Detection Of Neurocognitive Impairment In The Elderly Using TabNet Algorithm

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***Abstract*—As the global population ages, neurocognitive disorders like the Alzheimer's disease which is a form of dementia, and several other forms of dementia are becoming more commonplace. These conditions significantly impair the quality of life for patients and present a growing challenge for healthcare systems worldwide. Early detection is critical to improving patient outcomes, yet traditional diagnostic methods often struggle to catch on to the very early and subtle signs of decline in cognitive function. In this paper, a deep learning algorithm, TabNet, is used on clinical data to detect neurocognitive impairment. Before applying the algorithm, Exploratory Data Analysis is also performed to get a better understanding of the dataset. This research is mainly focused on people with family history. The TabNet model, designed especially for tabular data easily and effectively learns the importance of each feature and their inter-dependencies. In future work, it is aimed to make this research more holistic by using Vision Transformer models to analyze MRI images. This study currently focuses on clinical data, which includes demographic, lifestyle, and cognitive assessments, and demonstrates how TabNet can be used to identify signs of cognitive impairment. Working with critical features, this study also focuses on data pre-processing and feature selection. This project's main aim is to utilize AI in healthcare to help with diagnoses that are otherwise somewhat difficult to make.**

Keywords- Neurocognitive Disorders, Alzheimer's Disease, TabNet, Exploratory Data Analysis(EDA), Clinical Data, Feature Selection, Deep Learning, Elderly Population, Early Diagnosis, Prediction Model, AI in Healthcare

I. Introduction

Neurocognitive disorders like Alzheimer's, Parkinson's, and several varieties of dementia are increasingly common as life expectancy rises across the globe. These conditions mostly begin with subtle cognitive symptoms that are difficult to detect using traditional diagnostic methods. Unfortunately, substantial brain damage might have already taken place by the time these symptoms are sufficiently evident for standard evaluation tools to detect them. Because of this, patients are frequently diagnosed later in life, when there are fewer options for treatment, which lowers the probability of an effective intervention.

Given how crucial early detection is, artificial intelligence (AI) presents an acceptable approach. Large volumes of clinical data can be analyzed by AI, particularly deep learning, to find hidden patterns that might not be immediately obvious to human observers. In the area of detecting neurocognitive disorders, where immediate diagnosis is necessary to improving patient outcomes, this ability is particularly helpful. Additionally, early diagnosis can help with interventions that improve quality of life, lessen symptom severity, and slow the progression of the disease.

In this work, the concentration is on clinical data from elderly patients to predict neurocognitive disorders using the TabNet deep learning algorithm. Since TabNet can handle tabular datasets and dynamically learn which features are most important for prediction, it will be suitable for this study. The goal is to use this model to create a diagnostic tool that will enable medical professionals to detect cognitive decline earlier and with greater accuracy than is possible with conventional techniques. Future research will include MRI images analyzed with the Vision Transformer model to offer a more thorough picture of brain health. This multimodal strategy will combine behavioral, cognitive, and structural data to further improve diagnostic accuracy. Additionally, understanding the dataset prior to any implementation is crucial. So, Exploratory Data Analysis is performed to understand the features better, which will be more insightful along with TabNet results.

The clinical dataset used in this study includes demographic information, lifestyle factors, medical history, and cognitive assessments, all of which are potential indicators of neurocognitive disorders. By using these input features, the TabNet model is trained to recognize the early stages of cognitive impairment with high accuracy. It will learn from every single feature and understand them thoroughly, it will understand their dependencies and use that to make the model more accurate. The integration of imaging data will be explored in future research and be combined with these insights gained from clinical assessments, thus providing a more holistic prediction system.

II. Related Works

This paper systematically reviews the use of SCAs [2] for neuropsychiatric disorder detection. It identified 17 studies based on disorders like depression, dementia, and other impairments in cognition, by using AI technologies in feature extraction and analysis through deep learning methods. Most systems that are related to verbal and audiovisual data for prediction validation lack comprehensiveness, especially as regards reliability and usability. Though the field holds great promise and is increasingly integrating AI, current SCAs are not yet validated for clinical use.

Predictive models were created in a different study [10] to evaluate the change from mild to serious neurocognitive dysfunction. Over a two-year period, 132 subjects' clinical, demographic, and neuropsychological data were incorporated into the model. It identified important risk variables such as high body mass index and alcohol intake with an accuracy of 83.7%. The danger was decreased by characteristics like being female and having better praxis ability. The generalizability of the model was constrained by the small dataset.

By combining a Support Vector Machine (SVM) with a Feature Extraction Battery (FEB) [8], the proposed FEB-SVM algorithm sought to enhance dementia prediction. The model outperformed 12 state-of-the-art techniques, reaching accuracy of 98.28% on training set and accuracy of 93.92% on testing set. FEB's created features were successful in increasing prediction accuracy, but they were ineffective in pinpointing the precise causes of dementia. More feature development was stressed throughout the study in order to gain deeper insights.

Population and care data were merged in a Swedish longitudinal study (SNAC) [13] to record the aging process and care requirements in various locations. Many aspects of senior health, care, and social services were examined in this study. The multidisciplinary methodology made it possible to analyze aging holistically. Unfortunately, the extensive breadth necessitated complicated and resource-intensive data collection and study design. The article emphasized the difficulties of overseeing a dataset this size.

In a study of Saudi patients, an AI-based method [12] for diagnosing neurocognitive problems that employed logistic regression and SVM models achieved up to 95.5% accuracy. Important variables like chronic illnesses and educational attainment were brought to light by the study. Even though the SVM model worked well, more research was needed to determine whether it could be applied to other populations. The study found that in order to improve generalizability, it is crucial to use a variety of datasets.

Using 2D MRI data, a Bi-Vision Transformer (BiViT) model [4] provided a novel transformer-based method for classifying cognitive diseases, including Alzheimer's disease. The model used cutting-edge feature learning modules to achieve 96.38% accuracy. It captured intricate patterns in medical photos better than previous deep learning techniques. Its application in real-world scenarios is constrained in the absence of more data due to its poor performance in smaller or unbalanced datasets.

An analysis of AI-augmented neurocognitive screening tests [5] examined the ways in which deep learning and speech recognition are examples of AI and machine learning techniques that have enhanced cognitive evaluations. The study covered how AI might improve exam accuracy and lessen biases. Notwithstanding these developments, issues with technological accessibility, data privacy, and dependability nonetheless exist. It was noted that older-friendly designs and more validation were required.

By merging weak learner models, the StackEnsembleMind [15] model improved mental health assessments through a stack-based ensemble machine learning technique. The model identified mental states including stress and worry with 98% accuracy. Reliability was increased by addressing class imbalances with SMOTE. Unfortunately, the model's intricacy limited its practical application by making it challenging to understand and apply in healthcare settings.

Another paper explores the application of machine learning, particularly deep learning [11] , for the classification of three neurodegenerative diseases: cerebral ataxia, Alzheimer's disease, and Parkinson's disease. The authors uses a two-step methodology, employing pre-trained neural network architectures in the form of VGG16 and ResNet101. In fine-tuning these models for each disease, the researchers enhance the networks' ability to differentiate among them. Optimizations techniques like SGD, Rmsprop, and Adam are used to get the best result; evaluation metrics such as accuracy, loss are applied for the assessment of the model. The model is deployed through the Flask web framework, making it accessible and user-friendly.

A paper discusses the use of machine learning algorithms in disease diagnosis, focusing on the application of these algorithms in Electronic Health Records (EHRs) [3]. Because of the ever-expanding patient data, machine learning is promising for improving the efficiency and accuracy of diagnosis. The study uses anonymized EHRs to include the medical history, laboratory results, and clinical notes to build models for predicting diseases. Various ML algorithms were implemented and evaluated against their interpretability, computational efficiency, and diagnostic accuracy. The results show that machine learning-based methods are superior compared to conventional diagnostic methods, providing improved accuracy and efficiency in disease diagnosis and prediction.

In order to predict mild cognitive impairment (MCI) [7] based on emotional arousal and valence tasks, a study that classified MCI from behavioral responses using machine learning. The model's accuracy in differentiating between MCI and normal cognition was around 90%. Comparing this non-invasive technology to traditional ones revealed practical advantages. To capture more sophisticated signs of cognitive impairment, the fundamental components of the activities needed to be further refined.

Analysis of vocal characteristics [14] such as speech rate and voice activity in natural conversations was the main goal of a long duration study about the use of voice data for Alzheimer's disorder detection. The technique used a Bayesian classifier and obtained 68% accuracy. Non-invasive speech data was a promising early diagnosis technique because of how easy it was to use. The quantity of the dataset, however, hampered its accuracy, indicating the need for further data to enhance performance.

A machine learning-based dual-task gait assessment model [6] was developed to detect Alzheimer's disorder and mild to medium cognitive decline. When the DSM-5 criteria were compared to those of other diagnostic systems, the model discovered that DSM-5 detected more cases than DSM-IV. Still, diagnosis accuracy for less severe illnesses like MCI was only moderately high. Although more work needed to be done, the study indicated that the DSM-5 criteria could help with early cognitive decline identification.

MRI data was utilized to build a 2D Convolutional Neural Network (CNN) [1] to identify moderate cognitive impairment (MCI) at early stage, which produced a user-friendly diagnostic tool. The model showed promise for application in resource-constrained clinical settings and performed well even with little datasets. But because of system constraints, crucial preprocessing stages like skull stripping were omitted, which might have affected performance. The study made recommendations for future developments in data preparation.

Alzheimer's disease was diagnosed using a multimodal technique that included gene expression data and MRI images, using deep learning models like CNN and SpinalNet [9] A complete method of diagnosis was made possible by the combination of genetic and imaging data. However, the method's processing cost restricted its full capacity areas with insufficient resources. The study underlined the need for more effective implementations while also highlighting the possibilities of multimodal techniques.

A paper proposed a system that aims to detect Parkinson's Disease (PD) [16] at an early stage using Magnetic Resonance Imaging (MRI) and artificial intelligence. MRI is very essential in identifying the characteristics of Parkinson's features, and this study makes use of deep learning, more importantly, a Deep Ensemble Network, to enhance its detection process. The combined system uses a CNN model and LSTM optimized using the ADAM algorithm. The accuracies, precisions, recalls, and F1 values obtained are used to depict the performance of the proposed model, which attains an astonishing 98% accuracy. Comparison with existing approaches proves that the proposed method ensures effective early detection of PD.

III. PROPOSED METHODOLOGY

A. *Problem Definition:*

This paper aims to develop a predictive model to identify neurocognitive disorders based on clinical data from elderly patients. The scope of such data would include demographics, lifestyle, and cognitive assessment. Though the future work will be deployed with regard to integrating Vision Transformers for MRI image analysis into more proper diagnosis, this paper concentrates on the clinical data analysis via the use of the TabNet model.

B. *Dataset:*

The data set includes measures of many types of features that are known to be associated with neurocognitive degradation. These include demographics, such as Age and Gender, as well as Ethnicity. Lifestyle factors, such as Smoking, Alcohol_Intake, Phy_Activity, EatingQuality; and medical history items including Family_History, Diabetes, CardiovascularDisease are also included. Cognitive and behavioral assessment tools such as the Mini-Mental State Examination (MMSE) and markers of memory complaints, confusion, and disorientation are also included.

Dataset Description

The dataset’s features are as follows:
Demographics: P_ID, Age, Gender, Ethnicity, Level_of_Education

Health Factors: BMI, Smoke_habits, Alcohol_Intake, Phy_Activity, Eating_Quality, Sleeping_Quality, Family_History, Cardiovascular_Disease, Diabetes, Depression, Head_Injuries, Hypertension, Systole_BP, Diastole_BP, Cholest_Total, Cholest_lLDL, Cholest_HDL, Cholest_Triglycerides

Cognitive/Behavioral Assessments: MMSE_Score, Function_Assessment, Memory_related_Complaints, Behavior_Problems, ADL, Confusion, Dis-orientation, Personality_Change, Difficulty_Completion_Tasks, Forgetfulness, Diagnosis

C. *Data Preprocessing and Feature Selection*

Exploratory Data Analysis is performed. It is used to summarize the dataset after preprocessing it. It is important for understanding the dataset and getting key insights. Preprocessing of data can be considered one of the most important steps of this study since it ensures the dataset is prepared enough to train the TabNet model. Missing values are addressed by imputing them using appropriate statistical methods for continuous variables through Mean, and for categorical, Mode. Other categorical variables like Gender and Ethnicity are encoded in one-hot encoding so that the format can change for the model to take. Continuous variables, such as BMI and blood pressure, are normalized in order to minimize the influence of outliers and skewness. Then univariate and bivariate analysis is done to get a proper comparison and understand the dependencies between the features. Univariate analysis gives the information about the distribution of each variable, while bivariate analysis gives information about the relation between each variable and the target variable. This study also analyzed the distribution of the target variable, to check if the dataset is imbalanced or balanced.

In addition, feature selection is another important part of the methodology. TabNet, unlike typical machine learning models, has an intrinsic feature selection mechanism- during training, it learns dynamically which features are most important. This is very valuable for the domain of medicine because there are certain health indicators that carry more predictive weight than others. Hence, for instance, the variables might be FamilyHistory or MMSE scores-these are much more indicative of cognitive decline than SleepQuality or AlcoholConsumption. In that way, TabNet is able to draw attention to such vital features, keeping it interpretable and predictions made therefrom on most relevant data.

D. System Architecture

Data preparation starts with the system architecture. The clinical dataset is cleaned and standardized. Missing values for continuous variables were filled by Mean. For categorical features such as Gender, missing values were filled using Mode, and one-hot encoding was applied to the categorical variables. Continuous features like BMI are normalized, which reduces the effect of outliers. All the data that is unnecessary was filtered out through feature engineering after preprocessing, leaving only the features useful in the prediction of neurocognitive disorders. This processes the data into the best optimum in respect of hyperparameters, which makes the TabNet model achieve better accuracy.

The process in EDA is to visualize how features are distributed to identify relationships with neurocognitive conditions. Sometimes, features like Age and Gender follow typical patterns because cognitive disorders are more common among elderly people. From histograms, preliminary sense of how these variables correlate with the outcome under consideration can be seen. For eg, Correlation analysis is utilized in mapping relations between factors like Hypertension and CardiovascularDisease. These are very closely associated factors. Last but not least, features like BMI are checked for outliers; clinically relevant values like high blood pressure are retained, but extreme values of BMI might get capped in the process to keep the model sharply focused. Box plots and Histograms are displayed as results of this EDA, to give the final key insights.

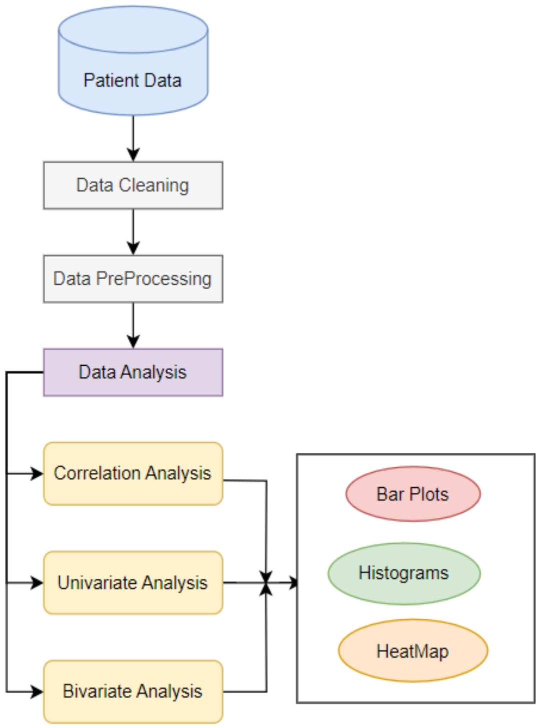

Figure 1: Working of EDA

In the neurocognitive disorder dataset, features have varying predictive strength, where some health indicators are more representative of a disease than others. The sequential attention mechanism in the model dynamically assigns greater attention to features at the decision step, such as FamilyHistory, MMSE scores, and Hypertension. The TabNet model will prefer the most informative features like this over the irrelevant ones, thereby filtering out the noise and focusing on high impact predictors. The fact that this model dynamically and adaptively focuses ensures that clinically important variables are emphasized for optimal accuracy and interpretability.

TabNet also has the ability to handle clinical data by transforming the raw data features with the feature transformer layers. These layers are applied to create more sophisticated representations, allowing the model to understand complex interactions among variables. For example, Age, SystolicBP, and CardiovascularDisease are feature interactions that influence the score of cognitive health all at once and are computed to highlight their interaction effect on neurocognitive disorders. The raw inputs being transformed to high-dimensional representations here enable deeper discovery of subtle dependencies relevant to making precise predictions.

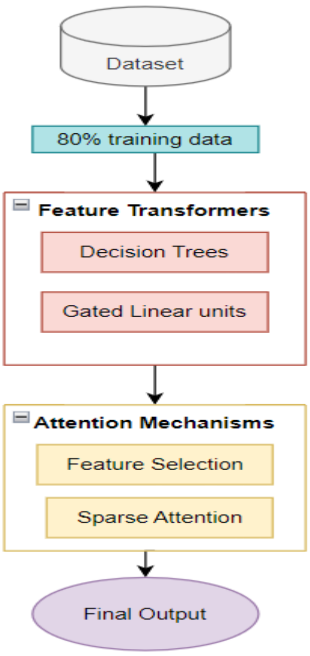

Figure 2: Working of TabNet Algorithm

Lastly, in the attentive transformer layers of TabNet, the refined feature representations are obtained through selective gating of only the most pertinent pathways. It utilizes the techniques of batch normalization and sparsity regularization to avoid overfitting and guarantee generalization to vastly diverse patient profiles in their health histories. This architecture improves interpretability through highlighting features most impactful on the predictions while making TabNet robust especially with complex clinical datasets. Following training, the model predicts neurocognitive impairment probability using a holistic view of the patient's health profile.

The system architecture thus begins with the use of EDA to clean and structure the clinical data in a clean manner so that it's ready for accurate analysis. After that, it is taken over by TabNet, which smartly pays attention to the specific factors like family history and cognitive scores in order to make precise predictions. Combining EDA groundwork with the focused learning of TabNet, this system effectively turns complex health data into meaningful predictions regarding support for the early identification of neurocognitive disorders. This model will prove to be even more useful for patients who had family history get themselves diagnosed, even when their symptoms are very subtle and early.

E. *Performance Metrics:*

Accuracy:

This metric evaluates the model's overall prediction performance by determining the ratio of correct predictions—both true positives (TP) and true negatives (TN)—to the total instances in the dataset.

Precision:

Precision reflects the accuracy of the model's positive predictions by calculating the proportion of true positives out of all instances labeled as positive. It is computed with the formula:

$$TP / (TP + FP)$$

where FP represents false positives and TP stand for True Positives.

Recall (Sensitivity):

Recall, or sensitivity, gauges the model's effectiveness in identifying positive cases within the dataset. This metric is determined by the formula:

$$TP / (TP + FN)$$

where FN represents false negatives.

F1 Score: The F1 score combines both precision and recall into a single metric, offering a balanced view of the model's performance. It is the harmonic mean of these two metrics and is calculated as:

$$2 * (Precision * Recall) / (Precision + Recall).$$

Error checking

Confusion Matrix: This matrix organizes predictions into true positives, false positives, true negatives, and false negatives, allowing for a structured summary of the model's performance. From these values, various other metrics can be derived.

Results and Discussion

A. *Experimental Setup*:

The whole project was built on a Windows 11 operating system in a system with intel core i5 processor 3rd gen configuration, 8GB RAM, and 512GB SSD. The application is based on Python 3.11 and built using jupyter notebook from anaconda version 3. In Python, libraries: Panda, Seaborn and Matplotlib were used for Exploratory Data Analysis. PyTorch and sci-kit learn libraries were used additionally for TabNet algorithm. A lot of hyperparameter tuning was also done to achieve best results. Data was cleaned and pre-processed before usage in the experiment.

Observations:

On observing the dataset using bar charts, with the features: Smoking, CardioVascularDisease, Diabetes, HeadInjury, MemoryComplaints and FamilyHistory against count of diagnosed individuals, it was observed that family history and smoking played a major role in prognosis of neurocognitive impairment. Memory complaints was also prominently faced by diagnosed individuals. Although head injury is the highest on the scale, it can be seen that head injury does not account or play a major role in getting any form of dementia.

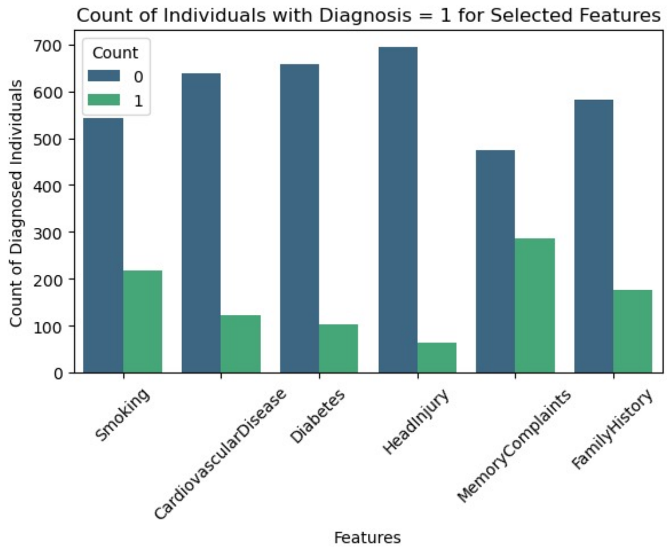

Figure 3: Key Features vs Diagnosed Count

On further analyzing the features, this study visualized 18 key features using a heatmap. Memory complaints and behavioral problems were highly correlated with diagnosis which showed that these were the highest popular symptoms among the individuals with neurocognitive impairment. It can also be seen that the correlation among the other features were comparatively lower, which also shows why medical professionals have a hard time detecting these diseases. The implementation of deep learning algorithms in this field would definitely prove to be fruitful.

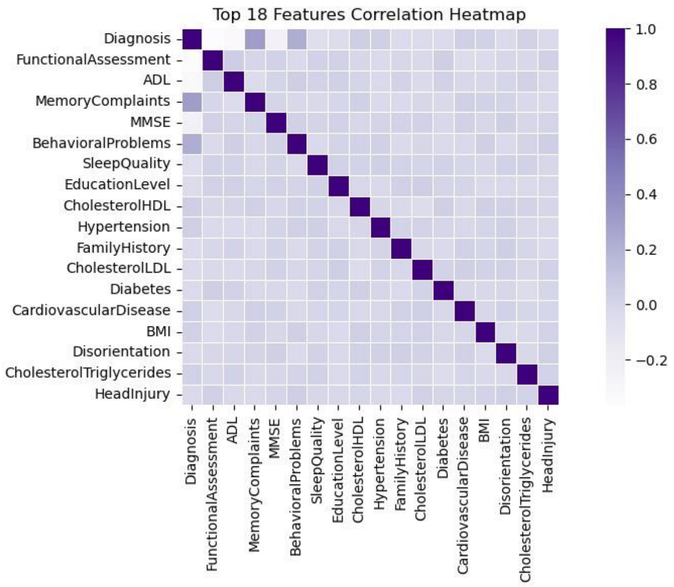

Figure 4: Correlation among 18 features

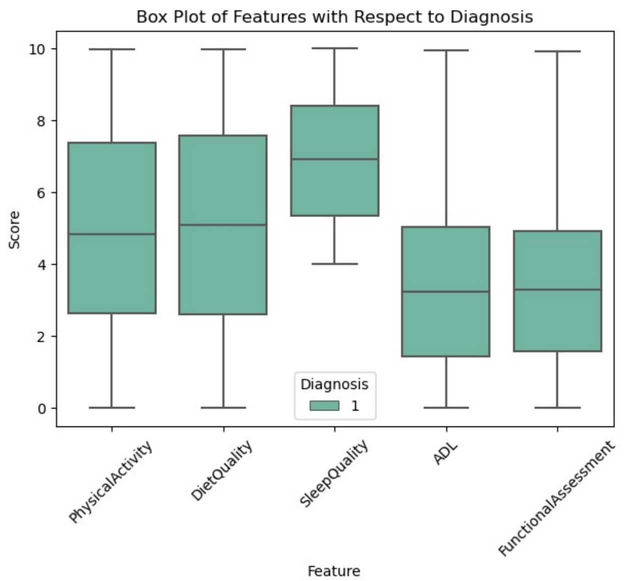

Figure 5: Box-Plot

Some other features were also visualized and analyzed using Box Plot, against a score with a scale of 0 to 10, with respect to diagnosis. Even though sleep quality seems to be comparatively better, ADL (Activities of Daily life such as consuming food, washing, writing, dressing-up etc) and Functional Assessments which also tests patient's ability to do simple tasks, has a very low score. These are most affected by neurocognitive impairment.

With medians of roughly 6 and 5, respectively, Physical Activity and Diet Quality show modest average scores but notable variability, with a wide range of 1 to 10. The range of sleep quality scores is from 2 to 10, with a higher median score near 7 indicating that patients have better average sleep quality. Activities of Daily Living (ADL) and Functional Assessment scores, on the other hand, are lower, with ranges between 1 and 8 and medians close to 3 and 4, respectively, suggesting that these areas may be more difficult for people with this diagnosis.

Precision	Recall	F1-score	Accuracy
0.89	0.82	0.85	0.90

Figure 6: Performance metrics for TabNet

Then TabNet algorithm is implemented on the dataset. For the hyperparameters, epochs count was kept at 150 and patience was kept at 20. Decision and attention dimension, unique to TabNet was kept at 16 and 16 respectively. Learning rate was 0.01. From experimental results, it can be seen that the accuracy is 90%. Precision is 0.89, Recall is 0.82 and F1 score is 0.85.

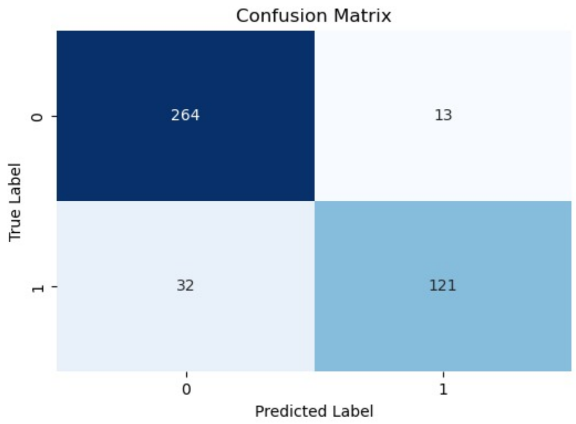

Figure 7: Confusion Matrix

A confusion matrix is a table that is easy to understand and helps to compare how well a classification model's predictions line up with the actual results. It categorizes predictions into four types: correct positives, correct negatives, and two kinds of mistakes: false positives and false negatives. This table helps to look at a glance where the model gets things right and where it goes wrong, making it easier to improve accuracy.

As it can be seen the TabNet algorithm's confusion matrix, true positive and true negative's count is higher than the falsely classified count, which shows that the algorithm is performing really well.

Figure 8: Training loss over epochs

This graph shows the training loss decreasing as it run more epochs. Training loss is usually high in the beginning as the model does not predict accurately, but as it passes more epochs, it learns the patterns and starts predicting with better accuracy, and hence the graph starts dipping. The curve starts at 0.9 during the 1st epoch and then starts falling and reaches below 0.2 at the 150th epoch. This means the algorithm is working well.

IV. Conclusion and Future Work

This study used the TabNet algorithm to analyze tabular data for the early identification of neurocognitive disorders. This model performed the function very well by providing an identification of complex patterns within structured datasets for predictive accuracy and valuable patient health insights. Its strength with handling missing data and interpretation capabilities made it a highly promising tool in the medical field.

The addition of a Vision Transformer will be integrated within the future version of this model in an attempt to study data regarding images as much as data in tabular formats. This multi-modality can be leveraged towards more robust and strong detection methods with better overall accuracies. With that application having images of a demented brain included within its database, neurocognitive disorders are looked forward to being understood extensively at every level, providing proper detection and intervention policies well before the patient crosses some particular threshold.

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