the early detection and prognosis of disease development; furthermore, a significant number of people with MCI develop dementia in the long run. Doctors can begin early interventions, optimize treatment strategies, and improve patient care management when dementia is detected early on [1]. The rapid increase in neurodegenerative diseases due to the world's aging population emphasizes the need for accurate and trustworthy models to predict how dementia will progress. Advances in computational intelligence, clinical evaluation methodologies, and neuroimaging have greatly aided the development of diagnostic tools for neurodegenerative illnesses that rely on machine learning [2]. Biomarkers that can be used to detect patterns of cognitive deterioration include demographic characteristics, structural magnetic resonance imaging (MRI), and scores on cognitive assessments [3]. Research on dementia prediction has mostly made use of traditional statistical methods, such as linear models and logistic regression. However, the high-dimensional, nonlinear interactions present in medical data are often misrepresented by these

methods [4]. The optimization and the machine learning have become feasible choices to improve the accuracy and robustness of forecasts. Several machine learning algorithms have been explored for the classification of Alzheimer's disease and for the prediction of MCI progression, including Support Vector Machines (SVMs), Random Forest (RFs), Convolutional Neural Networks (CNNs) and Gradient Boosting techniques. [5]. Ensemble learning methods, especially GBC, have shown improved prediction accuracy by learning repeatedly from classification errors and representing complex relations in the data. However, feature selection and hyperparameter optimization are critical for the success of machine learning models [6]. The high-dimensional data sets with redundant and duplicate characteristics might significantly effect the model generalizability and computational complexity. Feature selection techniques are important to make models more efficient and more interpretable. RFE is a prominent feature selection method that identifies the most informative subset of characteristics by iteratively deleting less important features [7]. However, the search for the optimal feature subset still is an optimization problem. Metaheuristic optimization approaches such as PSO have been used to rapidly search the space for optimal feature combinations that improve predictive performance . have shown remarkable efficiency in addressing difficult optimization issues by simulating swarm collective behavior [8].In order to enhance classification accuracy and reduce duplicate features, frameworks for dementia and Alzheimer's disease prediction have successfully utilized PSO-based feature optimization algorithms [9]. In a similar vein, SMBO powered by the Optuna framework offers a versatile and astute method for hyperparameter tweaking, efficiently exploring the hyperparameter search space to find the best possible model settings [10]. These advancements inspired the study, which used the OASIS dataset to introduce a hybrid predictive model for forecasting the progression of mild cognitive impairment (MCI) to dementia. By integrating RFE, PSO, SMBO, and GBC, the proposed method enhances the model's resilience, feature optimization, and prediction accuracy. Addressing missing values, encoding category features, and eliminating redundant information are the initial steps in using preprocessing techniques. PSO improves the feature subsets to increase classification efficiency, while RFE is used to find clinically relevant features. In addition, the GBC model's hyperparameters are optimized using Optuna-based SMBO to get the optimal configuration. The results show that the suggested hybrid framework accurately and precisely predicts the course of dementia, and it also recalls the information well. Further, the impact of cognitive and neuroimaging biomarkers on prediction results can be better understood by SHAP-based interpretability analysis, which offers therapeutically relevant reasons. A trustworthy and understandable decision-support system for early dementia risk assessment and individualized healthcare management can be built by combining optimization methods with machine learning.

The major contributions of this study are summarized as follows:

1. The suggested approach efficiently predicts outcomes by utilizing clinical and neuroimaging factors retrieved from the OASIS dataset.
2. Analyzing interpretability using SHAP (SHapley Additive Explanations) enhances the predictive model's transparency and clinical credibility.
3. To increase classification performance and generalization capacities while decreasing overfitting, an optimal feature selection and hyperparameter tuning approach is proposed for predicting the shift from mild cognitive impairment to dementia.

2. Literature survey

The early detection and prediction of Alzheimer's disease (AD) and MCI have been greatly enhanced by recent advancements in neuroimaging and machine learning. Multiple studies have investigated the feasibility of using cognitive biomarkers in conjunction with neuroimaging data and clever predictive algorithms to track the development of dementia from MCI. The significance of feature selection, optimization methods, and ensemble learning techniques in improving classification accuracy and model robustness has been highlighted in previous studies. A marked decline in cognitive capacities and maintenance of everyday autonomy characterize MCI, which is defined by Petersen et al. [11] as a transitional stage between normal aging and dementia. The study's findings—that persons with MCI are at a higher risk of acquiring AD highlight the need of early prediction and management. A meta-analysis was conducted by Belleville et al. [12] to find out how well neuropsychological tests, when combined with machine learning algorithms, can diagnose MCI and predict whether it would progress to AD. The results demonstrated that Machine Learning algorithms significantly improve classification accuracy and help find important neuropsychological biomarkers associated with cognitive decline. Akan et al. [13] discussed how neuroimaging and AI are important for the diagnosis of neurodegenerative illnesses. Deep learning algorithms, clinical biomarkers, and structural MRI can better detect patterns associated with dementia progression, according to their study. The authors argue that AI models should be explicable and non-invasive biomarkers should be given priority in clinical decision support systems.

Regardless of the course of the disease, Ding et al. [14] demonstrated that Machine Learning models trained using MRI scans and clinical evaluations can correctly classify individuals with AD and MCI. The study discovered that intelligent diagnostic tools might reliably assist in the diagnosis of dementia using a range of datasets and scanning procedures. Mathotaarachchi et al. [15] introduced a supervised machine learning system for AD illness prediction using longitudinal MRI scans, demographic data, and clinical biomarkers. Gradient Boosting approaches outperform many traditional classifiers, according to their study, which achieved an overall accuracy of 97.58%. Feature selection methods have become critical due to the proliferation of high-dimensional datasets in the medical field.According to a study of feature selection methodologies by Singh et al. [16], the existence of duplicated and irrelevant features increases both the computational cost and model generalizability in high-dimensional datasets. To improve classification performance, the study found that finding beneficial features to use was the most important factor. Enhanced Recursive Feature Elimination, or EnRFE, was created by Yan et al. [17] to improve the performance of standard RFE in high-dimensional classification problems. The approach outperformed conventional RFE methods by improving the model's accuracy and generalizability through the elimination of superfluous attributes. Wang et al. [18] offered a system for selecting critical MRI features associated with MCI and Alzheimer's disease. Universe SVM and recursive feature reduction were also incorporated. Findings demonstrated a considerable improvement in the study's categorization accuracy when comparing subjects with MCI and AD symptoms. Several studies have used deep learning in conjunction with feature selection approaches to forecast the onset of dementia. The use of CNNs in conjunction with RFE for structural MRI-based dementia classification was explored by Hosseini-Asl et al. [19]. Their findings demonstrated that feature selection and deep learning models significantly simplify the process of distinguishing MCI converters from non-converters. Hyperparameter optimization techniques have also recently become very popular in the machine learning community. Hutter et al. [20] proposed SMBO as a means to automate the optimization and configuration of algorithms' hyperparameters. Their findings demonstrate that SMBO efficiently explores the search space to discover optimal solutions to various computing problems. Metaheuristic algorithms such as PSO have demonstrated remarkable effectiveness in tackling challenging optimization problems. Similar to how swarm intelligence works, PSO uses feature subsets and parameter combinations to obtain the best possible outcome. The optimization of features, the elimination of redundancy, and the promotion of classification accuracy are all enhanced when PSO is integrated with Machine Learning classifiers in high-dimensional healthcare datasets. Several studies have investigated machine learning techniques for Alzheimer's disease prediction; nevertheless, present methodology still face challenges with feature redundancy, computational complexity, and model interpretability. Due to this, the proposed research introduces a mixed-model Machine Learningsystem that uses RFE, PSO, SMBO and GBC to foretell whether a person suffering from mild cognitive impairment will eventually develop dementia. The study aims to develop an efficient and user-friendly decision-support system for early dementia prediction using this proposed framework. The goal is to increase the accuracy of our forecasts while making them easy to understand.

3. Proposed Methodology

The proposed framework consists of three major processes: data collection and preprocessing, optimized feature selection, and model training with performance evaluation which is shown in Figure 1. The main objective of the framework is to predict the progression from MCI to dementia using the OASIS dataset.

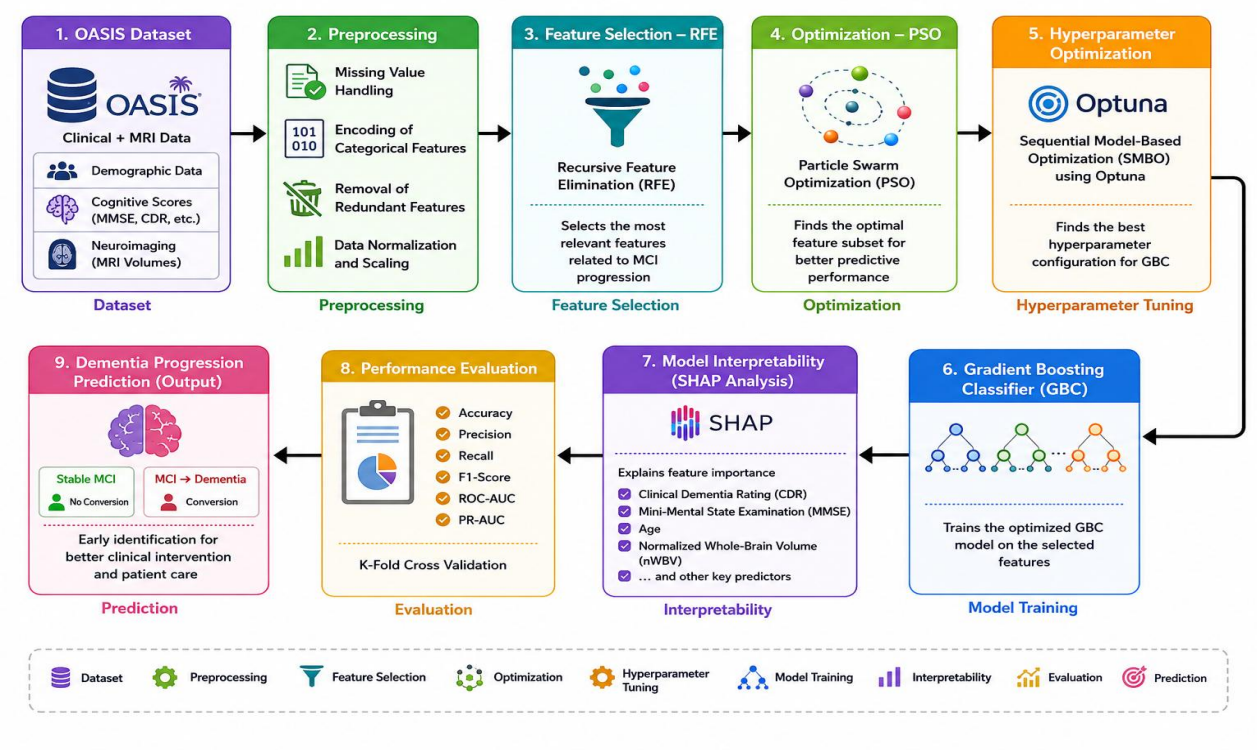

Figure 1. The Framework Architecture of the system

The Current method employ RFE, SMBO, Optuna and GBC for feature selection, hyperparameter optimization and classification. The improved framework makes use of PSO to fortify the model's predictive capabilities and boost feature selection. To begin, the OASIS dataset is preprocessed to remove any inconsistent data and make it acceptable for training the machine learning model. This will ensure that the model can make accurate predictions. Following preprocessing, RFE is used to determine which traits are most indicative of a progression from MCI to dementia. The RFE is able to accomplish its goal by iteratively training the model and discarding features that aren't crucial to the model's classification performance. As a result, dimensionality is decreased, superfluous attributes are removed and interpretability is enhanced. The suggested model relies on RFE choosing a small subset of clinically relevant characteristics that have a major impact on dementia stage. Following the RFE stage, PSO is incorporated to further improve feature selection. The population-based optimization method known as PSO takes its cues from the way fish and birds navigate their environments. In this model, the swarm looks for the optimal combination of features to achieve maximum classification accuracy, with each particle standing in for a potential feature subset. We update the particle's position and velocity depending on our best and the world's best solutions. A more optimal feature subset, less redundancy, and better model generalization are all outcomes of the framework's use of RFE and PSO together. The PSO-optimized feature subset is then used for training the GBC and it is an ensemble learning algorithm that combines several weak decision tree learners to form a strong predictive model. It improves classification performance by learning from previous prediction errors in an iterative manner. Since the performance of GBC depends strongly on suitable hyperparameter values, Optuna-based SMBO is used for hyperparameter tuning. SMBO searches the hyperparameter space intelligently and identifies the best configuration for parameters such as number of estimators, learning rate, maximum depth and subsampling ratio. The final optimized GBC model is trained using the selected features and evaluated using the testing data. The performance of the model is measured using accuracy, precision, recall, F1-score, ROC-AUC, Precision-Recall AUC and confusion matrix. The framework also includes SHAP-based interpretability analysis to explain the influence of individual features on the prediction outcome. Features such as CDR, MMSE, age and nWBV are expected to contribute significantly to the prediction of dementia progression. Thus, the proposed framework integrates RFE, PSO, SMBO and GBC to develop an optimized and interpretable machine learning model for predicting MCI progression to dementia. The inclusion of PSO improves the feature optimization process, while SMBO enhances model tuning. This hybrid approach supports early dementia risk prediction and provides useful assistance for clinical decision-making, patient monitoring and personalized intervention planning.

A. OASIS Dataset

This study used the OASIS dataset to forecast the development of dementia from mild cognitive impairment. The OASIS neuroimaging dataset is open to the public and was created to aid studies on aging, Alzheimer's disease, and other neurodegenerative disorders. People with normal and decreased cognitive abilities, ranging in age from 60 to 96 years, are included in the longitudinal clinical and MRI data collection. Patients completed a battery of MRI scans and clinical appointments after being hand-picked from the Alzheimer Disease Research Center (ADRC) at Washington University in St. Louis [21]. The dataset comprises demographic, clinical and neuroimaging-related parameters that are very significant to dementia progression study. The following important attributes are used in this study: age, sex, years of education, socioeconomic status (SES), MMSE score, CDR, Atlas Scaling Factor (ASF), estimated Total Intracranial Volume (eTIV), normalized Whole Brain Volume (nWBV), subject ID, MRI ID, group and visit information. These traits provide important information about cognitive decline, structural brain abnormalities and disease severity related to dementia progression. The data preparation involved the application of preprocessing techniques to increase the quality and consistency of the dataset. Missing data were handled appropriately, redundancy was removed and categorical attributes have been transformed into numerical representations suited for machine learning techniques. Then the dataset was split into training and testing subsets to build and evaluate the model. The OASIS dataset is particularly appropriate for this investigation, as it includes longitudinal information that enables an analysis of cognitive change across time. The integration of demographic, cognitive and neuroimaging indicators offers a complete picture of the patients' situations and paves the way for the construction of precise predictive models of dementia progression [22]. The dataset description used in this work is presented in Table 1.

Table 1. Description of OASIS Dataset

Sl.No	Features	Description
1.	Age	Age at time of image acquisition (years)
2.	Sex	Male or Female
3.	Education	Years of education
4.	SES	Socioeconomic status
5.	MMSE	Mini-Mental State Examination score
6.	CDR	Clinical Dementia Rating
7.	ASF	Atlas scaling factor
8.	eTIV	Estimated total intracranial volume
9.	nWBV	Normalized whole-brain volume
10.	Subject ID	Subject ID of the patient
11.	MRI ID	MRI ID of the patients who visited
12.	Group	Demented or Non-Demented group
13.	Visit	Number of Visit made by patients

B. Feature Selection using RFE and PSO

By determining which characteristics are most strongly linked to the development of dementia, feature selection helps to make machine learning models more accurate and easier to understand and work with. Duplicate or unimportant characteristics in high-dimensional datasets can make classification more difficult and computationally expensive [23]. To determine the best subset of variables for predicting the development of dementia from MCI, the suggested framework combines RFE and PSO. The first step is to use RFE to prioritize the OASIS dataset's features. RFE is a method for selecting features that iteratively trains a classifier by removing features that aren't very important until the target number of attributes is reached [24]. The approach uses the GBC significance scores to determine each

feature's relative value. Reduced dimensionality and improved model interpretability are the results of RFE's elimination of unimportant and uninformative characteristics [25]. During the RFE process, the correlation between feature selection frequency and model correctness is examined. Once the ideal feature subset is reached, performance stabilizes, but initially, accuracy increases with informative feature selection. Among the features that were chosen for inclusion are clinically important ones, like age, nWBV, CDR and MMSE, all of which have a substantial role in predicting the course of dementia.The relationship between negative accuracy and the number of selected features is depicted in Figure 2. At first, accuracy rises quickly and peaks at about two or three features. After a discernible decline at four features, the performance levels off at 0.95 as the number of features rises [26]. This suggests that the ideal feature subset is between two and three features; adding more features does not considerably enhance model performance beyond that point.

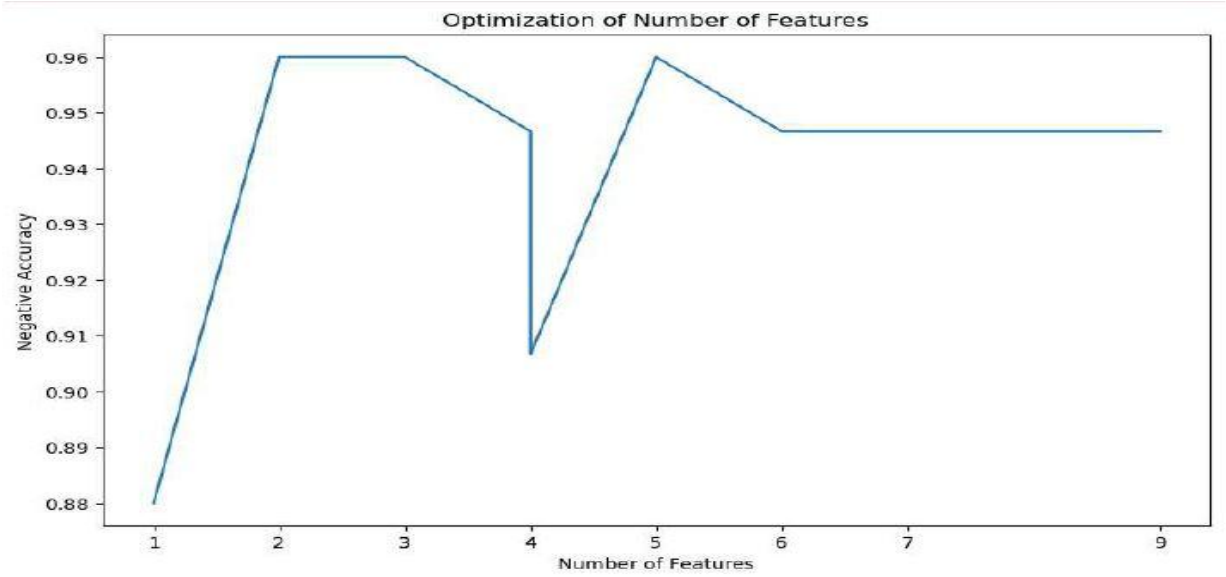

Figure 2. Optimization of number of features

Following the RFE stage, PSO is integrated to enhance feature selection even further. PSO is an optimization algorithm that uses swarm intelligence and takes its cues from the way fish and birds move together [27]. Under the suggested architecture, a swarm of particles stands in for potential feature subsets, and their collective goal is to find the best possible combination of features to achieve the highest possible classification accuracy. Iteratively updating particle velocities and positions according to their individual and global optimum solutions is what the optimization process is all about.

The velocity update equation of PSO is represented in equation 1 as

$$v_i^{t+1} = wv_i^t + c_1 r_1 (p_i - x_i^t) + c_2 r_2 (g - x_i^t) \quad (1)$$

The particle position update equation is given in equation 2 as

$$X_i^{t+1} = x_i^t + v_i^{t+1} \quad (2)$$

where v_i^{t+1} represents the updated particle velocity, X_i^{t+1} denotes the updated particle position, $p_i$is the personal best solution, g represents the global best solution, w is the inertia weight and c_1 and $c_2$are acceleration coefficients.The combination of RFE and PSO enhances the selection of an optimal feature subset by effectively exploring the search space and minimizing redundant information. This hybrid feature selection strategy enhances the model generalization capability, reduces overfitting and improves the predictive performance of the classification model. The selected optimized features are then used as input to the GBC for further training and evaluation.

C. Sequential Model-Based Optimization (SMBO) with Optuna

SMBO is employed in the proposed framework to optimize the hyperparameters of GBC for predicting the progression from MCI to dementia. Hyperparameter tuning plays a crucial role in improving model performance, reducing overfitting and enhancing generalization capability. Traditional optimization approaches such as grid search

and random search are computationally expensive and inefficient for high-dimensional search spaces. Therefore, the proposed framework utilizes SMBO integrated with the Optuna framework to efficiently identify the optimal hyperparameter configuration [28].SMBO constructs a probabilistic surrogate model to approximate the relationship between hyperparameter configurations and model performance. Based on previously evaluated trials, the surrogate model predicts promising hyperparameter combinations that are likely to maximize classification accuracy. At each iteration, the optimization algorithm selects the next hyperparameter set by maximizing an acquisition function that balances exploration and exploitation.The mathematical representation of SMBO is given in equation 3 as

The optimization objective is mathematically represented as

x_t= sampler(s_t) (3)

where x_t represents the set of sampled hyperparameters at iteration t and sampler(S_t) sampler(S_t) denotes the sampling function that selects hyperparameters from the search space S_t

The objective function used during optimization is represented as in equation 4

$f(n_f)$=-$P(n_f)$ (4)

where n_f denotes the number of selected features and $P(n_f)$ represents the model performance. The optimization process aims to maximize classification performance by minimizing prediction error.After evaluating multiple trials, Optuna identifies the best hyperparameter configuration using the optimization function

Study.optimize() (5)

In comparison to more traditional techniques of hyperparameter tuning, such as manual or grid search, the efficiency of SMBO with Optuna integration is much higher. Improved generalization performance, enhanced learning capacity, and improved prediction accuracy for dementia development can all be attributed to the adjusted hyperparameters of the GBC. Classification and performance evaluation are additional uses of the optimized model.

D. Model Selection using Gradient Boosting Classifier

The GBC is employed in the proposed framework for predicting the progression from MCI to dementia. GBC is an ensemble learning technique that combines multiple weak decision tree learners to construct a strong predictive model. The algorithm iteratively improves classification performance by minimizing the residual errors generated by previous learners. Due to its ability to model nonlinear relationships and handle complex feature interactions, GBC is highly suitable for medical prediction tasks involving heterogeneous clinical and neuroimaging data.

The optimized feature subset is sent into the GBC after its selection by RFE and PSO, as well as hyperparameter optimization through SMBO with Optuna. To determine the model's predictive power, it is trained on the training dataset and then tested on the testing dataset. The classifier improves the model's accuracy with each boosting iteration by adding weak learners sequentially, which minimizes the loss function [29].

The Gradient Boosting prediction model is mathematically represented as in equation 6

$F_m(x)= \sum_{m=1}^{M} \gamma_m \; h_m(x)$ (6)

where $F_m(x)$ represents the final boosted model, $h_m(x)$ denotes the weak learner at iteration m, γ_m is the weight assigned to the weak learner and M indicates the total number of boosting iterations.

The boosting process updates the model iteratively according to equation 7

$F_m(x)=F_{m-1}(x)+\eta h_m(x)$ (7)

where $F_m(x)$ is the boosted model at iteration m, $F_{m-1}(x)$ denotes the previous ensemble model, $h_m(x)$ represents the newly added weak learner and η is the learning rate controlling the contribution of each learner.The classification performance of the optimized GBC model is evaluated using many performance metrics such as accuracy, precision, recall, F1-score, ROC-AUC and Precision-Recall AUC. The confusion matrix is also studied to measure the number of correctly and erroneously identified cases. The optimized model has a good prediction power to discriminate stable MCI and individuals transformed to dementia.

4. RESULTS AND DISCUSSIONS

The proposed hybrid framework integrating RFE, PSO, SMBO and GBC demonstrated significant performance in predicting the progression from MCI to dementia. The performance of the model was evaluated using multiple classification metrics including accuracy, precision, recall, F1-score, ROC-AUC and Precision-Recall AUC. Figure 3 shows the ROC curve, which quantifies the proposed model's ability to differentiate across classes. When different threshold values are displayed against the True Positive Rate (TPR) and False Positive Rate (FPR), the ROC curve is depicted. Maintaining a close proximity to the top left corner of the graph suggests a high level of sensitivity with few false positive rates. The suggested model achieves far better results than the random classifier, whose performance is depicted by the dashed diagonal line. The model's dependability for early dementia prediction tasks is confirmed by its robustness and effectiveness in reliably classifying MCI cases, as indicated by the high AUC value.

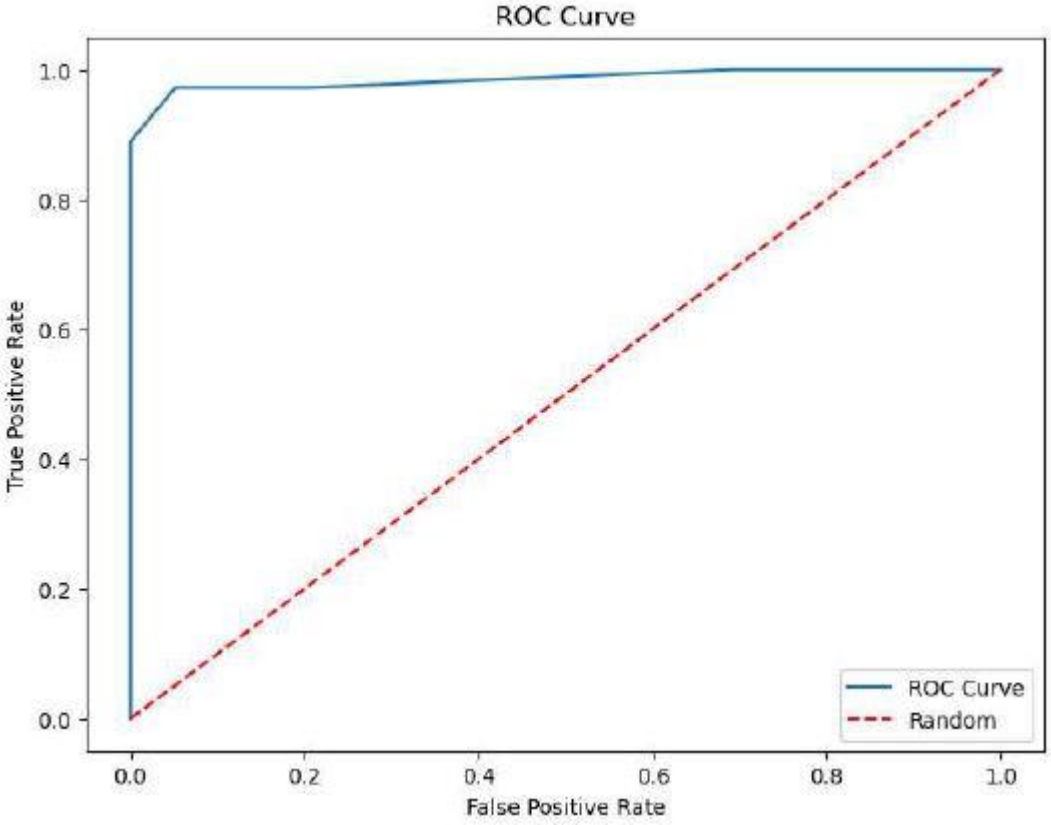

Figure 3. ROC curve of the proposed classification model for MCI prediction

The proposed evaluation metrics provide a comprehensive evaluation of the classification power and robustness of the developed model. The optimized model achieved an overall classification accuracy of 96%, indicating its effectiveness in distinguishing between stable MCI subjects and subjects progressing towards dementia. This high accuracy demonstrates the potential of the proposed framework in revealing inherent patterns associated with neurodegenerative progression by leveraging clinical and neuroimaging data from the OASIS dataset. The integration of PSO with RFE fine-tuned the selection of optimal feature subsets and the application of SMBO with Optuna improved the hyperparameter tuning process, resulting in significant improvements in prediction performance.

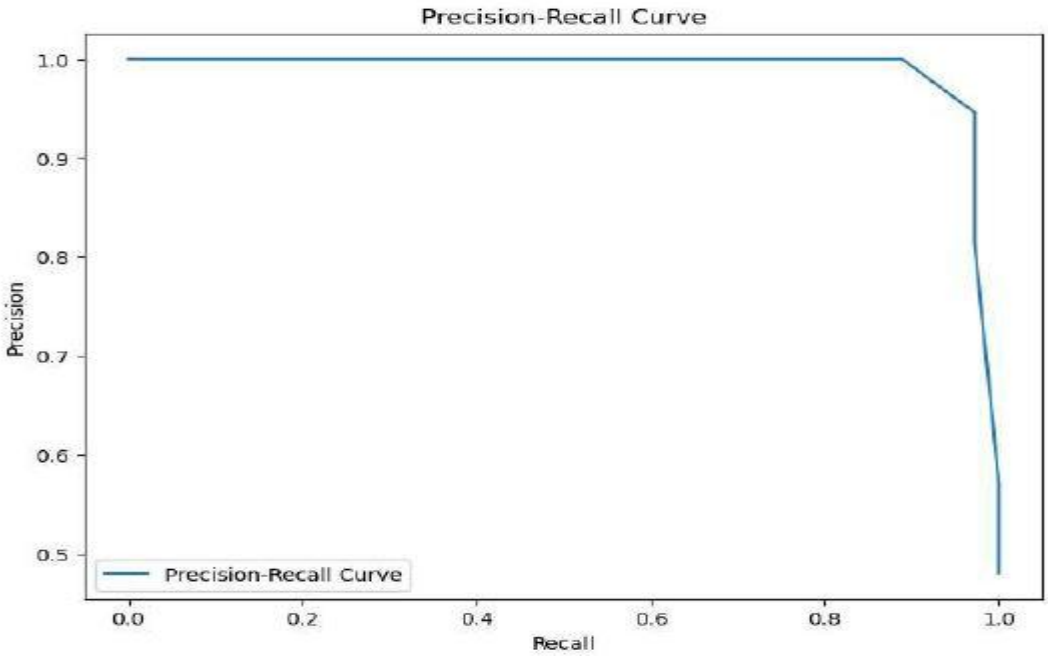

Figure 4. Precision–Recall (PR) curve of the proposed MCI classification model.

Figure 4 shows the curve that represents the trade-off between recall and precision for various threshold values. Strong predictive power and dependable classification performance are indicated by the model's high precision across a broad range of recall values. This curve shows that the suggested model keeps its precision close to ideal for the majority of recall values, which means that it can make very accurate predictions and has strong classification capabilities. As anticipated when the model aims to capture almost all positive cases, a modest decrease in precision is only noticed at extremely high recall levels. All things considered, the PR curve proves that the suggested model is capable of handling classification tasks with low rates of misclassification and high reliability, which makes it a good fit for applications involving early-stage dementia diagnosis.To enhance interpretability and clinical reliability, SHAP-based analysis was performed to determine the contribution of individual features toward prediction outcomes. The suggested model's classification performance for predicting the progression of MCI is presented in Table 2. With a total accuracy of 96%, the model proved to be very accurate. The model achieved a high reliability in properly detecting MCI patients with a precision of 0.97, recall of 0.95, and F1-score of 0.96 for the MCI class. Similarly, the model detected people likely to proceed toward dementia with a precision of 0.95, recall of 0.97, and F1-score of 0.96 for the "MCI Converted to Dementia" class. Both the weighted average and macro average values of 0.96 further demonstrate that the suggested architecture consistently and evenly performs across both classes. These outcomes prove that the model is reliable and useful for predicting the onset of dementia and providing clinical decision support.

Table 2. The Classification Report

	Precision	Recall	F1-Score	Support
MCI	0.97	0.95	0.96	39
MCI Converted to Dementia	0.95	0.97	0.96	36
Accuracy		0.96	75	
Macro avg	0.96	0.96	0.96	75
Weighted avg	0.96	0.96	0.96	75

5. PERFORMANCE RESULTS

The comparative performance analysis of Logistic Regression, Random Forest, and the proposed hybrid model using evaluation metrics such as Accuracy, Precision, Recall, and F1-Score is shown in Figure 5.

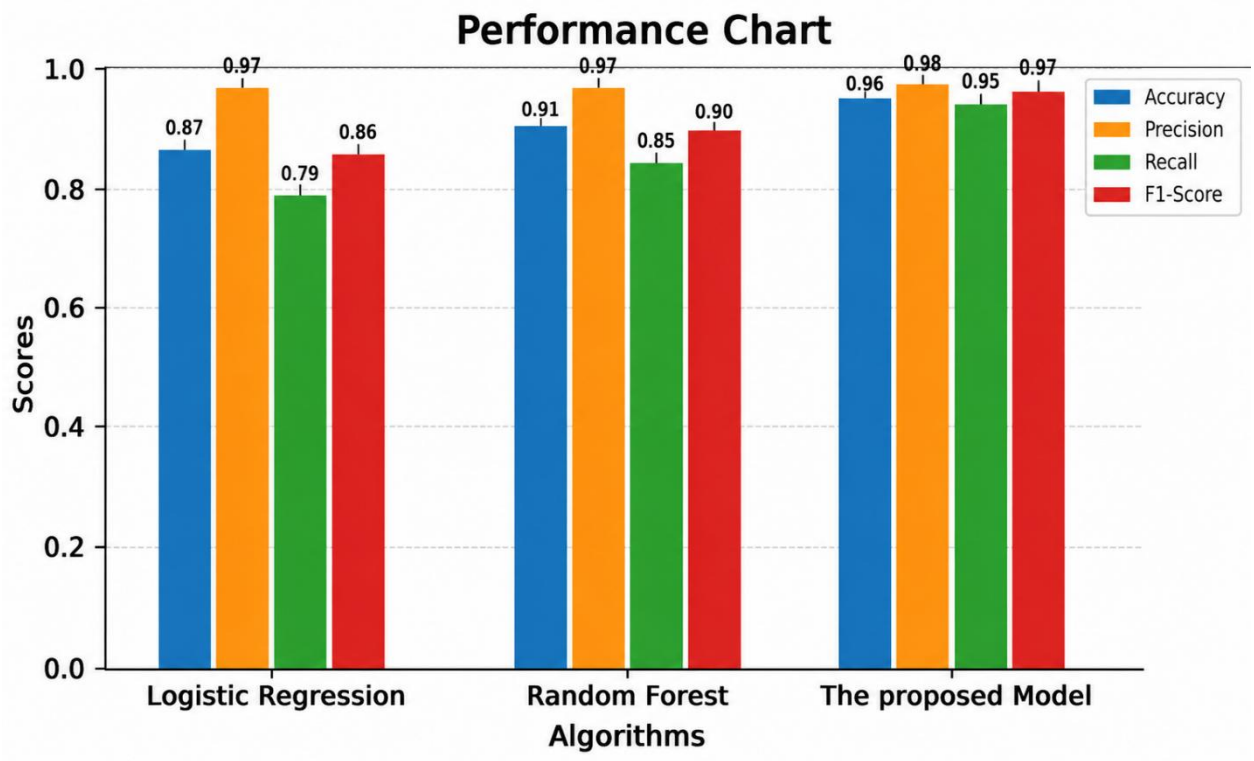

Figure 5. Performance comparison of different classification algorithms

Among the evaluated algorithms, the proposed model achieved superior performance with an accuracy of 96%, precision of 98%, recall of 95%, and F1-score of 97%. In comparison, Logistic Regression obtained lower performance metrics with an accuracy of 87%, recall of 79%, and F1-score of 86%, while Random Forest achieved moderate performance with an accuracy of 91%, recall of 85%, and F1-score of 90%. The improved results of the proposed framework demonstrate the effectiveness of integrating RFE, PSO, SMBO and GBC for predicting the progression from MCI to dementia. The higher precision and recall values indicate the robustness and reliability of the proposed model in accurately identifying dementia progression cases.

6. MODEL INTERPRETABILITY

The interpretability study revealed that CDR, MMSE, age and nWBV were the most significant predictors of dementia progression. The proposed model gained greater credibility in clinical contexts as a result of the SHAP framework's elucidation of classification decisions. The results demonstrate that the optimization of features, tuning of models and prediction performance are all improved when PSO is combined with RFE and SMBO.With SHAP, study evaluates the model's output by feature, which increases the clinical transparency and interpretability of the proposed predictive framework. SHAP decomposes each prediction into a baseline value and the additive contribution of each feature, which helps to explain the model's prediction. This framework shows promise as an intelligent decision-support system for early dementia detection and tailored healthcare management.According to the interpretability analysis, there were patterns that were clinically meaningful. CDR had the most favorable impact in predicting the progression of MCI to dementia, which is evidence of its preeminent position in the model. With lower MMSE scores, the likelihood of conversion increased, which is an indication of the severity of cognitive decline. Similar to the risks associated with epidemiological factors, advanced age was a moderate contributor. Researchers found a correlation between decreased normalized nWBV and increased progression likelihood, which lends credence to neurodegenerative biomarkers. In order to improve clinical credibility, the SHAP-based interpretability method provides explanations that are transparent and specific to the patient. This makes the approach more trustworthy and makes it easier to include into decision support systems that are used in the real world.

7. CONCLUSION AND FUTURE ENHANCEMENT

Using the OASIS dataset, the suggested hybrid machine learning architecture offers a dependable and efficient method for forecasting the progression of MCI to dementia. Feature selection, hyperparameter optimization, and classification performance were all much enhanced by integrating RFE, PSO, SMBO and GBC. The suggested methodology produced a high classification accuracy of 96% with great precision, recall, and F1-score values, and it successfully identified clinically significant variables associated with dementia progression. By minimizing redundant information and conducting efficient searches for suitable feature subsets, PSO improved the feature optimization process. Similarly, The GBC'shyperparameters were tuned by SMBO combined with the Optuna framework, leading to better generalization capabilities and less overfitting. Experiment results showed that the suggested framework reliably and robustly distinguished stable MCI cases from dementia conversion cases, with excellent ROC-AUC and Precision-Recall AUC scores. By including SHAP-based interpretability analysis, which provides clear explanations of how specific traits affect prediction outcomes, the framework's clinical credibility was further enhanced. There were identified to be significant predictors of dementia progression, including CDR, MMSE, age and nWBV. This model has the potential to be used in clinical decision-support systems for early dementia risk assessment and tailored patient management in the real world because of its interpretability capabilities. Improving predictive analytics in neurodegenerative disease research is made possible by merging optimization techniques with ensemble machine learning models, as shown by the proposed framework. For efficient and reliable treatment of high-dimensional clinical and neuroimaging datasets, a hybrid integration of RFE, PSO, SMBO and GBC is recommended. Improving the suggested framework's generalizability across various patient demographics and clinical contexts can be the subject of future research that utilizes bigger and more diverse datasets for validation. Genetic data, positron emission tomography (PET) scans, speech recognition software, and cognitive behavioral biomarkers are all examples of multimodal data sources that might improve prediction accuracy. To further enhance automation, interpretability, and clinical application, one can additionally investigate architectures based on deep learning and explainable AI techniques. Better early diagnosis, intervention planning, and individualized treatment approaches for dementia care may also be possible with the use of real-time predictive technologies and longitudinal patient monitoring.

References

1. Petersen, R.C. (2004), Mild cognitive impairment as a diagnostic entity. Journal of Internal Medicine, 256: 183-194. https://doi.org/10.1111/j.1365-2796.2004.01388.x
2. Akan, T., Akan, S., Alp, S., Ledbetter, C. R., Tafti, A. P., Arevalo, O., &Bhuiyan, M. A. N. (2025). Deep learning in neuroimaging for neurodegenerative diseases: State-of-the-art, challenges, and opportunities. Journal of the Neurological Sciences, 478, 123735. https://doi.org/10.1016/j.jns.2025.123735
3. Wang Y, Guiler W, Patel A, Pepper S, Walpitage N, Ratnayake I, Honea R, Mudaranthakam DP(2025) . Predicting dementia risk using neuroimaging and cognitive assessment. doi: 10.1016/j.jarlif.2025.100040.
4. Bhattrai, Dipendra&Ud Din, Fareed &Shafiabady, Niusha. (2026). Predictive Models for Early Detection and Prognosis of Dementia Using Artificial Intelligence and Machine Learning. 10.1007/978-3-032-07267-2_9.
5. Mathur, A., Dwivedi, R. K., &Rastogi, R. (2024). A survey of machine learning-based approaches for Alzheimer's disease prediction. Educational Administration: Theory and Practice, 30(1), 1114–1127. https://doi.org/10.53555/kuey.v30i1.5984
6. Hossain MK, Ashraf A, Islam MM, Sourav SH, ShimulMMH(2025). Optimizing Alzheimer's disease prediction through ensemble learning and feature interpretability with SHAP-based feature analysis. Aug 8;17(3):e70162. doi: 10.1002/dad2.70162.
7. Yan, K., Zhang, D., & Su, J. (2013). Enhanced recursive feature elimination. Pattern Recognition, 46(10), 2663–2671. https://doi.org/10.1016/j.patcog.2013.03.008
8. Zhang, Q., et al. (2025). Enhanced particle swarm optimization for feature selection in dementia prediction. Scientific Reports.
9. Mandave, P., et al. (2023). Bio-inspired computing algorithms in dementia diagnosis. Healthcare Analytics, 4, 100214.
10. Akiba, T., Sano, S., Yanase, T., Ohta, T., & Koyama, M. (2019). Optuna: A next-generation hyperparameter optimization framework. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 2623–2631).
11. Petersen, R. C., Smith, G. E., Waring, S. C., Ivnik, R. J., Tangalos, E. G., &Kokmen, E. "Mild Cognitive Impairment: Clinical Characterization and Outcome." Archives of Neurology, vol. 56, no. 3, 1999, pp. 303–308. https://doi.org/10.1001/archneur.56.3.303
12. Belleville, S., Fouquet, C., Hudon, C., Zomahoun, H. T. V., &Croteau, J. "Neuropsychological Measures That Predict Progression from Mild Cognitive Impairment to Alzheimer's Type Dementia in Older Adults: A Systematic Review and Meta-Analysis." Neuropsychology Review, vol. 27, no. 4, 2017, pp. 328–353. https://doi.org/10.1007/s11065-017-9361-5

13. Mathur, A., Dwivedi, R. K., &Rastogi, R. “A Survey of Machine Learning-Based Approaches for Alzheimer’s Disease Prediction.” Educational Administration: Theory and Practice, vol. 30, no. 1, 2024, pp. 1114–1127. https://doi.org/10.53555/kuey.v30i1.5984
14. Ding, Y., Sohn, J. H., Kawczynski, M. G., et al. “A Deep Learning Model to Predict a Diagnosis of Alzheimer Disease by Using 18F-FDG PET of the Brain.” Radiology, vol. 290, no. 2, 2019, pp. 456–464. https://doi.org/10.1148/radiol.2018180958
15. Mathotaarachchi, S., Pascoal, T. A., Shin, M., et al. “Identifying Incipient Dementia Individuals Using Machine Learning and Amyloid Imaging.” Neurobiology of Aging, vol. 59, 2017, pp. 80–90. https://doi.org/10.1016/j.neurobiolaging.2017.06.027
16. Singh, D. A. A. G., Balamurugan, S. A., &Leavline, E. J. “Literature Review on Feature Selection Methods for High-Dimensional Data.” International Journal of Computer Applications, vol. 136, no. 1, 2016, pp. 9–17.
17. Yan, K., Zhang, D., & Su, J. “Enhanced Recursive Feature Elimination.” Pattern Recognition, vol. 46, no. 10, 2013, pp. 2663–2671. https://doi.org/10.1016/j.patcog.2013.03.008
18. Wang, H., Nie, F., Huang, H., et al. “From Phenotype to Genotype: An Association Study of Longitudinal Phenotypic Markers to Alzheimer’s Disease Relevant SNPs.” Bioinformatics, vol. 28, no. 18, 2012, pp. i619–i625. https://doi.org/10.1093/bioinformatics/bts470
19. Hosseini-Asl, E., Keynton, R., & El-Baz, A. “Alzheimer’s Disease Diagnostics by Adaptation of 3D Convolutional Network.” 2016 IEEE International Conference on Image Processing (ICIP), 2016, pp. 126–130. https://doi.org/10.1109/ICIP.2016.7532332
20. Hutter, F., Hoos, H. H., &Leyton-Brown, K. “Sequential Model-Based Optimization for General Algorithm Configuration.” Proceedings of the 5th International Conference on Learning and Intelligent Optimization, 2011, pp. 507–523. https://doi.org/10.1007/978-3-642-25566-3_40
21. Marcus, D. S., Fotenos, A. F., Csernansky, J. G., Morris, J. C., & Buckner, R. L(2010). “Open Access Series of Imaging Studies: Longitudinal MRI Data in Nondemented and Demented Older Adults.” Journal of Cognitive Neuroscience.
22. Daniel S. Marcus, Tracy H. Wang, Jamie Parker, John G. Csernansky, John C. Morris, Randy L. Buckner(2007) ; Open Access Series of Imaging Studies (OASIS): Cross-sectional MRI Data in Young, Middle Aged, Nondemented, and Demented Older Adults. J CognNeurosci; 19 (9): 1498–1507. doi: https://doi.org/10.1162/jocn.2007.19.9.1498
23. MayuraTapkire, VanishriArun, M. S. Lavanya, R. Shashidhar (2025); Gluten Identification from Food Images Using Advanced Deep Learning and Transfer Learning Methods. J Food SciTechnol; 62(6): 1164–1172. doi: https://doi.org/10.1007/s13197-024-06463-9
24. M. S. Lavanya, VanishriArun, MayuraTapkire, K. P. Suhaas (2024); Transfer Learning Based Facial Emotion Recognition. SN ComputSci; 6 (1): 35. doi: https://doi.org/10.1007/s42979-024-03527-2
25. Mayura D. Tapkire, VanishriArun (2023); Application of Artificial Intelligence to Correlate Food Formulations to Disease Risk Prediction: A Comprehensive Review. J Food SciTechnol; 60(9): 2350–2357. doi: https://doi.org/10.1007/s13197-022-05676-5
26. M. S. Lavanya, VanishriArun, MayuraTapkire, YuliaShichkina (2024); A Review on Facial Expression Recognition Approaches, Datasets and Technologies. In: International Conference on Intelligent Systems; Cham: Springer Nature Switzerland. pp. 53–68. doi: https://doi.org/10.1007/978-3-031-77770-4_5
27. VanishriArun, B. M. Shashikala, H. Y. Vani, MayuraTapkire, M. A. Anusuya, M. S. Lavanya (2024); Object Detection Using TensorFlow for Road Navigation: Enhancing Safety for the Visually Impaired. In: International Conference Summit on Artificial Intelligence; Singapore: Springer. pp. 209–220. doi: https://doi.org/10.1007/978-981-97-7241-6_17
28. M. S. Lavanya, VanishriArun, S. Dhananjaya, B. M. Nandini, A. Srivatsa, H. R. Lokesha (2026);DeepCog: Classification of Mild Cognitive Impairment Using Structural MRI. J Appl Data Sci; 7 (2): 1408–1422.
29. T. Vinesh, M. S. Lavanya, VanishriArun, JasniJuremi, MayuraTapkire, B. M. Shashikala, A. M. S. Fatin (2026); AI-Powered Assessments for Mild Cognitive Impairment Detection: A Comprehensive Review. In: AIP Conference Proceedings; 3440 (1): 020038. AIP Publishing LLC. doi: https://doi.org/10.1063/5.0269625