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Optimized Transfer Learning Based Dementia Prediction System for Rehabilitation Therapy Planning

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Abstract: Dementia is a progressive neurodegenerative disease leading to cognitive decline, and current medical interventions can only slow its progression. Early prediction of dementia onset holds potential for preventive measures. This study aims to develop a machine learning model using transfer learning from magnetic resonance imaging (MRI) data to predict dementia. The project employs k-fold cross-validation and various parameter optimization algorithms during model training to enhance prediction accuracy. The final voting classifier and optimized Transfer Learning algorithms achieved an impressive accuracy, surpassing the performance of competing methods on the same dataset. This suggests the efficacy of the proposed transfer-learning approach in predicting dementia data. The developed model enables early diagnosis of dementia, a crucial factor in halting neurological deterioration associated with the disease. This is particularly relevant for regions with limited access to human physicians, providing a valuable tool for underserved populations. The proposed system holds promise for planning rehabilitation therapy programs for dementia patients. As a tool for early diagnosis and intervention, the model not only contributes to improved patient outcomes but also addresses the challenges faced by regions lacking access to sufficient healthcare resources. And also include ensemble methods (Voting Classifier, Stacking Classifier) and a hybrid CNN-LSTM approach are employed for improving accuracy, with the Voting Classifier achieving an impressive 100% accuracy. To facilitate user testing, a user-friendly front end using the Flask framework, incorporating user authentication, was proposed for seamless application of this advanced dementia prediction system.
Index terms: Dementia prediction, machine learning, magnetic resonance imaging (MRI), parameter optimization, transfer learning.

I. INTRODUCTION

Dementia is a chronic degenerative disease [3], [4] characterized by a progressive and irreversible [1], [2], decline in brain function; in particular, it induces behavioral changes and impedes a patient's ability to perform activities of daily living (ADLs). Dementia affects millions of people worldwide and is becoming more prevalent as the planet's population ages. The World Alzheimer Report 2019, published by Alzheimer's Disease (AD) International, estimated that more than 50 million people live with dementia globally. They estimated that this number will increase to 152 million by 2050, equivalent to one person developing dementia every 3 s. Nonetheless, rapid and timely diagnosis can slow this decline in brain function. Manual tools for predicting dementia are inaccurate [2], [5], [6], complex, and require cognitive tests to be administered over a long time. Therefore, previous studies have formulated machine-learning tools [7], [8]. based on the k-nearest neighbor, decision tree, support vector machine (SVM), and extreme gradient boosting (XGBoost) approaches; these tools have been extensively used for rapid and timely diagnosis and clinical decision-making.

One study [9] used an algorithm to distinguish healthy participants from participants with dementia on the basis of behavioral data; in a sequence prediction task, participants with dementia had significantly lower peak accuracy scores (11%) than healthy patients. Sequential pattern discovery using equivalence classes was employed to identify various parameters for early-stage dementia diagnosis. The algorithm could detect early dementia symptoms without the need for expensive clinical procedures. In contrast to the aforementioned study, [10] formulated a method that uses language samples instead. They considered speech and language impairments, which are common in several neurodegenerative diseases, in their cognitive impairment analysis to achieve early diagnosis and identify the onset of cognitive decline.

They further introduced several original lexical and syntactic features in addition to a previously established lexical syntax to train machine-learning classifiers to identify the etiologies of AD, mild cognitive impairment (MCI) and possible AD (PoAD). A decline in linguistic function is associated with neurodegenerative diseases and cognitive decline, and the statistical analysis of lexicosyntactic biomarkers may facilitate the early diagnosis of these diseases. Dementia is closely related to cognitive impairment, but cognitive impairment does not necessarily lead to dementia. According to a report by the Chang Gung Dementia Center, MCI is a transitional period during which the cognitive function of the patient differs from that of a normal older adult. The probability of this MCI progressing to dementia is approximately 10%–15%, far greater than 1%–2% for a group of individuals without MCI. Electroencephalography (EEG) signals obtained during cognitive tests have also been subject to iterative filtering decomposition for dementia prediction [2]. Continuous EEGs were recorded in two resting states (i.e., eyes open and closed) and two cognitive states (i.e., finger-tapping test and continuous performance test). The EEG signals were decomposed using iterative filtering, and four key EEG features were used for multiclass classification. The method was effective for the early diagnosis and prediction of dementia and was superior to decision tree, k-nearest neighbor, SVM, and ensemble classifiers. Similarly, [11] proposed a method for early prediction of dementia by using an innovative travel pattern classification. Environmental passive sensor signals were employed to sense the movements of the inhabitants of a space. The system segmented the movements into travel episodes and classified them using a recurrent neural network. The recurrent neural network was selected because it can process raw movement data directly and does not require domain-specific knowledge for feature engineering. Finally, imbalance in the data with respect to travel pattern classes was handled using the focal loss, and the discriminative ability of the deep-learning features was enhanced using a center loss function. Multiple experiments were performed on real-life datasets to verify the system’s accuracy. Another study [6] used the XGBoost algorithm to predict dementia risk. The XGBoost-based dementia risk prediction model was constructed using variables extracted from quantitative data on dementia, and its hyperparameters were optimized. This method generates top-N groups by extracting the most important variables. Hyperparameter optimization was performed in accordance with the features of the data for each top-N group. The performance of the XGBoost-based model in determining dementia risk was evaluated using the group with the best performance.

This study employed transfer learning and parameter optimization algorithms to produce a dementia prediction model. In the transfer learning framework of this model, multiple weak classifiers were combined into a strong classifier to reduce training time and expedite data aggregation. This framework was integrated with parameter optimization algorithms to improve model accuracy without the need to adjust relevant parameters manually. Other models, namely multilayer perceptron (MLP) [12], random forest [13], support vector classification (SVC) [14], AdaBoost [15], and XGBoost [16], were also used for model training and were used in evaluations of the proposed transfer-learning model. The results of this study were also compared with the prediction results of [6] and [17], which were based on the same dataset. In these comparisons, the accuracy of the proposed model was higher than that of the other models. In addition, various parameter optimization algorithms were applied to improve the accuracy of the final model. This study’s model facilitates the early diagnosis of dementia, which is key to arresting neurological deterioration from the disease, and is useful for underserved regions where many do not have access to a human physician.

II. LITERATURE SURVEY

A. Ambulatory gait behavior in patients with dementia: A comparison with Parkinson’s disease:

Accelerometry-based gait analysis is a promising approach in obtaining insightful information on the gait characteristics of patients with neurological disorders such as dementia and Parkinson's disease (PD). In order to improve its practical use outside the laboratory or hospital, it is required to design new metrics capable of quantifying ambulatory gait and their extraction procedures from long-term acceleration data. This paper presents a gait analysis method developed for such a purpose. Our system is based on a single trunk-mounted accelerometer and analytical algorithm for the assessment of gait behavior that may be context dependent. The algorithm consists of the detection of gait peaks from acceleration data and the analysis of multimodal patterns in the relationship between gait cycle and vertical gait acceleration. A set of six new measures can be obtained by applying the algorithm to a 24-h motion signal. To examine the performance and utility of our method, we recorded acceleration data from 13 healthy, 26 PD, and 26 mild cognitive impairment or dementia subjects. Each patient group was further classified into two, comprising 13 members each, according to the severity of the disease, and the gait behavior of the five groups was compared. We found that the normal, PD, and MCI/dementia groups show characteristic walking patterns which can be distinguished from one another by the developed gait measure set. We also examined conventional parameters such as gait acceleration, gait cycle, and gait variability, but failed to reproduce the distinct differences among the five groups. These findings suggest that the proposed gait analysis may be useful in capturing disease-specific gait features in a community setting.

B. Efficient and explainable risk assessments for imminent dementia in an aging cohort study:

As the aging US population grows, scalable approaches are needed to identify individuals at risk for dementia. Common prediction tools have limited predictive value, involve expensive neuroimaging, or required extensive and repeated cognitive testing. None of these approaches scale to the sizable aging population who do not receive routine clinical assessments. Our study seeks a tractable and widely administrable set of metrics that can accurately predict imminent (i.e., within three years) dementia onset. To this end, we develop and apply a machine learning (ML) model to an aging cohort study with an extensive set of longitudinal clinical variables to highlight at-risk individuals with better accuracy than standard rudimentary approaches. Next, we reduce the burden needed to achieve accurate risk assessments for those deemed at risk by (1) predicting when consecutive clinical visits may be unnecessary, and (2) selecting a subset of highly predictive cognitive tests. Finally, we demonstrate that our method successfully provides individualized prediction explanations that retain non-linear feature effects present in the data. Our final model, which uses only four cognitive tests (less than 20 minutes to administer) collected in a single visit, affords predictive performance comparable to a standard 100-minute neuropsychological battery and personalized risk explanations. Our approach shows the potential for an efficient tool for screening and explaining dementia risk in the general aging population

III. METHODOLOGY

A. Proposed Work:

Revolutionary transfer-learning machine-learning model is proposed to predict dementia from magnetic resonance imaging data. In training, k-fold cross-validation and various parameter optimization algorithms namely gray wolf optimization (GWO), the genetic algorithm (GA), monarch butterfly optimization (MBO), and particle swarm optimization (PSO), were used to increase prediction accuracy. The modified model based on transfer learning is compared with other models. It also includes, ensemble methods, the Voting Classifier and Stacking Classifier which leverages the collective insights from multiple individual models and a hybrid approach, blending Convolutional Neural Networks (CNN) [27] with Long Short-Term Memory (LSTM)were implemented to enhance predictive accuracy. Notably, the Voting Classifier achieved a remarkable 100% accuracy, underscoring the effectiveness of combining diverse model predictions. To facilitate user testing, an interactive front end using the Flask framework, coupled with user authentication, was proposed, ensuring a user-friendly interface for the application of this advanced dementia prediction system.

B. System Architecture:

This study was conducted according to the guidelines of the Declaration of Helsinki and approved by the Human Research Ethics Committee, National Chung Cheng University (Application number: CCUREC111090601). A confusion matrix was used to visualize the prediction results. A two-class confusion matrix is presented in Fig. 1. The columns and rows of the matrix represent predicted and ground-truth class instances, respectively, and indicates whether the model makes erroneous predictions.

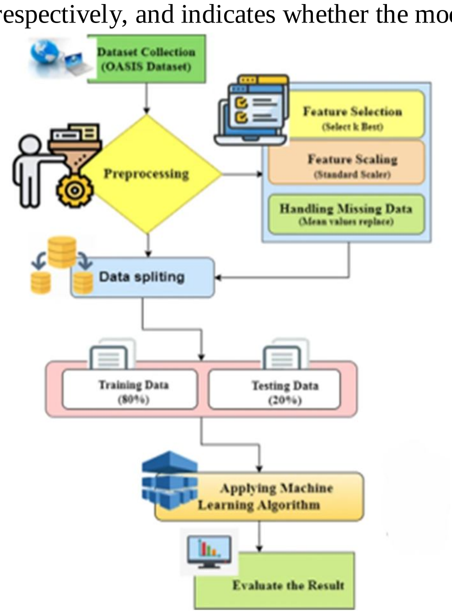

Fig.1 Proposed architecture

C. Dataset collection

The data sets employed in this study were obtained from the Open Access Series of Imaging Studies (OASIS), a series of neuroimaging data sets that are publicly available for research and analysis [18]. The data sets contain numerical brain magnetic resonance imaging (MRI) [6, 18] data from righthanded individuals with and without dementia and aged 60–96 years. The sample comprised 150 individuals (both sexes) who underwent two or more MRI scans 1 year apart for a total of 373 MRI scans. The variables in the data set are presented in Table I [6], these are number of MRI scans, time interval between two or more MRI scans, sex, age, years of education, socioeconomic status (SES), mini-mental state examination (MMSE) score, clinical dementia rating (CDR), estimated total intracranial volume (eTIV), normalized whole brain volume (nWBV), and Atlas scaling factor (ASF). SES was scored from 1 (low) to 5 (high). The Mini-Mental State Examination (MMSE) score [19] were used to indicate cognitive ability and dementia severity and range from 0 (highest risk of dementia) to 30. CDR is an evaluation of six items, namely memory, orientation, judgment, and problem solving, community affairs, home and hobbies, and personal care; memory is the main evaluated item. The eTIV, nWBV, and ASF values were extracted from the MRI data. eTIV is the estimated total intracranial volume, nWBV is the normalized whole brain volume, and ASF is the Atlas scaling factor. Preprocessing was performed prior to model training to remove unnecessary variables and data. All individuals were right-handed; hence, this variable was removed. The numerical patient identifier was also removed. Finally, some individuals had missing data, and their data were removed from the data set. A correlation analysis was conducted on the remaining variables.

D. Data Processing

Data processing involves transforming raw data into valuable information for businesses. Generally, data scientists process data, which includes collecting, organizing, cleaning, verifying, analyzing, and converting it into readable formats such as graphs or documents. Data processing can be done using three methods i.e., manual, mechanical, and electronic. The aim is to increase the value of information and facilitate decision-making. This enables businesses to improve their operations and make timely strategic decisions. Automated data processing solutions, such as computer software programming, play a significant role in this. It can help turn large amounts of data, including big data, into meaningful insights for quality management and decision-making.

E. Feature selection

Feature selection is the process of isolating the most consistent, non-redundant, and relevant features to use in model construction. Methodically reducing the size of datasets is important as the size and variety of datasets continue to grow. The main goal of feature selection is to improve the performance of a predictive model and reduce the computational cost of modeling.

Feature selection, one of the main components of feature engineering, is the process of selecting the most important features to input in machine learning algorithms. Feature selection techniques are employed to reduce the number of input variables by eliminating redundant or irrelevant features and narrowing down the set of features to those most relevant to the machine learning model. The main benefits of performing feature selection in advance, rather than letting the machine learning model figure out which features are most important.

F. Algorithms

1) *Random Forest:* Random Forest is an ensemble learning algorithm that constructs a multitude of decision trees during training. The output of the Random Forest is determined by aggregating the predictions of individual trees, typically using a "majority vote" approach. Random Forest is likely employed due to its ability to handle complex datasets, including those with numerous features like MRI data. It mitigates overfitting and provides robust predictions by aggregating multiple decision trees, contributing to the overall model's accuracy [13].
2) *Support Vector Machine (SVM):* Support Vector Machine is a supervised machine learning algorithm used for classification and regression tasks. It works by finding the hyperplane that best separates data points into different classes while maximizing the margin between them. SVM is likely utilized due to its effectiveness in handling high-dimensional data, which is common in MRI datasets. SVM can identify complex patterns in the data and is known for its versatility in classification tasks, making it suitable for predicting dementia based on MRI features [14].
3) *AdaBoost:* AdaBoost (Adaptive Boosting) is an ensemble learning technique that combines the predictions of multiple weak classifiers to create a strong classifier. It assigns weights to data points, adjusting them during training to give more emphasis to misclassified instances in subsequent iterations. AdaBoost is chosen for its ability to improve the overall model's performance by focusing on challenging instances.

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In the context of dementia prediction, where the dataset may have imbalances or areas of difficulty, AdaBoost helps in refining the model's accuracy by iteratively addressing misclassifications [15].

4) *XGBoost:* XGBoost (Extreme Gradient Boosting) is an ensemble learning algorithm known for its efficiency and performance in classification and regression tasks. It builds a series of decision trees sequentially, each correcting the errors of the previous ones.
5) *Voting Classifier (Random Forest + Decision Tree*): A Voting Classifier combines the predictions of multiple individual classifiers (Random Forest and Decision Tree in this case) and outputs the class that receives the majority of votes. The Voting Classifier is employed to leverage the strengths of both Random Forest and Decision Tree. Random Forest contributes robustness and accuracy through ensemble learning, while Decision Tree offers simplicity and interpretability. Combining them aims to improve overall model performance by capturing diverse aspects of the data [28].
6) *Stacking Classifier (Random Forest + MLP with LightGBM):* Stacking is an ensemble learning technique that combines predictions from multiple base classifiers (Random Forest and MLP with LightGBM in this case) using a meta-classifier. Usage in the Project: Stacking is employed to leverage the complementary strengths of Random Forest, which excels in ensemble learning, and MLP with LightGBM, which is efficient in handling complex patterns. This combination aims to enhance overall prediction accuracy by capturing diverse aspects of the data.
7) *Transfer Learning (TL) with Convolutional Neural Network (CNN) using Grey Wolf Optimization (GWO):* Definition: Transfer Learning involves using knowledge gained from one task to improve the learning of another. In this case, TL is applied to CNN using GWO, which is a metaheuristic optimization algorithm inspired by the hunting behavior of grey wolves. Usage in the Project: TL with GWO is likely utilized to transfer knowledge learned from related tasks to improve the efficiency and accuracy of the CNN. This combination is beneficial for handling complex image data such as MRI scans, enhancing the model's ability to identify patterns associated with dementia [33].
8) *Transfer Learning (TL) with Convolutional Neural Network (CNN) using Particle Swarm Optimization (PSO):* Definition: Similar to TL with GWO, TL with PSO involves using knowledge transfer in CNN, but with the optimization method inspired by the social behavior of birds. Usage in the Project: TL with PSO is applied to enhance the learning of the CNN, particularly in identifying patterns relevant to dementia in MRI data. This approach capitalizes on the adaptability of PSO to optimize model parameters effectively, contributing to improved overall predictive performance
9) *Transfer Learning (TL) with Convolutional Neural Network (CNN) using Genetic Algorithm (GA)*: Definition: Transfer Learning involves leveraging knowledge gained from one task to improve performance on another. In this case, TL is applied to a CNN using GA, which is a metaheuristic optimization algorithm inspired by natural selection and genetics. Usage in the Project: TL with GA is likely used to transfer knowledge from related tasks to enhance the learning of the CNN. GA optimizes model parameters effectively, aiding in identifying complex patterns in MRI data associated with dementia [32,33].
10) *Transfer Learning (TL) with Convolutional Neural Network (CNN) using Memetic Algorithm (MBO)*: Definition: Similar to TL with GA, TL with MBO involves knowledge transfer in CNN but using a Memetic Algorithm, which combines evolutionary algorithms with local search methods. Usage in the Project: TL with MBO is employed to capitalize on the adaptability of Memetic Algorithms in optimizing CNN parameters. This approach aims to improve the model's ability to identify subtle patterns in MRI data associated with dementia.
11) *CNN + LSTM (Convolutional Neural Network + Long Short-Term Memory):* Definition: A combination of CNN, which excels at feature extraction in spatial data, and LSTM, a type of recurrent neural network designed to capture patterns in sequential data. Usage in the Project: CNN + LSTM is chosen for its effectiveness in handling both spatial and temporal aspects of MRI data. This combination is suitable for capturing complex patterns and temporal dependencies, providing a comprehensive approach to dementia prediction from sequential MRI scans.

IV. EXPERIMENTAL RESULTS

1) *Precision*: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives.

Fig.2 Precession comparision graph

2) *Recall*: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

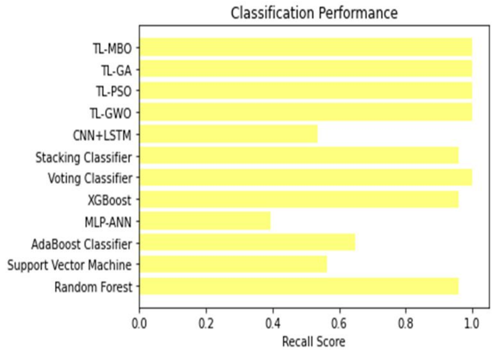

Fig.3 Recall comparision graph

3) *Accuracy*: Accuracy is the proportion of correct predictions in a classification task, measuring the overall correctness of a model's predictions.

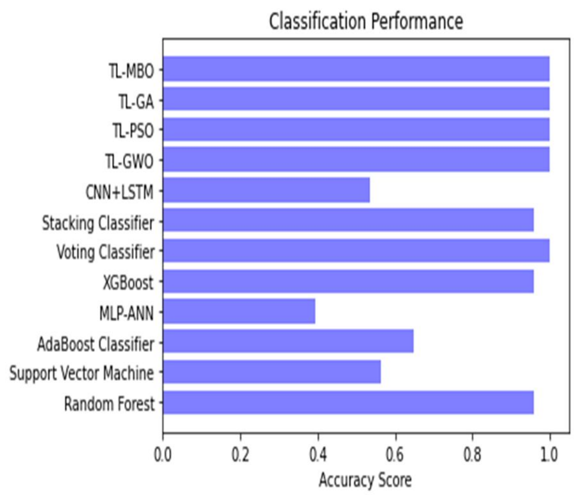

Fig.4 Accuracy comparision graph

4) *F1 Score*: The F1 Score is the harmonic mean of precision and recall, offering a balanced measure that considers both false positives and false negatives, making it suitable for imbalanced datasets.

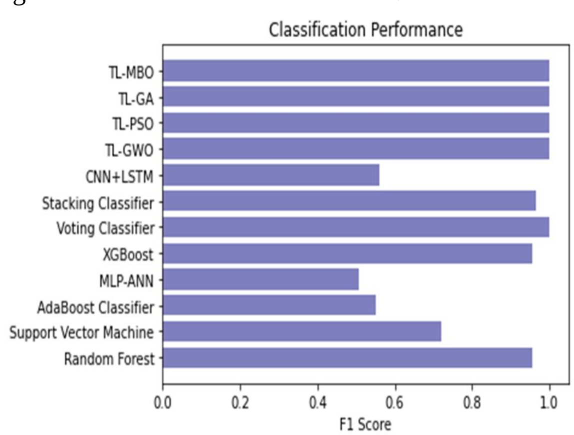

Fig.5 F1 score comparision graph

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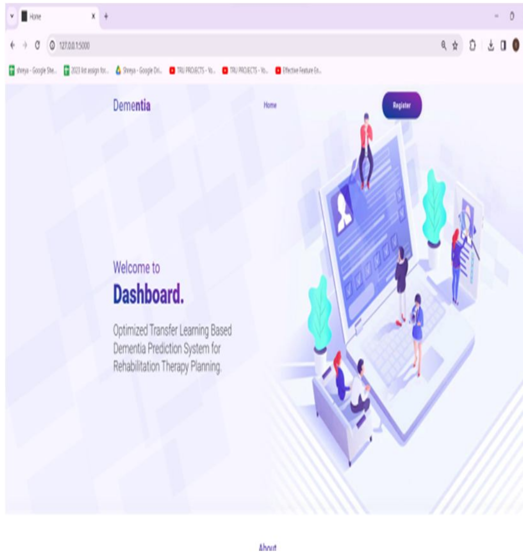

Fig.8 Home page

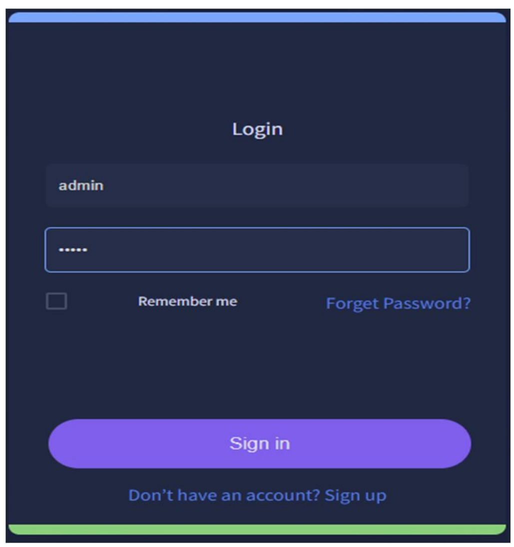

Fig.9 Sign in page

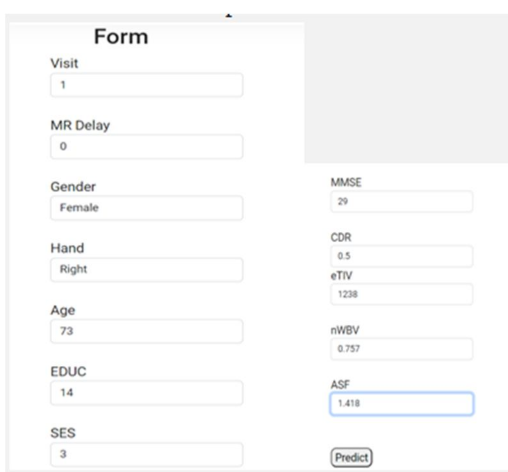

Fig.10 User input

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Fig.11 Predict result for given input

V. CONCLUSION

The project has successfully introduced an innovative diagnostic framework leveraging machine learning and diverse diagnostic tools, to enhance the accuracy and efficiency of dementia prediction. With a focus on global impact, the developed model addresses the increasing prevalence of dementia worldwide. Its applicability in underserved regions contributes to improved accessibility to timely diagnoses and rehabilitation planning. Comparative analyses reveal the superiority of the proposed model over traditional tools and existing models, establishing its efficacy in early dementia detection and neurological preservation. The integration of various machine learning algorithms , parameter optimization, and the incorporation of diverse data sources showcase a comprehensive approach to developing a robust dementia prediction model applicable in real-world scenarios. The another algorithm, showcasing exceptional performance, particularly with the 100% accuracy achieved by the Voting Classifier, has undergone rigorous testing in the user-friendly front end. The algorithm seamlessly incorporates feature values, providing a robust and accurate tool for early diagnosis of dementia. The project's outcomes have significant clinical implications, offering a valuable tool for planning rehabilitation therapy programs. Furthermore, its global accessibility and accuracy contribute to societal well-being by addressing the challenges posed by the increasing prevalence of dementia.

VI. FUTURE SCOPE

The suggested system has the potential to evolve into a leading model for dementia prediction, becoming a key reference in the diagnostic process. Expanding the system's capabilities could involve diagnosing dementia and devising occupational therapy plans, offering comprehensive support throughout patients' rehabilitation. Future investigations might explore integrating additional imaging modalities or biomarkers to boost the precision and dependability of dementia prediction. Adapting and tailoring the proposed system for specific populations or subgroups could enhance prediction accuracy and overall effectiveness.

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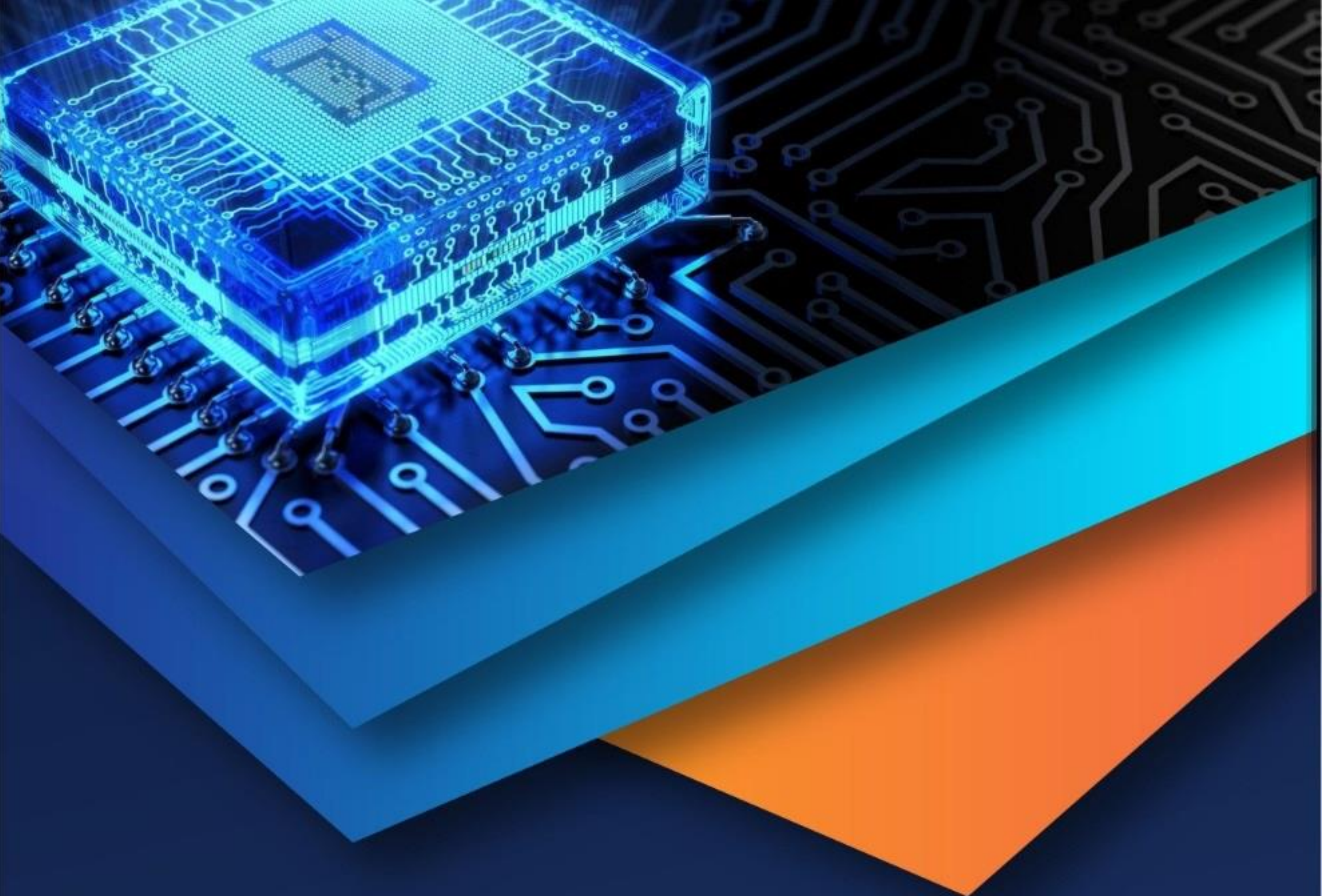

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