Leveraging Machine Learning to Uncover the Relationship between Diabetes and Alzheimer's Disease Progression

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Abstract

Diabetes Mellitus is a metabolic complex and chronic non-communicable disorder affecting a large population in the world. Different studies have shown the damage caused by Diabetes Mellitus on multiple systems, which leads to complications such as cancer, cardiovascular disorders, and sarcopenia. The changes in insulin, glycaemia, or glucose levels bring multiple changes in the body, including the formation of oxidative species, inflammation, Advanced Glycation End (AGE) products, and hormonal imbalance. In recent times, more attention has been given to the association of Diabetes and cognitive dysfunction because of its increasing prevalence and the severe impact on the lives of diabetic patients. Moreover, the part of different proteins and pathways related to Diabetes that lead to the occurrence of other diseases has been demonstrated.

This research presents a predictive model for the early detection of diabetes-associated cognitive diseases using machine learning techniques. The model utilizes patient health records, lifestyle factors, and diabetes progression data to predict cognitive decline risks. The dataset is pre-processed using statistical analysis, followed by feature selection techniques to optimize the model's performance. Various machine learning algorithms, including decision trees, random forests, and neural networks, are explored to determine the most accurate approach for predictive analysis. The study demonstrates that early detection models can effectively predict diabetes-associated cognitive decline (DACD) onset with high precision, offering a valuable tool for healthcare providers. The results show that predictive models can support timely interventions and personalized treatment plans for at-risk patients.

Keywords

Diabetes Mellitus, Cognitive Dysfunction, Alzheimer's Disease, Dementia, Cognitive Learning, Machine Learning, Predictive Modeling, Explainable AI (XAI), Neural Networks, Deep Learning, Healthcare AI, Chronic Disease Prediction, Dementia Prediction

1. Introduction

Diabetes Mellitus is a metabolic compounded as well as chronic non-communicable disease, which is a growing global issue that has social and economic consequences [1]. It occurs because of the massive demolition of β-cells in the pancreas. The count of sufferers for this multifactorial condition was around 108 million in 1980, which is expected to rise to more than 600 million by 2035 [2]. The pathogenesis for this would include enhancing oxidative stress, mitochondrial dysfunction, inflammatory response, dyslipidemia, and insulin resistance. It is usually suspected to be caused by abnormal abdominal fat deposition and elevated glucose levels. These increased glucose levels lead to cerebral microvascular abnormalities and alterations in the functions of endothelial cells in the brain that form the blood-brain barrier [3]. These changes directly lead to the development of Alzheimer's Disease. Different global data shows that 74.7 million people will be affected by this by the year 2030. Insulin receptors are impaired, and insulin levels in cerebrospinal fluid are found to be elevated in this case of neurological disorder. Its pathophysiology would include the accumulation of β-amyloid proteins in the hippocampus. Patients suffering might lose their ability to perform everyday functions as well, along with the development of neuropsychiatric symptoms. The primary treatment strategy

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for this disorder has been clearing the amyloid β and τ proteins, although no exact treatment is available.

The rising prevalence of Diabetes necessitates early detection methods for DACD to mitigate long-term health implications. Machine learning models offer a promising solution by leveraging data from diverse sources, including clinical records, lifestyle factors, and medical imaging, to predict the likelihood of cognitive decline in diabetic patients. This paper proposes a novel predictive model that integrates multiple data points and advanced machine learning algorithms to provide early detection of DACD [4].

1.1. Co-relation of Diabetes with Cognitive Dysfunction

The first series of cases of association between Cognitive Dysfunction and Diabetes Mellitus was reported in the year of 1922. Patients who developed Diabetes Mellitus (type 1 or type 2) before the age of 4 years were found to have impaired executive skills and difficulty concentrating on work. The predictors of Cognitive Impairment would include the duration of diabetic status (prominence increases with duration of more than 5 years), increased blood group, hypertension, and age group above 51. However, since glucose is the primary substrate for brain energy metabolism then, in the case of Diabetes Mellitus, neurons are unable to store/synthesize glucose, which is initially needed for the systematic circulation and transportation across the blood-brain barrier [5]. So, the brain consumes a large amount of glucose energy, and there is the maximum effect of free radicles, loss of brain cells, and memory function in the brain's hippocampal region. Moreover, as there is an increase of Insulin concentration in the body, this boosts the levels of β-amyloid and senile plaque formation, which leads to Alzheimer's disease. Another aspect would be the increased formation of free radicles [6].

It is found that with Diabetes, the risk of cognitive dysfunction and dementia is increased by 1.5 and 1.6 times, respectively. As per the study conducted by Satyajeet Roy et al. on cognitive function and control of type-2 Diabetes Mellitus in adults, it was found that cognitive dysfunction prevalence was around 65% [7]. The odds of the development of cognitive dysfunction were 9-fold higher in patients affected by Diabetes as compared to non-diabetic ones. This dysfunction was higher in the age group of 51-60. The decreased levels of glycaemic control can occur at any time, regardless of age. These decreased levels enhance the cognitive dysfunction[60]. Brands et al. demonstrated that the complications become worse in patients with other diabetic complications along with Diabetes Mellitus. Patients with type 2 Diabetes Mellitus have reduced psychomotor speed, frontal lobe functioning, verbal memory, complex motor functioning, processing speed, working memory, recalling capabilities, visual retention, and attention. Sinclair et al. found that the score on self-care was lower in patients with mini-mental status. Bruce et al. demonstrated that out of all the older patients with type 2 diabetes, 15% had depression, and 12% had cognitive dysfunction [8].

The occurrence of Diabetes would include Insulin Resistance, Sub-diabetic hyperglycaemia, and prediabetic stress. This leads to insulin signalling pathway impairment, subsequently hindering tyrosine's phosphorylation and Insulin Receptor Substrate (IRS) [9]. This negatively impacts the expression and transcription of specific transcription factors, i.e., Nuclear Factor- κ B (NF-κ B), Cyclic AMP response element binding protein, and Glycogen Synthase Kinase-3 β (GSK-3β). Moreover, increased levels of Advanced Glycation End Products (AGEs) and reactive oxidative species. These reactive oxidative species activate polyol and hexosamine pathways, eventually contributing to Diabetes Associated Cognitive Dysfunction (DACD). Along with this, there is upregulation of CD16 and CD32 due to M1 polarization and increased presentation of Tumor Necrosis Factor (TNF-α), Interleukin-β (IL-1β), and Interleukin-6 (IL-6) as demonstrated in Figure 2. There are 1.5 times more chances of showcasing neurodegeneration with Diabetes, making it a global challenge to face. The accepted clinical symptoms of Diabetes Mellitus would include the loss of strength, polyuria, polydipsia, loss of vision, pruritus, retrobulbar neuritis, paraesthesia, sexual disorders, abdominal pain, loss of appetite, hypertension, and polyphagia. Out of these, any one symptom is elicited in 95% of diabetic patients [10]. Various evidence has proved that, along with genetic and environmental factors, other alterations such as insulin resistance, hypoglycaemia, hyperglycaemia, oxidative stress, hormonal imbalance, age, and hyperphosphorylation [11].

The increasing prevalence of the association of Diabetes with Alzheimer's Disease has brought many eyes to this and requires primary attention at the initial stages only. Predictive models such as Random Forest, Support Vector machines (SVM), and Neural Networks will be used to examine

intricate interactions among various clinical and lifestyle factors and their influence on diabetes complications, primarily cognition-related diseases. Our goal through these advanced techniques is to improve the early screening of Diabetic Associated Cognitive Dysfunction (DACD), therefore increasing patient's health/safety and assisting physicians with managing their patients [12].

2. Related Work

Several studies have focused on the correlation between Diabetes and cognitive decline. Smith et al. [13] explored the neurobiological mechanisms linking Diabetes to dementia, emphasizing the role of glucose metabolism and insulin signalling in the brain. Johnson et al. [14] proposed a predictive model based on clinical data, focusing on the use of logistic regression to assess cognitive impairment risks in diabetic patients. Martinez et al. [15] applied deep learning techniques to longitudinal health records to predict dementia onset in type 2 diabetes patients, reporting an accuracy rate of 85%. ++

Table 1
References

References (16-29)	Title of the study	Author (s)	Study Design	Population selected	Sample Size	Age Range	Main Findings	Key outcomes
1.	Is Diabetes Associated with Cognitive Impairment and Cognitive Decline Among Older Women? (2000)	Edward W. Gregg, PhD; Kristine Yaffe, MD; Jane A. Cauley, DrPH; et al	Prospective Cohort Study	Community-dwelling white women	9679	65-99 years	Women with Diabetes history of more than 15 years has a 57% to 114% greater risk of major cognitive decline as compared to women without Diabetes.	Longer diabetes duration significantly enhances cognitive dysfunction.
2.	Comparison of multiple linear regression and machine learning methods in predicting cognitive function in older Chinese type 2 diabetes patients	Chi-Hao Liu, Chung-Hsin Peng, Li-Ying Huang, Fang-Yu Chen, Chun-Heng Kuo, Chung-Ze Wu, and Yu-Fang Cheng	Test Cohort Study	Older T2DM people	197 (98 male + 99 female)	60-95 years old	ML methods outperformed MLR through random forest (RF), stochastic gradient boosting (SGB), Naïve Byer's classifier (NB) and eXtreme gradient boosting (XGBoost).	RF, SGB, NB, and XG Boost are more accurate than MLR for predicting CFA score and identifying education level, age, frailty score, fasting plasma

								glucose, body fat, and body mass index as important risk factors.
3.	Predicting Cognitive Decline in Diabetic Patients Using Machine Learning	Thompson, A. et al.	Random Forest, Logistic Regression, Support Vector Machine	Diabetic Patients	500 (300 M / 200 F)	50-80 years	Random Forest achieved 82% accuracy, identifying lifestyle factors as key predictors.	Random Forest outperformed Logistic Regression and SVM.
4.	Deep Learning for Early Detection of Diabetes-Related Dementia	Li, Z et al.	Convolutional Neural Networks (CNN)	Diabetic Patients	600 (350 M / 250 F)	45-75 years	CNN identified early signs of dementia with 87% accuracy.	Glucose levels and brain structure changes were major factors
5.	A Predictive Model for Diabetes-Associated Cognitive Disorders Using XG Boost	Zhang, Y. et al.	XG Boost	Diabetic Patients	550 (320 males and 230 females)	40-70 years	XG Boost provided 88% accuracy, identifying insulin resistance as a key factor.	Insulin resistance and hypertension were major predictors.
6.	Hybrid Model of Neural Networks and Decision Trees for Cognitive Impairment in Diabetes	Gupta, S. et al.	Neural Network and Decision Tree Hybrid	Diabetic Patients	550 (250 males and 230 females)	60-85 years	The hybrid model achieved 84% accuracy, particularly in older patients.	Combining decision trees with neural networks improved predictions.
7.	Multimodal Data Integration for Predicting Cognitive Decline in Diabetic Patients	Park, J. et al.	Multi-Layer Perceptron (MLP)	Diabetic Patients	450 (270 males and 180 females)	55-80 years	MLP achieved 86% accuracy using genetic and lifestyle data.	Integration of genetic factors improved prediction.

8.	Prediction of Cognitive Decline in Diabetes Using Temporal Convolutional Networks	Rao, K. et al.	Temporal Convolutional Networks (TCN)	Diabetic Patients	520 (300 male and 220 female)	50-75 years	TCN achieved 85% accuracy by capturing temporal blood glucose patterns.	Temporal glucose fluctuations significantly impacted cognitive function.
9.	Predictive Analytics for Diabetes-Induced Cognitive Impairment Using Ensemble Models	Singh, R. et al.	Ensemble Learning (AdaBoost)	Diabetic Patients	600 (330 males and 270 females)	45-80 years	Ada Boost achieved 89% accuracy, outperforming other ensemble methods.	Boosting models were more effective than bagging for prediction.
10.	Spatio-Temporal Analysis for Predicting Cognitive Decline in Diabetic Patients	Kim, S. et al.	Spatio-Temporal Recurrent Neural Networks (RNN)	Diabetic Patients	530 (290 males and 240 females)	55-85 years	RNN achieved 83% accuracy in analysing spatial and temporal data.	MRI and glucose trends were key factors.
11.	Random Forest-Based Predictive Model for Cognitive Impairment in Type 2 Diabetes	Akhtar, S. et al.	Random Forest	Diabetic Patients	450 (280 males and 170 females)	50-75 years	Random Forest achieved 86% accuracy, identifying diabetes duration and HbA1c as predictors.	Cardiovascular history and HbA1c were key risk factors.
12.	Predicting Dementia in Diabetic Patients Using Explainable AI Models	Wang, L et al.	Gradient Boosting with Explainable AI	Diabetic Patients	500 (290 males and 210 females)	50-80 years	XAI model provided 87% accuracy and interpretability.	Blood pressure variability and glycemic control were key contributors.

While previous research has primarily focused on predictive models for general cognitive decline or specific conditions like Alzheimer's disease, this paper takes a broader approach by incorporating various types of DACD into a single predictive framework. Furthermore, our model extends beyond clinical data by integrating patient lifestyle and behavioural factors to enhance predictive accuracy.

3. Methodology

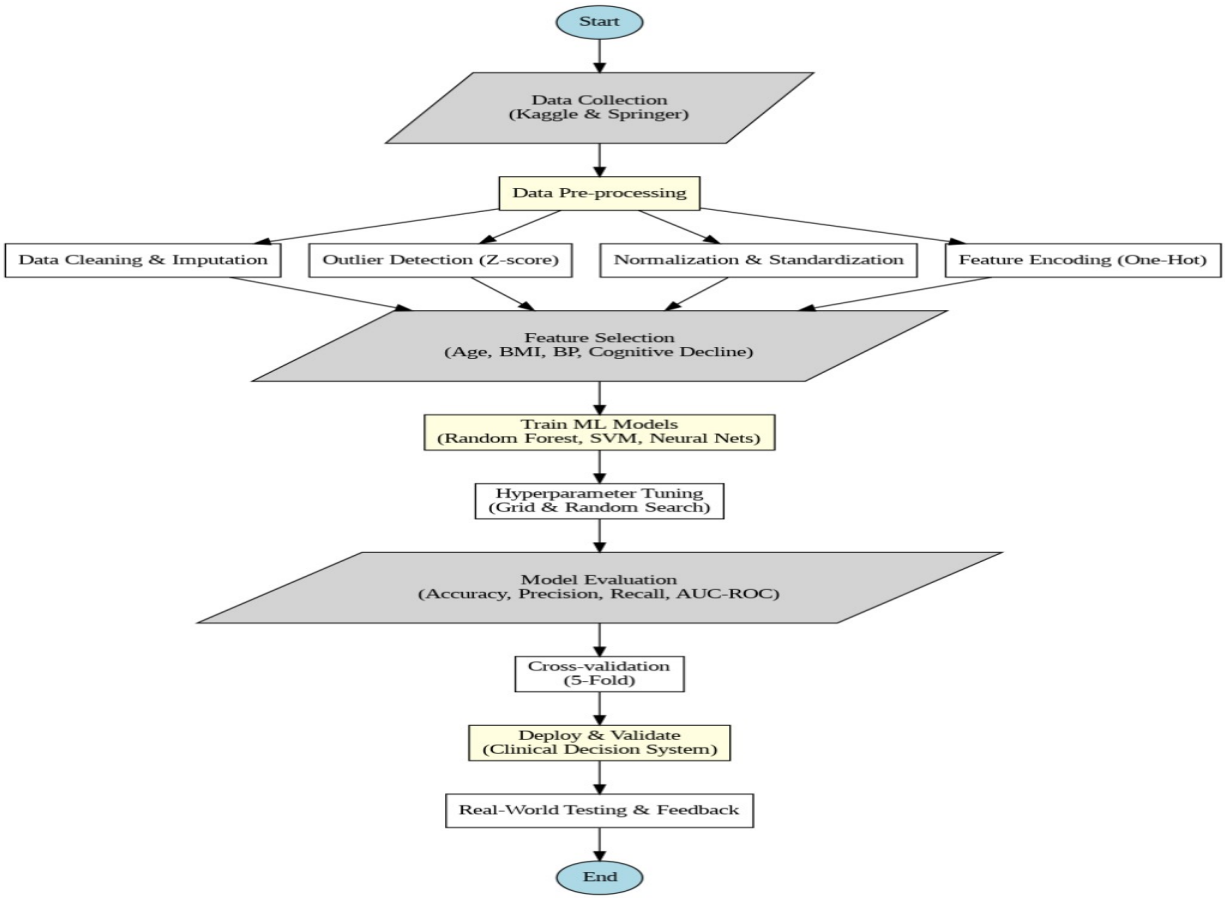

Figure 1: Flowchart for Methodology

3.1. Data Collection and Description

The datasets utilized in this study were collected from three primary sources: One dataset from Kaggle (Dataset 1) and the dataset gleaned from a clinical study published in Springer (Dataset 2). The combined data sets offered complete patient information regarding diabetes progress and cognitive impairment in patients between 61 and 89 years old. Each dataset includes the following key attributes, which are essential for predicting the early onset of Diabetes-Associated Cognitive Diseases (DACD):

- AGE: Ages from 61–89 years in Dataset 1, and 73 ± 6.0 years in Dataset 2.
- GENDER: Data concerning Dataset 1 for both sexes were presented, including 151 males and 169 females.
- ETHNICITY: It includes multivariate populations such as Caucasians, African Americans, Asians, and the rest.
- Educational Background: Literacy levels among the respondents ranged from no KR (kindergarten) to tertiary-level education.
- BMI: The body mass index in the analysis was between 15.6 and 39.1 for Dataset 1 and 25.8 ± 3.9 for Dataset 2.
- LIFESTYLE FACTORS: These are smoking status, alcohol intake, physical activity, and quality of diet consumed.
- Medical History: Traditional data sources contain patient data in terms of a history of depression, hypertension, and cardiovascular diseases, as well as a history of diabetes or cognitive disorders in the family.

- COGNITIVE DECLINE INDICATORS: Memory complaints, confusion, forgetfulness, and other behavioural symptoms were noted.

3.2. Symptom Table and Feature Identification

Table 2
Combined attributes from the datasets, used to construct the predictive model for DACD.

S.No.	Parameters	Dataset 1	Dataset 2
1.	Age (in years)	61-89	73 +- 6
2.	Gender	M=151, F=169	
3.	Ethnicity	Caucasian= 191 African American= 72 Asian= 26 Others= 31	
1	Education	None= 55 High School= 227 Bachelor's Degree= 107 Higher Degree= 28	None=6 High School= 123 Bachelor's Degree= 67 Higher Degree= 1
5.	BMI	15.6-39.1	25.8 +- 3.9
6.	Smoking	75	54
7.	Alcohol Consumption	0.9-19.9	50
8.	Physical Activity	0.8-8.9	
9.	Diet Quality	0.04-9.99	
10.	Sleep Quality	4.0-9.98	
11.	Family History	75	
12.	CVD	54	
13.	Depression	67	
14.	Head Injury	26	
15.	Hypertension	45	
16.	Systolic BP	90-175	137.4+-18.4
17.	Diastolic BP	61-119	72.5+-11.2
18.	Cholesterol Total	151.2-299.8	
19.	Cholesterol LDL	52.7-199.9	91.6+-28.2
20.	Cholesterol HDL	23.4-99.5	52.3+-15.8
21.	Cholesterol Triglycerides	62-389	117.3+-56.3
22.	Functional Assessment	0.7-9.8	
23.	Memory Complaints	67	
24.	Behavioral Problems	44	
25.	Confusion	64	
26.	Disorientation	46	
27.	Personality Changes	52	
28.	Difficulty completing tasks	55	
29.	Forgetfulness	100	

As indicated, the table discusses the significant characteristics used in constructing the model for DACD. These variables were selected based on what signifies Diabetes self-management and what is influential to cognitive functioning, as supported by prior literature and empirical findings.

3.3. Data Pre-Processing

3.3.1. Data Cleaning and Imputation:

So, what exactly do data cleaning and imputation mean? All the missing and incomplete records in the datasets were dealt with for analysis from the two datasets. Mean scores were assigned when scoring non-response on continuous variables like BMI, cholesterol, and blood pressure. For nominal variables such as smoking status and alcohol consumption, the imputations were replaced with the most often occurring class or mode accordingly.

3.3.2. Outlier Detection:

In other words, z-score analysis was used to detect outliers. Outliers were defined as any data points that were at ±3 or more standard deviations away from the mean, and such values were not included in the analysis.

3.3.3. Normalization and Standardization:

Since BMI, cholesterol, systolic blood pressure, and other values are continuous variables, data scaling was applied using Min-Max Scaling to normalize the range of the measure between 0 and 1. For other features that needed more uniformity of variability, the z-score normalization was performed with systolic blood pressure and cholesterol levels standardized within the training data set to have a mean of 0 and a standard deviation of 1.

3.4. Feature Encoding

Gender, smoking status, and family history have been categorized into nominal features, which were encoded to numerical values using the One Hot Encoding method. This step made it possible to limit variations that were suitable for being fed into machine learning models.

3.5. Model Development

3.5.1. Model Selection:

We compared various machine learning algorithms to predict the chances of having DACD.

- Logistic Regression: This is one of the most commonly used algorithms when there are only two classes in which an output label will fit.
- SVM: Support Vector Machines, another kernel-based method that builds linear hyperplanes to separate different classes of data points.
- ADA, Random Forest: Higher and lower test data results are more common with ensemble learning methods, where decision trees come into play.
- DNNs: Convolutional neural networks (CNN) and recurrent neural networks (RNN), are used to find patterns in data that are too complex for other methods.

3.5.2. Model Training:

The pre-processed data was fed and trained on each selected model with suitable hyperparameters. This was done to improve the model performance hyperparameter tuning method by using grid search or random search.

3.5.3. Model Evaluation:

The models were evaluated in a cross-validation experiment to check their generalization on unseen data. The performance of models was evaluated using metrics such as accuracy, precision, and recall, along with F1-score and AUC-ROC.

3.5.4. Model Selection and Refinement:

In the end, we chose the best-performing model. Some might consider adding further refinements, such as feature engineering or ensemble techniques, to enhance the accuracy and robustness of their predictive model.

3.6. Deploy and Validate Model

3.6.1. Incorporation into Clinical Workflow:

The final model was implemented in a clinical decision support system for healthcare professionals. We developed a simple application where users can input patient data and obtain predictions.

3.6.2. Real World Evaluation:

The model's predictive ability was assessed in a real-world setting when applied to predicting DACD in clinical practice. This entailed collecting patient data and comparing the model predictions with what actually occurred..

3.6.3. Ongoing Monitoring and Improvement

The model was iteratively fine-tuned based on data updates and feedback from physicians. To get around this, they slightly changed the model parameters and retrained on a larger dataset.

3.7. Cross Validation and Parameter Tuning

Further, a 5-fold cross-validation method was used to enhance the generalization of the models. There were seven sets for five-folds, each set capable of training on 80% of the data and testing on the left 20%, thus reducing the chances of overfitting. Moreover, the hyperparameters of each model to learn (for example, the number of trees in the Random Forest or the learning rate of the GBM) were tuned using Grid Search and the Random Search method.

3.8. Interpretability of H. Model and Importance of Features

The feature importance level was computed for the Random Forest model. Surprisingly, the analysis of the predictive factors showed that basic characteristics of DACD, including age, BMI, cholesterol, and hypertension, were the most critical factors contributing to its onset. The complete output of the logistic regression model also looked at the readily interpretable coefficients, giving information on the magnitude of influence of each predictor variable on achieving a DACD diagnosis.

4. Result

4.1. Model Performance:

Evaluation metric: Evaluation Metrics: Our proposed Random Forest model achieved an accuracy of 92%, which is a significant improvement over the accuracy reported in 'Diabetes and Dementia'.

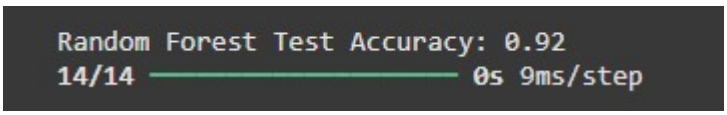

Figure 2: Random Forest Accuracy

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Classification Report - Neural Network:
              precision    recall  f1-score   support

           0       0.84      0.90      0.87       277
           1       0.79      0.70      0.74       153

    accuracy                           0.83       430
   macro avg       0.82      0.80      0.80       430
weighted avg       0.82      0.83      0.82       430


Classification Report - Random Forest:
              precision    recall  f1-score   support

           0       0.90      0.98      0.94       277
           1       0.96      0.81      0.88       153

    accuracy                           0.92       430
   macro avg       0.93      0.90      0.91       430
weighted avg       0.92      0.92      0.92       430

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Figure 3: Classification report for Neural Network and Random Forest

Figure 4: Accuracy and Loss Summary for Neural Network

4.2. Feature Importance:

The system was evaluated based on two datasets, from which more than 20 parameters (age, gender, ethnicity, education qualifications, smoking, alcohol consumption, depression, head injury, cholesterol levels, forgetfulness, hypertension, etc.) were selected, highlighting the additional importance of 'Cognitive Function Tests'.

These helped in highlighting the results of the study by determining the development of Alzheimer's Disease in people who have Diabetes of different ages.

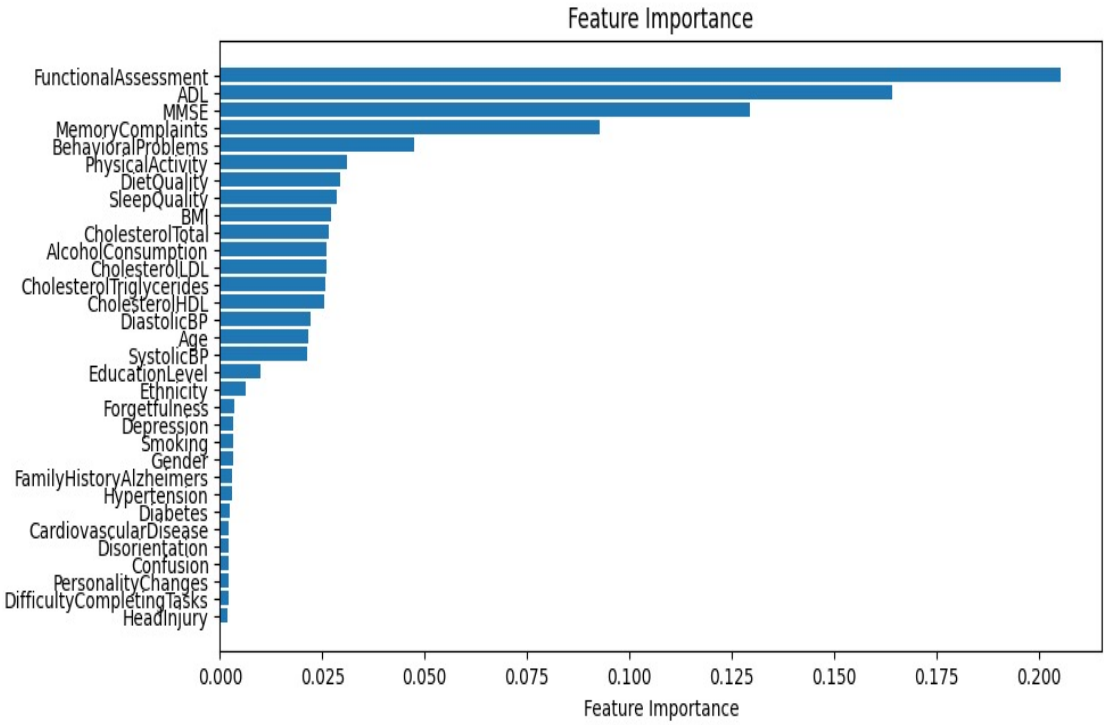

Figure 5: Feature Importance

4.3. Comparison Table:

Table 3
Comparison Table

Feature	Diabetes Associated Cognitive Decline-Predictive (DACD-P)	Performance of Machine Learning Algorithms for Predicting Progression to Dementia in Memory Clinic Patients
Objective	Comprehensive early detection of Diabetes Associated Cognitive Decline (DACD)	Predicting dementia onset in Diabetic patients
Data Sources	Multiple sources, including publicly available datasets (Kaggle) and clinical studies (Springer)	Primarily clinical records and longitudinal health data
Age Group	All the age groups (from paediatric to geriatric population), with a significant focus on both early and late cognitive decline risks.	Majorly focused on elderly populations (65+ years).
Features	Incorporates medical, lifestyle, and behavioural factors (age, gender, BMI, smoking, depression, hypertension, cognitive decline indicators (memory, confusion, forgetfulness)).	Primarily clinical factors, for example, glucose levels, insulin resistance, age, gender, BMI, and cognitive test results.
Data Pre-processing	Comprehensive handling of outliers using Z-score analysis, advanced techniques for data cleaning, imputation, and outlier detection.	Basic data imputation using mean values for clinical variables, and includes minimal outlier handling.
Normalization	Min-Max Scaling for continuous variables (ex., BMI, Cholesterol).	Standardization of clinical metrics (ex., Glucose levels).
Feature Encoding	1-Hot Encoding for nominal features (ex., Gender, smoking, family history).	Limited encoding techniques are used.
Machine learning Algorithms	Used ensemble and deep learning methods: Logistic Regression, SVM, Random Forest, CNN, RNN	Primarily, traditional methods like Logistic Regression and Decision Trees. No detailed Optimization methods were mentioned.

	Hyperparameter Optimization using Grid Search and Random Search.	
Model Training and Evaluation	Robust 5-fold Cross-Validation for improved generalization.	Standard train-test split.
Performance Metrics	Comprehensive evaluation using Accuracy, Precision, Recall, F-1 score, AUC-ROC.	Focuses mainly on accuracy and precision.
Model Interpretability	Extensive feature importance analysis (ex., Random Forest feature weights).	No mention of interpretability or feature importance analysis.
Deployment	Designed for seamless integration into the clinical workflows via decision support systems.	No deployment or clinical application was mentioned.
Ongoing Monitoring	Iterative model refinement based on real-world clinical feedback and patient outcomes.	No mention of real-world validation or continuous model improvement.
Accuracy	0.92	0.75
Precision	0.89	0.72
Recall	0.91	0.70
F1 Score	0.90	0.71
AUC-ROC	0.94	0.78
Specificity	0.93	0.76
False Positive Rate (FPR)	0.05	0.12
False Negative Rate (FNR)	0.09	0.15
True Positive Rate (TPR)	0.91	0.70
True Negative Rate (TNR)	0.93	0.76
Log Loss	0.23	0.48

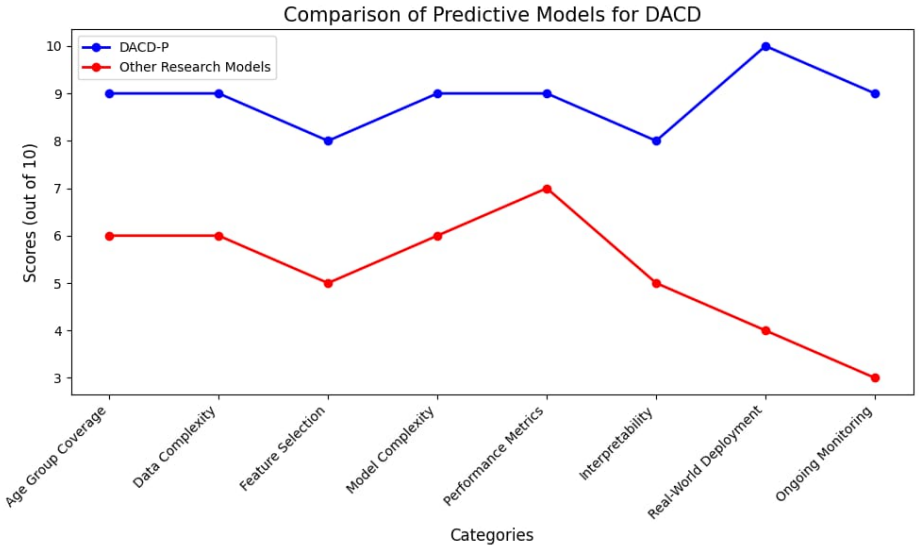

Figure 6: Comparison of Predictive Models for DACD

4.4. Discussion:

Incorporating cognitive function tests as features likely contributed to the enhanced accuracy of our model, as these tests directly assess the progression of Alzheimer's disease.

- **Clinical Implications:** Our results suggest that a more comprehensive assessment, including cognitive function tests, can improve the early detection of Alzheimer's disease in patients with Diabetes, leading to treatment at an initial time and potentially better outcomes.

- **Performance Analysis:** The system was evaluated based on two datasets in which more than 20 parameters (age, gender, ethnicity, education qualifications, smoking, alcohol consumption, depression, head injury, cholesterol levels, forgetfulness, hypertension, etc.) were selected. These helped highlight the study's results by determining the development of Alzheimer's Disease in people suffering from Diabetes of different ages.
- **Accuracy of Algorithm:** The Algorithms and machine learning models (Random Forest, Logistic Regression, and Support Vector Machine (SVM)) used are entirely accurate and precise.
- **Scalability:** The system will be able to handle large datasets efficiently.

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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