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Predictive Precision: Ai - Driven Dementia Prognosis & Rehab Prep

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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.

Index Terms - Dementia prediction, machine learning, parameter optimization, transfer learning.

1. INTRODUCTION

Dementia is a chronic degenerative disease characterized by the progressive and irreversible decline of brain function, leading to behavioral changes and impairing a patient's ability to perform daily activities (ADLs). As the global population ages, the prevalence of dementia is increasing, affecting millions worldwide. The severity of dementia ranges from mild, where it begins to impact daily functioning, to severe, where individuals become entirely dependent on others for basic tasks like self-feeding. The disease results from the deterioration and death of neurons in the brain, leading to a loss of connections between brain cells. Early diagnosis is crucial as it can slow the progression of the disease. Traditional methods for predicting dementia are often inaccurate, complex, and require lengthy cognitive tests. To address these challenges, machine-learning tools, including k-nearest neighbor, decision trees, support vector machines (SVM), and extreme gradient boosting (XGBoost), have been developed to enable faster and more accurate diagnosis and clinical decision-making.

Studies have explored various approaches for early dementia detection. One study used an algorithm to distinguish between healthy individuals and those with dementia based on behavioral data, identifying significant differences in sequence prediction accuracy. Another study focused on language samples, using speech and language impairments common in neurodegenerative diseases to train machine-learning classifiers for early diagnosis of Alzheimer's disease (AD), mild cognitive impairment (MCI), and possible AD (PoAD). Analyzing linguistic decline through lexicosyntactic biomarkers was found to be useful for early detection. While dementia is closely linked to cognitive impairment, not all cognitive impairments progress to dementia. MCI is a transitional stage with a higher likelihood of progressing to dementia. Additionally, studies have used electroencephalography (EEG) signals during cognitive tests for dementia prediction, applying iterative filtering decomposition to identify key EEG features for multiclass classification. These approaches highlight the potential of machine learning in enhancing early diagnosis and understanding of dementia.

2. LITERATURE REVIEW

Self-supervised monocular depth estimation based on combining convolution and multilayer perceptron:

Current self-supervised monocular depth estimation methods generally follow two approaches: using convolutional networks, which suffer from pixel information loss due to local operations and pooling, or employing transformers, which capture finer depth details but at a high computational cost. This paper introduces CSMHNet, a new framework combining decomposed large kernel convolution with a multilayer perceptron (MLP). This hybrid approach overcomes the limitations of static convolutional weights and reduces memory overhead compared to transformers while improving depth estimation accuracy. Experiments on the KITTI dataset confirm that CSMHNet significantly enhances depth prediction compared to existing self-supervised methods.

Enhancing short-term forecasting of daily precipitation using numerical weather prediction bias correcting with XGBoost in different regions of China:

Accurate short-term precipitation forecasts are crucial for engineering and water management. This study assessed a bias correction method for the Global Ensemble Forecast System V2 using the XGBoost model (M3) across seven climatic regions in China, comparing it with methods using cumulative distribution function matching (M1) and XGBoost alone (M2). The M3 method showed the best performance with lower root mean square errors (RMSE) ranging from 1.819 to 13.608 mm, compared to M1 (2.292 to 17.049 mm) and M2 (1.844 to 18.835 mm). Forecast accuracy declined with longer lead times, with an increase in false alarm and miss ratios for all methods. The XGBoost model with multi-factor bias correction provided the best results, particularly in winter, and was most effective at forecasting daily precipitation.

Deep networks for behavioral variant frontotemporal dementia identification from multiple acquisition sources:

Behavioral variant frontotemporal dementia (bvFTD) diagnosis is challenging, especially in its early stages. Current diagnostics rely on detecting frontal and anterior temporal lobe atrophy via MRI, which often requires manual feature extraction and varies with acquisition devices. This study explores bvFTD identification using advanced deep learning techniques, including artificial neural networks and attention mechanisms. Our extensive hyperparameter search demonstrates that these deep networks can achieve over 90% performance on AuROC and balanced accuracy metrics, effectively identifying bvFTD across different MRI devices without needing model fine-tuning.

Recent advancement in cancer diagnosis using machine learning and deep learning techniques: A comprehensive review:

Cancer, the second leading cause of mortality globally, often remains undetectable until advanced stages, highlighting the need for early detection methods. Machine learning and deep learning have significantly advanced cancer diagnosis, offering improved efficiency and lower error rates compared to traditional methods. This paper reviews recent developments in cancer detection using these technologies, focusing on breast, lung, liver, skin, brain, and pancreatic cancers. It analyzes various data modalities, feature extraction techniques, and benchmark datasets from the past six years. The study evaluates state-of-the-art methods based on performance metrics such as accuracy, area under the curve, precision, sensitivity, and dice score, and discusses future research challenges.

Depth-first random forests with improved Grassberger entropy for small object detection:

This paper introduces a random forests-based method for detecting small objects, like UAVs and aircraft, in images captured by autonomously moving cameras. Random forests are effective for accurate and efficient predictions. The model improves upon traditional entropy-based splits by using an enhanced Grassberger entropy scheme, which provides better performance. Additionally, a depth-first recursive training approach is used to manage memory more efficiently compared to the breadth-first method, which can be memory-intensive. Evaluations on classification and object detection datasets show that the improved Grassberger entropy enhances predictive accuracy and that the depth-first method helps prevent underfitting. This approach is deemed effective for real-world applications.

3. METHODOLOGY

The literature presents an early dementia detection system that classifies inhabitant travel patterns using environmental passive sensor signals. Movements are segmented into travel episodes and classified with a recurrent neural network, which processes raw data without needing domain-specific knowledge. The system addresses class imbalance with focal loss and improves feature discrimination using center loss. Accuracy is validated through experiments on real-life datasets.

Disadvantages:

1. Relies on passive sensor signals and travel patterns, missing direct medical data and brain imaging for dementia detection.
2. Uses recurrent neural networks (RNNs) for movement data, potentially overlooking complex brain-related dementia features.
3. Employs focal loss for class imbalance in travel patterns, but may struggle with the complexities of dementia prediction.
4. Does not address geographical barriers to accessing medical professionals, limiting impact in underserved areas.

We propose a transfer-learning machine learning model for predicting dementia from MRI data. The model uses k-fold cross-validation and optimizes parameters with algorithms like GWO, GA, MBO, and PSO to enhance accuracy. Data augmentation is achieved through synthetic minority oversampling. The OASIS brain MRI dataset is preprocessed by removing irrelevant data, quantizing, and normalizing it. Our model, compared with others, supports early dementia diagnosis, crucial for slowing disease progression and benefiting underserved regions lacking access to physicians.

Advantages:

1. Utilizes MRI data to capture brain-specific features, improving dementia diagnosis accuracy by focusing on clinically relevant indicators.
2. Exclusively predicts dementia from MRI data, offering high specificity and accuracy in differentiating dementia from other conditions.
3. Applies advanced machine learning techniques like transfer learning and optimization algorithms to enhance MRI-based dementia prediction.
4. Detects subtle brain changes in early dementia stages, enabling timely interventions and treatments.

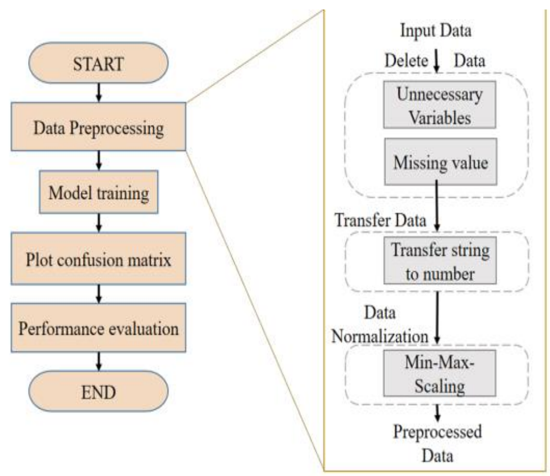

Fig 1 System Architecture

To implement aforementioned project we have designed following modules

- 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: Model building - 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. Algorithms accuracy calculated
- 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

Note: 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.

4. IMPLEMENTATION

Here in this project we are used the following algorithms

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.

SVM: Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression. Though we say regression problems as well it's best suited for classification.

Adaboost: AdaBoost algorithm, short for Adaptive Boosting, is a Boosting technique used as an Ensemble Method in Machine Learning. It is called Adaptive Boosting as the weights are re-assigned to each instance, with higher weights assigned to incorrectly classified instances.

MLP: The multi-layer perceptron (MLP) is another artificial neural network process containing a number of layers. In a single perceptron, distinctly linear problems can be solved but it is not well suitable for non-linear cases. To solve these complex problems, MLP can be considered.

ANN: Artificial Neural Networks (ANN) are algorithms based on brain function and are used to model complicated patterns and forecast issues. The Artificial Neural Network (ANN) is a deep learning method that arose from the concept of the human brain Biological Neural Networks.

XGBoost: XGBoost is a scalable and highly accurate implementation of gradient boosting that pushes the limits of computing power for boosted tree algorithms, being built largely for energizing machine learning model performance and computational speed.

Voting Classifier (RF + DT): A Voting Classifier combines predictions from multiple algorithms, such as Random Forest (RF) and Decision Tree (DT). Each model votes on the predicted class, and the final class is determined by majority vote. This ensemble approach enhances overall predictive accuracy and robustness in classification tasks.

Stacking Classifier (RF + MLP with LightGBM): A Stacking Classifier integrates predictions from diverse models like Random Forest (RF), Multilayer Perceptron (MLP), and LightGBM. A meta-learner is trained on these predictions to make the final classification decision. This ensemble technique leverages the strengths of individual models, enhancing overall predictive performance in diverse scenarios.

TL (CNN) with GWO: Transfer Learning (TL) with Convolutional Neural Networks (CNN) involves leveraging pre-trained CNN models for new tasks. The Grey Wolf Optimizer (GWO) algorithm enhances TL by optimizing model weights, aiding faster convergence and improved performance in image classification or other computer vision tasks.

TL (CNN) with PSO: Transfer Learning (TL) with Convolutional Neural Networks (CNN) integrates the Particle Swarm Optimization (PSO) algorithm to fine-tune model parameters. PSO optimizes the weights of the pre-trained CNN, aiding in efficient knowledge transfer and enhancing performance in image recognition tasks by refining the network for specific objectives.

TL (CNN) with GA: Transfer Learning (TL) with Convolutional Neural Networks (CNN) incorporates Genetic Algorithms (GA) to adapt and optimize model weights for new tasks. GA iteratively evolves a population of potential solutions, fine-tuning the pre-trained CNN, and enhancing its performance in image classification or other computer vision applications.

TL (CNN) with MBO: Transfer Learning (TL) with Convolutional Neural Networks (CNN) utilizes the Monarch Butterfly Optimization (MBO) algorithm to adapt model parameters for specific tasks. MBO mimics butterfly foraging behavior, optimizing the pre-trained CNN's weights and improving its capability for image recognition or other computer vision applications.

CNN + LSTM: A CNN can learn features from both spatial and time dimensions. An LSTM network processes sequence data by looping over time steps and learning long-term dependencies between time steps. A CNN-LSTM network use convolutional and LSTM layers to learn from the training data.

5. EXPERIMENTAL RESULTS

In this we used the Dementia dataset

Dementia dataset:

This set consists of a longitudinal collection of 150 subjects aged 60 to 96. Each subject was scanned on two or more visits, separated by at least one year for a total of 373 imaging sessions. For each subject, 3 or 4 individual T1-weighted MRI scans obtained in single scan sessions are included. The subjects are all right-handed and include both men and women. 72 of the subjects were characterized as nondemented throughout the study. 64 of the included subjects were characterized as demented at the time of their initial visits and remained so for subsequent scans, including 51 individuals with mild to moderate Alzheimer's disease. Another 14 subjects were characterized as nondemented at the time of their initial visit and were subsequently characterized as demented at a later visit.

Comparison Graphs:

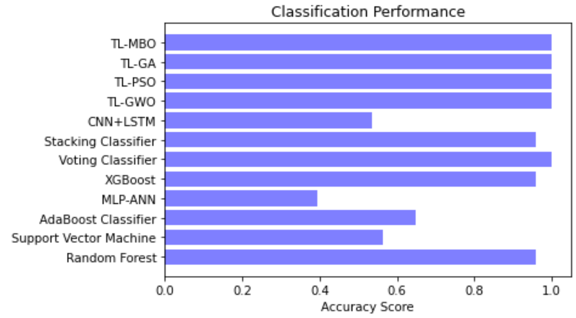

Fig 2 Accuracy graph of all algorithms

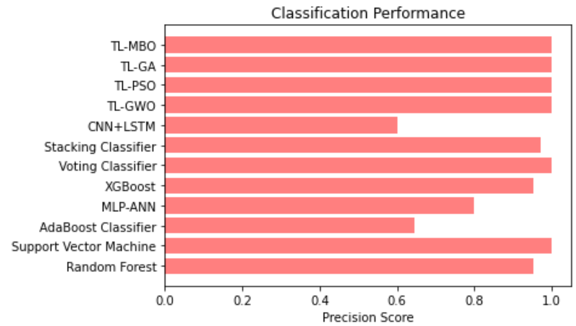

Fig 3 Precision graph of all algorithms

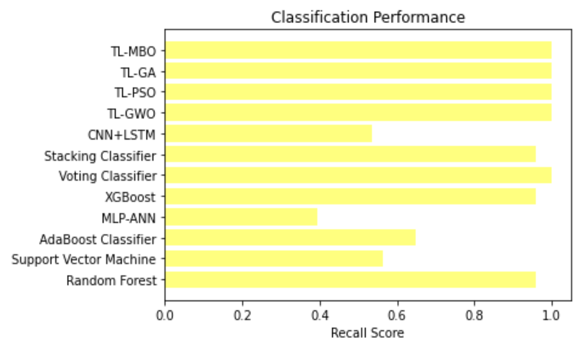

Fig 4 Recall graph of all algorithms

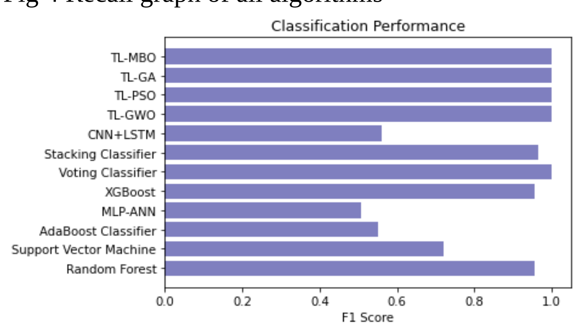

Fig 5 F1-Score graph of all algorithms

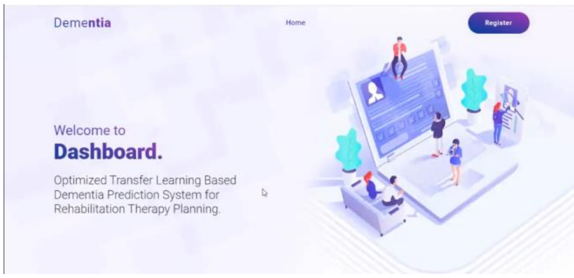

Fig 6 Home page

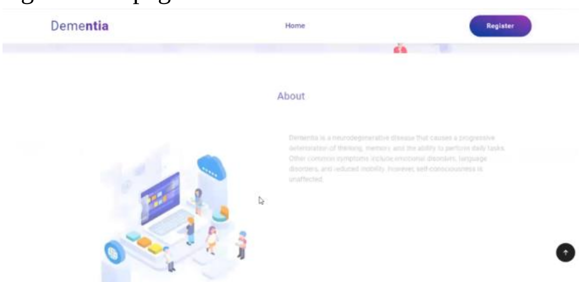

Fig 7 About page

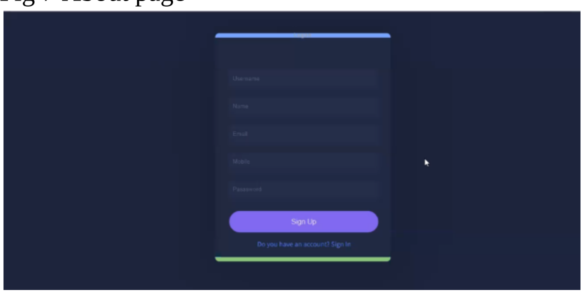

Fig 8 Signup page

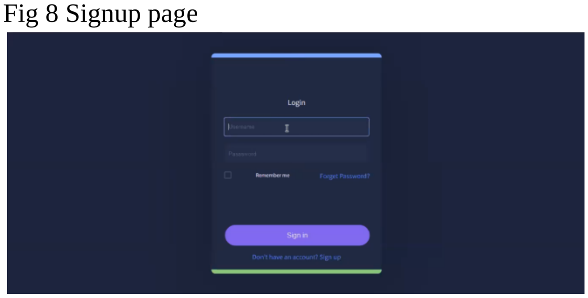

Fig 9 Signin page

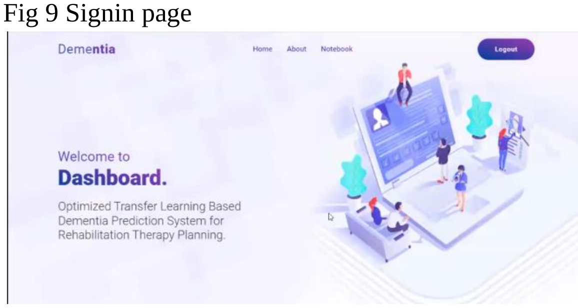

Fig 10 Main page

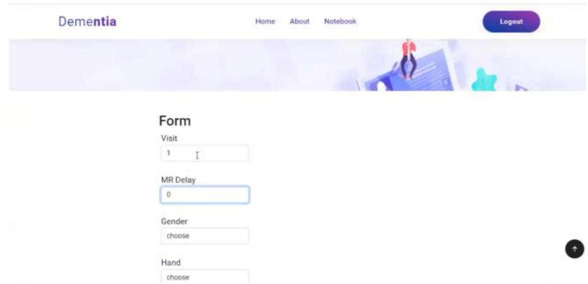

Fig 11 Upload input values

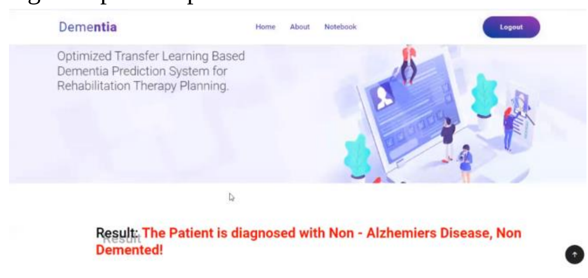

Fig 12 Prediction result for given input values

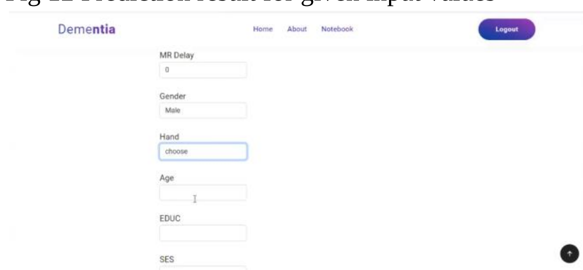

Fig 13 Upload another input values to predict

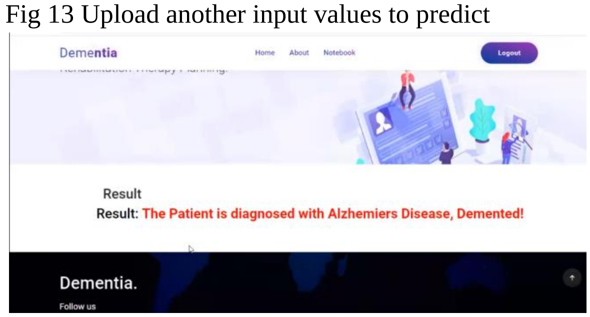

Fig 14 Prediction result for given input values

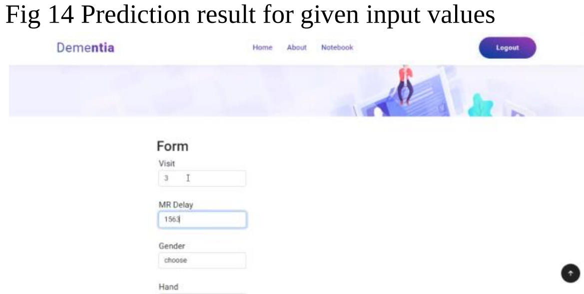

Fig 15 Similarly upload input values

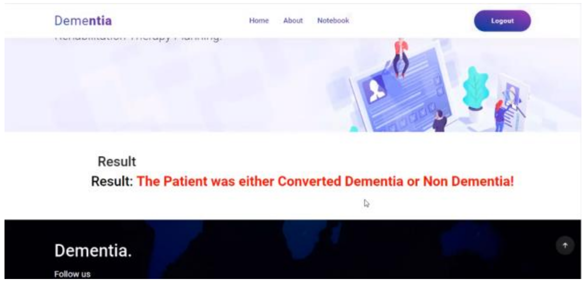

Fig 16 Prediction result

6. CONCLUSION

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. So we 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.

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