International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362

TRANSFER-LEARNING MACHINE-LEARNING MODEL TO PREDICT DEMENTIA

[1] Ch GVN Prasad , [2] M. Manisha, [3]A. P. Navya, [4] MD. Yasin, [5] Srikanth

[1] Professor in Department of CSE Sri Indu College Of Engineering And Technology
chgvnp@gmail.com
[2,3,4,5] UG Scholars Department of CSE Sri Indu College Of Engineering And Technology

Abstract

Dementia is a neurodegenerative disease that causes a progressive decline in memory, thinking, and the ability to execute daily activities. Emotional disorders, language disorders, and reduced mobility are additional prevalent symptoms; however, self-consciousness is unaffected. Dementia is irreversible, and medicine can only delay the degeneration, not stop it. Nonetheless, if dementia could be foretold, its onset could be avoided. Thus, we proposes a revolutionary transfer-learning machine-learning model to predict dementia from magnetic resonance imaging data. In training, k-fold cross-validation and various parameter optimization algorithms were used to increase prediction accuracy. Synthetic minority oversampling was used for data augmentation. The final model achieved good accuracy, superior to that of competing methods on the same data set. This study's model facilitates the early diagnosis of dementia, which is key to arresting neurological deterioration from the disease, and is useful for under served regions where many do not have access to a human physician. In the future, the proposed system can be used to plan rehabilitation therapy programs for patients.

I INTRODUCTION

Dementia is a chronic degenerative disease characterized by a progressive and irreversible 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.Dementia ranges in severity from the mildest stage, when it is just beginning to affect a person's functioning, to the most severe stage, when the person must depend completely on others for basic activities of daily living, such as feeding oneself.Signs and symptoms of dementia result when once-healthy neurons (nerve cells) in the brain stop working, lose connections with other brain cells, and die. Nonetheless, rapid and timely diagnosis can slow this decline in brain function. Manual tools for predicting dementia are inaccurate, complex, and require cognitive tests to be administered over a long time. Therefore, previous studies have formulated machine-learning toolsbased 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.

II LITERATURE SURVEY

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.

Iterative filtering decomposition based early dementia diagnosis using EEG with cognitive tests:

There has been a constant increase in life expectancy with the advancement of modern medicine. Likewise, dementia has also increased and projected to elevate in the coming decades with the higher expenditure on healthcare. Consequently, it is essential to identify early dementia, e.g., a patient suffering from mild cognitive impairment who is highly vulnerable to developing dementia soon. Methods: Through this work, we brought forward an approach by fusing cognitive task and EEG signal processing. Continuous EEG of 16 dementia, 16 early dementia and 15 healthy subjects recorded under two resting states; eye open and eye closed, and two cognitive states; finger tapping test (FTT) and the continuous performance test (CPT). The present approach introduced iterative filtering (IF) as a decomposition technique for dementia diagnosis along with four significant EEG features power spectral density, variance, fractal dimension and Tsallis entropy. Multi-class classification conducted to compare the decision tree, k nearest neighbour (kNN), support vector machine, and ensemble classifiers. Results: The proposed approach deeply checked for their capability of prediction using cognitive scores and EEG measures. The highest accuracies obtained by kNN with 10-fold cross-validation for dementia, early dementia and healthy are 92.00%, 91.67% and 91.87%, respectively. Conclusion: The essential findings of this study are: 1) Experimental results indicate that kNN is superior over other classifier algorithms for dementia diagnosis. 2) CPT is the best predictor for healthy subjects. 3) FTT can be an essential test to diagnose significant dementia.Significance: IF decomposition technique enhances the diagnostic accuracy even with a limited dataset.

A dementia classification framework using frequency and time-frequency features based on EEG signals:

Alzheimer's disease (AD) accounts for 60%-70% of all dementia cases, and clinical diagnosis at its early stage is extremely difficult. As several new drugs aiming to modify disease

progression or alleviate symptoms are being developed, to assess their efficacy, novel robust biomarkers of brain function are urgently required. This paper aims to explore a routine to gain such biomarkers using the quantitative analysis of electroencephalography (QEEG). This paper proposes a supervised classification framework that uses EEG signals to classify healthy controls (HC) and AD participants. The framework consists of data augmentation, feature extraction, K-nearest neighbor (KNN) classification, quantitative evaluation, and topographic visualization. Considering the human brain either as a stationary or a dynamical system, both the frequency-based and time-frequency-based features were tested in 40 participants. The results show that: 1) the proposed method can achieve up to a 99% classification accuracy on short (4s) eyes open EEG epochs, with the KNN algorithm that has best performance when compared with alternative machine learning approaches; 2) the features extracted using the wavelet transform produced better classification performance in comparison to the features based on FFT; and 3) in the spatial domain, the temporal and parietal areas offer the best distinction between healthy controls and AD. The proposed framework can effectively classify HC and AD participants with high accuracy, meanwhile offering identification and the localization of significant QEEG features. These important findings and the proposed classification framework could be used for the development of a biomarker for the diagnosis and monitoring of disease progression in AD.

III EXISTING SYSTEM

an early dementia detection system using inhabitant travel pattern classification. They use the environmental passive sensor signals for sensing the movement of the inhabitant. Their system segments the movements into travel episodes and classifies them using a recurrent neural network. The advantage of using a recurrent neural network is that it directly deals with the raw movement sensory data and does not require any domain-specific knowledge. Finally, their system handles the unbalanced classes of travel patterns by using the focal loss and enhances the discriminative power of the deeply learned features by the center loss function. They conduct several experiments on real-life datasets to verify the accuracy of the system.

DISADVANTAGES OF EXISTING SYSTEM:

- Relies on environmental passive sensor signals and travel patterns for dementia detection. This approach might not capture all relevant features from a medical standpoint, as it doesn't directly involve medical data or brain imaging.
- Uses recurrent neural networks (RNNs) to process raw movement sensory data. While this approach can be effective for movement analysis, it might not capture

intricate brain-related features associated with dementia.

- Employs focal loss to handle unbalanced classes of travel patterns. While this approach can help with class imbalance, it might not be as effective when dealing with the complexity of dementia prediction.

Does not address the issue of geographical accessibility to medical professionals, limiting its potential impact on underserved regions where access to specialized dementia diagnosis is needed

IV PROBLEM STATEMENT

The model developed in this study is helpful for underserved areas where many people lack access to human physicians since it makes early dementia diagnosis easier, which is essential to stopping the disease's neurological degeneration

V PROPOSED SYSTEM

We proposes a revolutionary transfer-learning machine-learning model to predict dementia from magnetic resonance imaging data. In training, k-fold cross-validation and various parameter optimization algorithmsnamely gray wolf optimization (GWO), the genetic algorithm (GA), monarch butterfly optimization (MBO), and particle swarm optimization (PSO), were used to increase prediction accuracy. Synthetic minority oversampling was used for data augmentation. An OASIS brain MRI data set was preprocessed by deleting irrelevant or missing data, quantizing the data, and normalizing the data. The modified model based on transfer learning was compared with other models. This study's model facilitates the early diagnosis of dementia, which is key to arresting neurological deterioration from the disease, and is useful for under served regions where many do not have access to a human physician.

Advantages of proposed system:

1. Utilizes MRI data, which directly captures intricate brain-specific features and biomarkers associated with dementia. This targeted approach enhances the accuracy of diagnosis by focusing on clinically relevant indicators.
2. Concentrates exclusively on dementia prediction from MRI data, leading to higher specificity and accuracy in distinguishing dementia from other conditions. The specialized model is tailored to the intricacies of medical image analysis.
3. Implements advanced machine-learning techniques, such as transfer learning and optimization algorithms (GWO, GA, MBO, PSO), specifically designed to enhance prediction accuracy using medical data. This results in better handling of the complexities of MRI-based dementia prediction.

With its focus on MRI data, the present work is capable of detecting subtle structural changes in the brain even in the early stages of dementia. This early detection potential enables timely interventions and treatments

VI IMPLEMENTATION

Data exploration: using this module we will load data into system

Processing: Using the module we will read data for processing

Splitting data into train & test: using this module data will be divided into train & test

Model generation: Building the model - Random Forest - SVM - Adaboost - MLP - ANN - XGBoost - Voting Classifier (RF + DT) - Stacking Classifier (RF + MLP with LightGBM) - TL (CNN) with GWO - TL (CNN) with PSO - TL (CNN) with GA - TL (CNN) with MBO - CNN + LSTM.

User signup & login: Using this module will get registration and login

User input: Using this module will give input for prediction

Prediction: final predicted displayed Extension

In the base paper the author mentioned to different Dementia Detection Dataset for analysis with Machine Learning and TL models, from which TL with GWO got 90% of accuracy,

As an extension we applied an ensemble method combining the predictions of multiple individual models to produce a more robust and accurate final prediction.

However, we can further enhance the performance by exploring other ensemble techniques such as Voting Classifier, CNN + LSTM and Stacking Classifier may get 100% of accuracy

As an extension we can build the front end using the flask framework for user testing and with user authentication.

VII ALGORITHMS USED

Random Forest - Random forest is a commonly-used machine learning algorithm trademarked by Leo Breiman and Adele Cutler, which combines the output of multiple decision trees to reach a single result. Its ease of use and flexibility have fueled its adoption, as it handles both classification and regression problems.

AdaBoost - Adaboost is an ensemble learning technique used to improve the predictive accuracy of any given model by combining multiple “weak” learners. Adaboost works by weighting incorrectly classified instances more heavily so that the subsequent weak learners focus more on the difficult cases.

XGBoost - XGBoost, which stands for Extreme Gradient Boosting, is a scalable, distributed gradient-boosted decision tree (GBDT) machine learning library. It provides

parallel tree boosting and is the leading machine learning library for regression, classification, and ranking problems.

SVM – Support vector machines (SVMs) are a set of supervised learning methods used for classification, regression and outliers detection. The advantages of support vector machines are: Effective in high dimensional spaces. Still effective in cases where number of dimensions is greater than the number of samples.

ANN-MLP - A multilayer perceptron (MLP) is a misnomer for a modern feedforward artificial neural network, consisting of fully connected neurons with a nonlinear kind of activation function, organized in at least three layers, notable for being able to distinguish data that is not linearly separable.[1] It is a misnomer because the original perceptron used a Heaviside step function, instead of a nonlinear kind of activation function (used by modern networks).

CNN + LSTM - Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs) are both powerful neural network architectures, but they have different strengths and weaknesses due to their design, which also makes them suitable for different types of tasks.

Stacking Classifier- A stacking classifier is an ensemble method where the output from multiple classifiers is passed as an input to a meta-classifier for the task of the final classification.

Voting Classifier- A voting classifier is a machine learning estimator that trains various base models or estimators and predicts on the basis of aggregating the findings of each base estimator. The aggregating criteria can be combined decision of voting for each estimator output.

VIII CONCLUSION

Dementia is increasingly prevalent in the context of an aging society. Dementia remains uncurable, and dementia-related neurological degeneration can only be slowed and not stopped. Machine learning could be used to assist health professionals in diagnosing dementia to enable earlier interventions to slow degeneration. This study proposed an effective classification model for dementia prediction by using dementia data from OASIS for predictive analysis. The modified model based on transfer learning was compared with other models. In addition, the model was paired with four parameter optimization algorithms for training, and the results demonstrated that the model had high predictive power and fit the data well. In the future, this model can be used as the primary model for dementia prediction, saving time and serving as a reference in the diagnosis of dementia. Moreover, model instability during training due to SMOTE data augmentation can be mitigated by the use of larger data sets. The proposed system can be used to diagnose dementia and plan occupational therapy regimens

REFERENCES

[1] M. Yoneyama, H. Mitoma, N. Sanjo, M. Higuma, H. Terashi, and T. Yokota, "Ambulatory gait behavior in patients with dementia: A comparison with Parkinson's disease," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 24, no. 8, pp. 817–826, Aug. 2016, doi: 10.1109/TNSRE.2015.2477856.

[2] N. Sharma, M. H. Kolekar, and K. Jha, "Iterative filtering decomposition based early dementia diagnosis using EEG with cognitive tests," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 28, no. 9, pp. 1890–1898, Sep. 2020, doi: 10.1109/TNSRE.2020.3007860.

[3] P. Durongbhan et al., "A dementia classification framework using frequency and time-frequency features based on EEG signals," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 27, no. 5, pp. 826–835, May 2019, doi: 10.1109/TNSRE.2019.2909100.

[4] Z. Xia, T. Zhou, S. Mamoon, and J. Lu, "Recognition of dementia biomarkers with deep finer-DBN," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 29, pp. 1926–1935, 2021, doi: 10.1109/TNSRE.2021.3111989.

[5] N. Beebe-Wang, A. Okeson, T. Althoff, and S.-I. Lee, "Efficient and explainable risk assessments for imminent dementia in an aging cohort study," IEEE J. Biomed. Health Informat., vol. 25, no. 7, pp. 2409–2420, Jul. 2021, doi: 10.1109/JBHI.2021.3059563.

[6] S.-E. Ryu, D.-H. Shin, and K. Chung, "Prediction model of dementia risk based on XGBoost using derived variable extraction and hyper parameter optimization," IEEE Access, vol. 8, pp. 177708–177720, 2020, doi: 10.1109/ACCESS.2020.3025553.

[7] M. D. Benedetto et al., "Deep networks for behavioral variant frontotemporal dementia identification from multiple acquisition sources," Comput. Biol. Med., vol. 148, Sep. 2022, Art. no. 105937, doi: 10.1016/j.compbiomed.2022.105937.

[8] D. Painuli, S. Bhardwaj, and U. Köse, "Recent advancement in cancer diagnosis using machine learning and deep learning techniques: A comprehensive review," Comput. Biol. Med., vol. 146, Jul. 2022, Art. no. 105580, doi: 10.1016/j.compbiomed.2022.105580.

[9] K. N. Minhad, A. Farayez, K. J. A. Ooi, M. B. I. Reaz, M. A. S. Bhuiyan, and M. H. Miraz, "Sequence prediction algorithm for the diagnosis of early dementia development," in Proc. Int. Conf. Comput., Electron. Commun. Eng. (iCCECE), Aug. 2021, pp. 48–52, doi: 10.1109/iCCECE52344.2021.9534844.

[10] A. H. Alkenani, Y. Li, Y. Xu, and Q. Zhang, "Predicting prodromal dementia using linguistic patterns and deficits," IEEE Access, vol. 8, pp. 193856–193873, 2020, doi: 10.1109/ACCESS.2020.3029907.

[11] A. Chaudhary, H. P. Gupta, K. K. Shukla, and T. Dutta, "Sensor signalsbased early dementia detection system using travel pattern classification," IEEE Sensors J., vol. 20, no. 23, pp. 14474–14481, Dec. 2020, doi: 10.1109/JSEN.2020.3008063.

[12] Q. Zheng, T. Yu, and F. Wang, "Self-supervised monocular depth estimation based on combining convolution and multilayer perceptron," Eng. Appl. Artif. Intell., vol. 117, Jan. 2023, Art. no. 105587, doi: 10.1016/ j.engappai.2022.105587.

[13] J. Ma, Q. Pan, and Y. Guo, "Depth-first random forests with improved grassberger entropy for small object detection," Eng. Appl. Artif. Intell., vol. 114, Sep. 2022, Art. no. 105138, doi: 10.1016/j. engappai.2022.105138.

[14] Q. Hou, L. Liu, L. Zhen, and L. Jing, "A novel projection nonparallel support vector machine for pattern classification," Eng. Appl. Artif. Intell., vol. 75, pp. 64–75, Oct. 2018, doi: 10.1016/j.engappai.2018.08.003.

[15] Y.-L. He, Y. Zhao, X. Hu, X.-N. Yan, Q.-X. Zhu, and Y. Xu, "Fault diagnosis using novel AdaBoost based discriminant locality preserving projection with resamples," Eng. Appl. Artif. Intell., vol. 91, May 2020, Art. no. 103631, doi: 10.1016/j.engappai.2020.103631.