Dementia Disease Detection and Prediction

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Abstract

Dementia is regarded a group of progressive neurocognitive degenerative disorders that causes the steady deterioration in global cognitive function and ability to conduct daily living tasks. The frequent type of dementia is Alzheimer's disease which process a strain on health care systems around the world. The significance of early diagnosis for diagnoses of dementia is widely proven since certain individuals can take medications that will slow the clinical course of dementia. The system will provide a holistic picture of the evidence basis for various ML algorithms, outlining advantages and drawbacks of typical techniques, including CNN for image-based analysis, SVM for classification tasks, RF for multi-feature datasets and XGBoost for high-performance prediction. Utility of hybrid or ensemble models will be highlighted for improving predictive performance. This project further involves a comparison of classical ML models with deep learning CNN- based models. Both model types will be trained on identically pre-processed datasets and their performances tested against multiple metrics. The comparative evaluation will establish which model type is better suitable for certain data modalities, such as structured clinical data, neuroimaging or speech features. Correspondingly, this framework will provide a comprehensive performance report for the generated predictions. This report provides an overall summary of the outcomes generated by each model while displaying confusion matrices and highlighting areas where model uncertainty and misclassification occur. Based on insights from this report, recommendations are expected to be derived for the best model in early dementia detection and identifying promising future improvements through data fusion and ensemble learning. Overall, the proposed framework includes the following modules: a modular-level ML pipeline for dementia detection, comprising preprocessing data, extracting features, training models, model comparison and validation along with a structured reporting mechanism for predictive performance analysis.

Keywords-Dementia Disease, Mini Mental State Exam, Convolutional Neural Networks

1. Introduction

Advancements in the field of medicine have led to better life expectancy around the world. However, a higher number of elderly citizens now have dementia. The symptoms involved in this disease include memory loss, improper brain functioning, impairment in Activities of Daily Living (ADL), and difficulties in communication and expression [1]. Dementia is not a disease but an overarching term that encompasses a continuum of neurodegenerative diseases with progressively diminishing loss of cognitive function like memory, thinking, language and problem-solving capacities. Such cognitive injuries ultimately result in a substantial loss of an individual's capacity to live everyday Daily activities of living, frequently with loss of autonomy and sadly, increased mortality. Among the various forms of dementia, the most important one is Alzheimer's disease (AD) shared and responsible for about a projected 60–70% of worldwide cases of dementia. The rise of dementia is closely connected to the shift of the world's population toward older populations. Present data suggests that greater than 55–57 lakh individuals are having dementia and this number is surge significantly in the subsequent decades. The worrying trend shows that a new case of dementia occurs roughly every 3 seconds somewhere in the world. This widespread prevalence makes dementia a big problem for public health that requires new and scalable ways to manage and detect it. It is now confirmed as the 7th leading cause of death globally. The best treatments for this growing epidemic rely on early and accurate detection. Early detection creates chances to start intervention strategies, which include medical treatment and lifestyle changes.Significant trends in increased protection against dementia through greater physical activity have been observed, and high levels of physical activity have been associated with reduced risk of cognitive impairment [7]. These measures can potentially slow the progression of the disease and improve the lives of the patients and their families. But traditional ways of diagnosing dementia often involve clinical evaluations that can be very subjective, costly and sometimes intrusive. Such conventional approaches frequently depend on comprehensive cognitive testing, rigorous histories of illness and neuroimaging procedures including The Magnetic Resonance Imaging (MRI) and Positron Emission Tomography efficient, their lack of accessibility, expense and propensity to observer bias tend to require the discovery of new and accurate screening devices. To help solve these problems the domains of machine learning (ML) and artificial intelligence (AI) have turned out to be mighty collaborators showing a lot of potential in transforming detection of dementia. Such higher-order computation processes can handle diverse and informative data sets and discovering hidden patterns and predictors of cognitive decline that might be unnoticed during human perception. For example, advanced speech and natural language algorithms can identify slight variations within the patterns of speech that are indicators of cognitive impairment. Likewise, ML and CNNs which is applicable to data from medical images (like MRI scan data) can distinguish Typical patterns of shifts pertaining to neurodegenerative disorders like AD.The study progresses through a conceptual system to identify and forecast dementia, continuing the contemporary works on machine learning. We will review the literature that already exists landscape of machine learning-based dementia identification exploring various data modalities and their effectiveness for various ML models. The design principle here is a way of including the various methods into a cohesive framework, emphasizing interpretability and user- friendliness—factors crucial for clinical usefulness and practical effect. Although this report is not of a full-report document, implementation it clearly defines the theoretical method, system requirements and architecture design, to act as a general future development plan within this critical area.ML is a process of training a computer to apply its past experience to solve a problem given to it. The concept of application of ML in different fields to solve problems faster than human has gained significant interest due to the current availability of cheaper computing power and inexpensive memory. This makes it possible to process and analyze a very large amount of data to discover insights and correlations amongst the data which are not so obvious to human eye. Its intelligent behavior is based on different algorithms which enables the machine to make abstractions based on experience, in order to produce salient judgments [8].

2. Related Work

Beyond the domain of clinical treatment, early detection by machine learning has several advantages. These resources can be used by researchers to better understand how diseases grow, pinpoint risk factors, and create focused interventions. Additionally, by tracking the evolution of symptoms over time, machine learning algorithms can assist clinicians in determining the effectiveness of various treatments. Personalized medicine is made possible by this feedback loop, which allows treatment plans to be customized for specific patients using prediction models generated from machine learning algorithms [10].

The goal of the machine learning-based early dementia disease detection system is to help identify those who are most at risk of acquiring dementia in a timely manner. This system attempts to assess several characteristics and indications that are connected with the onset of dementia by using cutting-edge machine learning algorithms and data analysis methodologies [10].

We conducted our experiments on the ADReSS Challenge dataset, which is matched for gender and age and consists of a statistically balanced, acoustically enhanced set of recordings of spontaneous speech [4].

With ethical and privacy issues becoming prominent in smart health solutions, there has to be a shift from the current approach to smart solutions for elderly care. One of such 100050 TABLE 8. Comparison of wearable and non-wearable technologies. solutions is Tiny Machine Learning (TinyML) which offers a promising solution for dementia care, and represents a significant advancement in the future of health monitoring management [9].

Computational analysis of spontaneous connected speech has the potential to enable novel applications for speech technology in longitudinal, unobtrusive monitoring of cognitive health. By focusing on AD recognition using spontaneous speech, the ADReSS-M signal processing grand challenge provided a platform for the investigation of alternative to neuropsychological and clinical evaluation approaches to AD detection and cognitive assessment [2].

The paper addressed the critical problem of imbalanced datasets using GAN augmentation to balance the class labels and created a newlybalanceddataset. Thebalancing dataset has been done with the help of two techniques: using geometric transformations, and the second method uses GAN. The GAN-based dataset proved to be superior to geo metric transformations as the spatial conformity of the image is unaltered, which helps the CNN model generalize well to unseen test samples [1].

Most existing dementia prediction systems primarily focus on single-modal approaches that utilize either clinical scores or MRI scans. These systems typically apply conventional machine learning algorithms, relying heavily on manual feature engineering.

Key Limitations of Existing Systems:

•Unimodal Dependency: Existing systems often rely on a single data source (e.g., clinical data or neuroimaging), missing out on the complementary strengths of multimodal data.

•Manual Feature Engineering: Feature selection and engineering are often manual, making the process labour intensive and subject to human error or bias.

•Low Scalability: Most existing pipelines are not modular and require significant re- engineering to incorporate new data types or improve performance.

•Black-box Models: High-performing models such as deep neural networks often lack interpretability, reducing trust among medical professionals and limiting their application in clinical settings.

•Generalization Issues: Existing systems may perform well on specific datasets but often fail to generalize across diverse populations or institutions due to overfitting and limited data diversity.

3. Materials and Methods

The dementia detection and prediction system is designed to assist healthcare professionals by providing early and accurate predictions of dementia onset using a multimodal data approach. The system uses deep learning and contemporary techniques for machine learning to make models that can predict clinical test results, brain MRI images and demographic data. The system automates data pre-processing, feature extraction, model training and result interpretation to ensure accurate and understandable results. This system is accessible to clinicians, researchers and healthcare providers via a user-friendly web application interface.

•Magnetic Resonance Imaging (MRI): High-resolution structural brain scans that reveal common anatomical changes associated with dementia such as hippocampal atrophy and cortical thinning. MRI pictures have been gathered from persons with normal cognitive abilities, people who have mild cognitive impairment and patients with confirmed dementia.

•Clinical Information: This includes the results of standardized cognitive tests, like the Mini-Mental State Examination (MMSE) and other cognitive evaluations that offer standardized metrics to differentiate the degree and rate of cognitive impairment.

•Demographic Information: Patient metadata like age, gender, lifestyle and level of education, gives crucial information for disease prediction.

Raw data is typically full of information, but rarely useful to simply plug into machine learning models. Consequently, a significant amount of the raw data undergoes extensive preprocessing and feature engineering to become a processed dataset. Ultimately, these features help to minimize problems associated with raw data and arrange the dataset to create the finest possible environment for the model.

Software Specifications: -

•Programming Languages: Python is being utilized as the primary language for ML/DL models, preprocessing and backend logic.

•Frameworks and Libraries: PyTorch for CNNs and Sklearn for traditional ML models. Streamlit or Flask will be used as a web interface.

Hardware Specifications: -

•Processing Units: High-performance CPU (Intel i7 or more) to preprocess the data and training of the traditional ML model. GPU (NVIDIA RTX series or otherwise) to train deep learning models inference acceleration.

•Memory: 16 GB RAM (at least, 32 GB and above to support large MRI).

•Storage: 512 GB or greater SSD storage required to support a high read/write rate of large files neuroimaging data and files.

•Network: High-speed clean internet connectivity that is reliable to transfer data and cloud deployment if applicable.

•User Devices: The system must be able to access through normal desktop, laptops and cool internet browsers.

Material Characterization: -

•Data Cleaning and Imputation: A combination of statistical imputation techniques (such as mean or median replacement) and ML techniques were handling missed values in the clinical records to get a complete dataset without introducing bias.

•Feature Extraction: Several neuroanatomical characteristics were automatically retrieved from theMRI images like hippocampal volume, cortical thickness measurements, gray matter density and other biomarkers for neurodegeneration. Convolutional neural networks used in the extraction process were trained to identify relevant structural features.

•Dimensionality Reduction: PCA and t-distributed Stochastic Neighbour Embedding (t-SNE) are two methods used to reduce complexity while maintaining the most informative features because neuroimaging data has a high dimensionality.

•Balancing the Dataset: To account the class imbalance, oversampling approaches like Synthetic Minority Over-sampling Technique are employed. This ensures that minority classes, such as early dementia cases, are sufficiently represented during training to avoid biased predictions.

•Multimodal Fusion: The processed dataset integrates features from all modalities— imaging, clinical, and demographic—into a single structured dataset. This multimodal fusion allows the models to leverage complementary information, improving overall predictive accuracy.

Analytical Techniques: -

[figure 1 found here]

4. Results and Discussion

We implemented and assessed the proposed "Dementia Detection and Prediction" system using the Kaggle dataset, which includes around 86,400 cross-sectional MRI scans of the brain. The images went through preprocessing steps like resizing, normalization and augmentation to improve generalization. We trained two different types of models: one set of CNN models and another set made up of classical models using the CSV file dataset from Kaggle. We evaluated the models that use metrics like accuracy, precision, F1-score and recall. The many models were trained, validated and tested showing a good percentage of accuracy. The web interface includes graphical representations of the evaluation metrics for all the models that were part of the study. It has five sidebar options, featuring the home page where we present a comparative study of all the models using confusion matrices and comparisons of their evaluation metrics using bar graphs. The experimental results confirm that the developed system effectively meets its main goals: to provide accurate, explainable and efficient dementia detection using both MRI scans and clinical data. The models that were trained, validated and tested can identify affected regions which further supports their clinical use as a computer-aided tool to help clinicians detect dementia early and accurately. The project also includes a combination of both the classical and CNN model evaluations. It provides a way to combine the evaluations of all the models. This means that even if individual models make mistakes the final results will be corrected as they will rely on the evaluations of all the models.

Once the system is deployed, users can:

- Open the homepage

  [figure 2 found here]

- Open the web application in a browser

  [figure 3 found here]

- Upload a Brain Cross-Sectional MRI image and enter Age, Gender, MMSE and Memory Complain (Yes or No)

  [figure 4 found here]

- Wait for the model to process and analyse the image and entered data.

  [Figure 5 found here]

- View the classification result (Demented/Non-Demented) with a bar graph.

  [figure 6 found here]

- Comparison of different models.

  [figure 7 and 8 found here]

- Download the detailed report in PDF format.

  [figure 9 found here]

5. Conclusion

In order to investigate how cutting-edge computational techniques can be successfully applied for the swift identification and forecasting of dementia, the project "Dementia Detection and Prediction using CNN for MRI and ML Models for Clinical Data" was started. Early diagnosis is important for timely medical treatment and care because dementia is a progressive brain condition that impacts memory, thinking and behavior. This study used CNNs to evaluate MRI brain images. Analyzing MRI images is necessary for spotting structural alterations in the brain associated with dementia. To classify the various stages of dementia "the CNN model" was trained to detect key parts of the MRI images. CNNs are well-suited for medical diagnostic imaging and predicting brain-related disorders because they can understand complicated image patterns. Patients' clinical and demographic data were used to develop different machine learning algorithms, like Support Vector Machine (SVM) and Random Forest (RF), XGBoost and Logistic Regression (LR) models. The models identified clinical characteristics such as age, gender, cognitive scores and medical history. The XGBoost and RF algorithms achieved the highest classifications because they can reduce the risk of overfitting which typically improves accuracy. One major advantage is the ability to analyze both visual and non-visual signs of dementia simultaneously using clinical and MRI data. The proposed hybrid framework shows the benefits of using deep learning to find features extracted from images with traditional learning to use machines for structured data analysis. This combined approach offers better prediction and addresses the limitations of each method. In the earlier system, preprocessing data, training models and testing the approach led to successful classification at both individual and group levels. The combination of CNN and ML models demonstrates that combining image-based and clinical information yields better generalization and reliability than using either type alone. Future research could focus on increasing the dataset size, fine-tuning hyperparameters and implementing explainable AI methods for improved interpretability.

References

[1] V. Jain et al., "A Novel AI-Based System for Detection and Severity Prediction of Dementia Using MRI," IEEE Access, vol.9,pp.155388155403,2021,doi:10.1109/ACCESS.2021.3127394.

[2] S. Luz et al., "Overview of the ADReSS-M Signal Processing Grand Challenge on Multilingual Alzheimer's Dementia Recognition," IEEE Open J. Signal Process., vol. 5, pp. 145–156, 2024, doi: 10.1109/OJSP.2024.3378595.

[3] T. M. Rutkowski, "Classifying Mild Cognitive Impairment from Behavioural Responses in Emotional Arousal and Valence Evaluation Task – AI Approach for Early Dementia Biomarker in Aging Societies," in Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC), Toronto, ON, Canada, Oct. 2020, pp. 4122–4127, doi: 10.1109/SMC42975.2020.9283141.

[4] L. Ilias and D. Askounis, "Explainable Identification of Dementia From Transcripts Using Transformer Networks," IEEE J. Biomed. Health Inform., vol. 26, no. 8, pp. 3813– 3824, Aug. 2022, doi: 10.1109/JBHI.2022.3155250.

[5] S. Jahan and M. S. Rahman, "Federated Explainable AI-Based Alzheimer's Disease Prediction With Multimodal Data," IEEE Access, vol. 13, pp. 23456–23470, 2025, doi: 10.1109/ACCESS.2025.3547343.

[6] Y. F. Khan, B. Kaushik, M. K. Imamrahmani, and M. E. Ahmed, "HSI-LFS-BERT: Novel Hybrid Swarm Intelligence-Based Linguistics Feature Selection and Computational Intelligent Model for Alzheimer's Prediction Using Audio Transcript," IEEE Access, vol. 10, pp. 123456–123470, 2022, doi: 10.1109/ACCESS.2022.3223681.

[7] J. Kim, S. Cheon, and J. Lim, "IoT-Based Unobtrusive Physical Activity Monitoring System for Predicting Dementia," IEEE Access, vol. 10, pp. 26565–26573, 2022, doi: 10.1109/ACCESS.2022.3156607.

[8] N. Dey, A. S. Ashour, S. Balas, and F. T. Zomaya, "Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances," IEEE Access, vol. 9, pp. 37622–37655, Feb. 2021, doi: 10.1109/ACCESS.2021.3062484.

[9] S. Addae, M. Kang, J. Kim, A. Smith, and P. Rajana, "Smart Solutions for Detecting, Predicting, Monitoring, and Managing Dementia in the Elderly: A Survey," IEEE Access, vol. 12, pp. 71345–71366, 2024, doi: 10.1109/ACCESS.2024.3421966.

[10] G. Nandan, A. Lakshmanan, and M. T. A. Reddy, "Early Detection of Dementia Disease Using Machine Learning," in Proc. Int. Conf. Inventive Comput. Technol. (ICICT), Coimbatore, India, 2024, pp. 123–128, doi: 10.1109/ICICT60155.2024.10544484.

[11] OASIS-1Cross-Sectional: https://doi.org/10.1162/jocn.2007.19.9.1498.

[12] https://www.kaggle.com/datasets/ninadaithal/imagesoasis

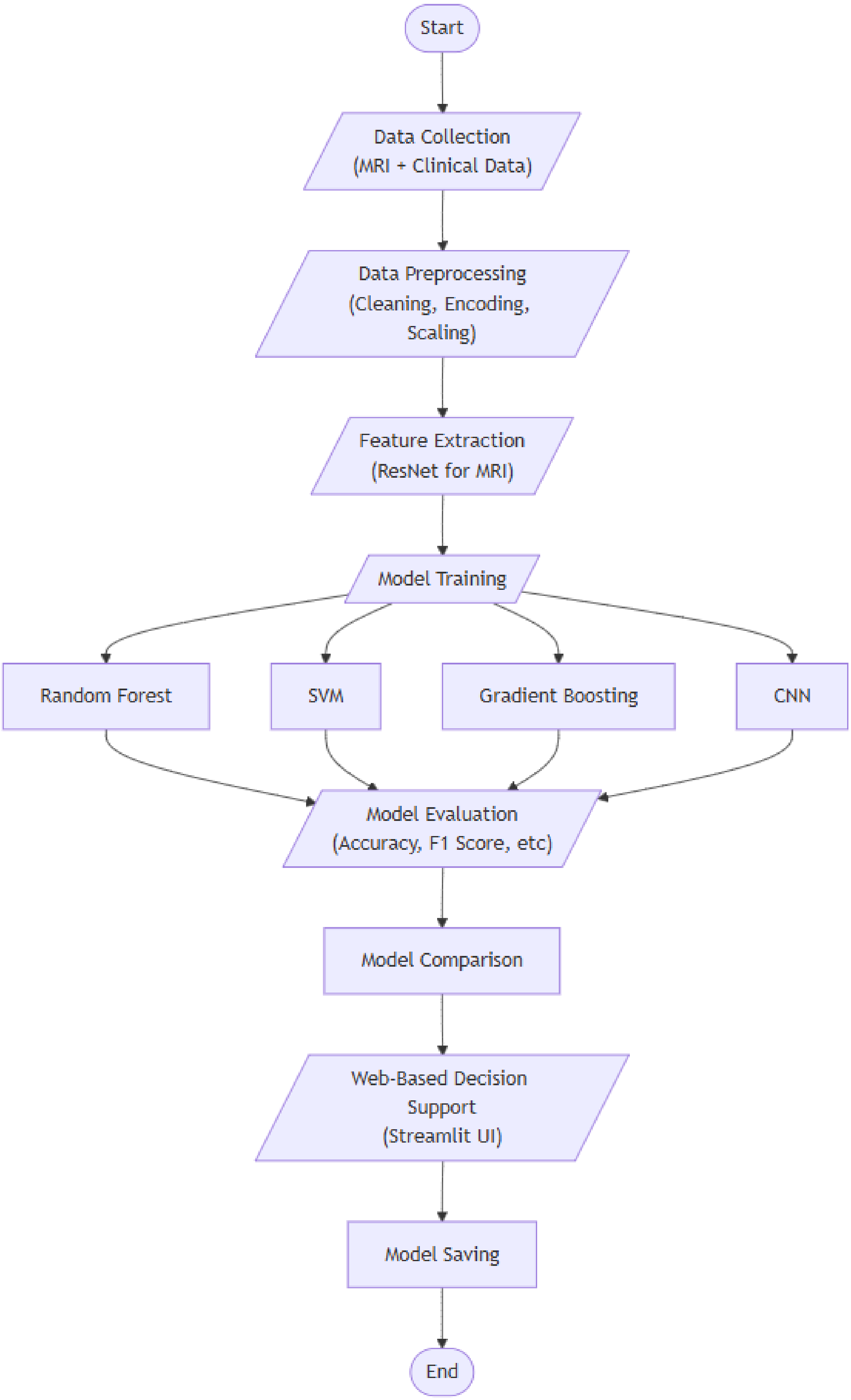

Start
Data Collection
(MRI + Clinical Data)
Data Preprocessing
(Cleaning, Encoding,
Scaling)
Feature Extraction
(ResNet for MRI)
Model Training
Random Forest
SVM
Gradient Boosting
CNN
Model Evaluation
(Accuracy, F1 Score, etc)
Model Comparison
Web-Based Decision
Support
(Streamlit UI)
Model Saving
End

Figure 1

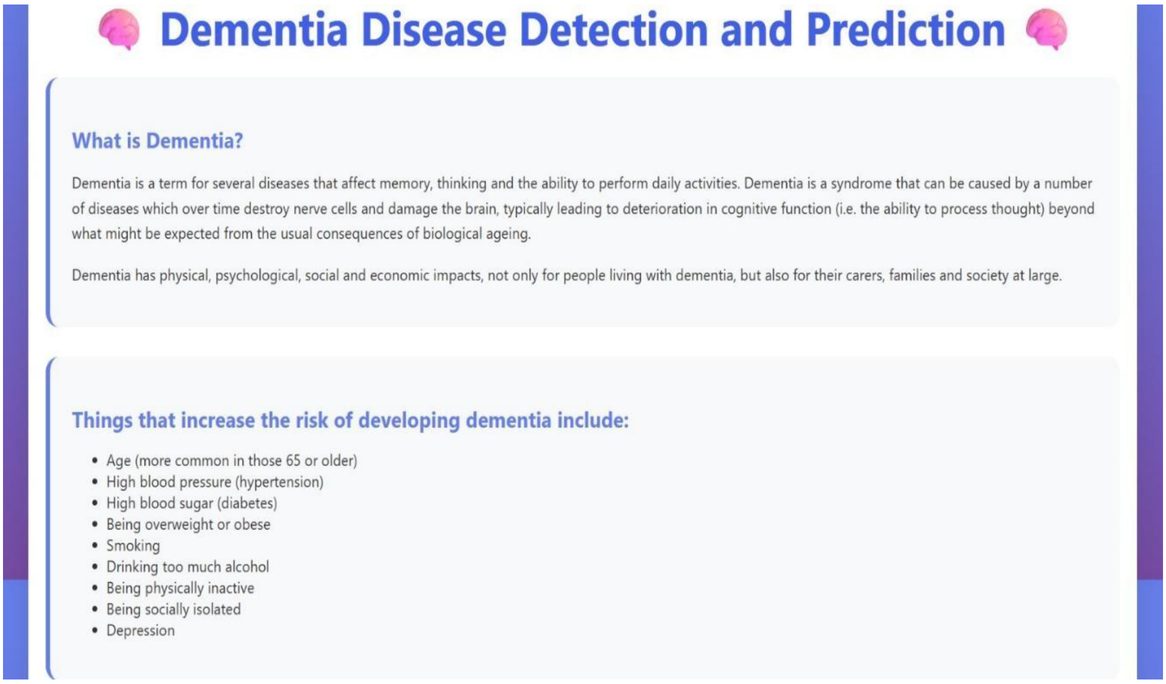


Figure 2

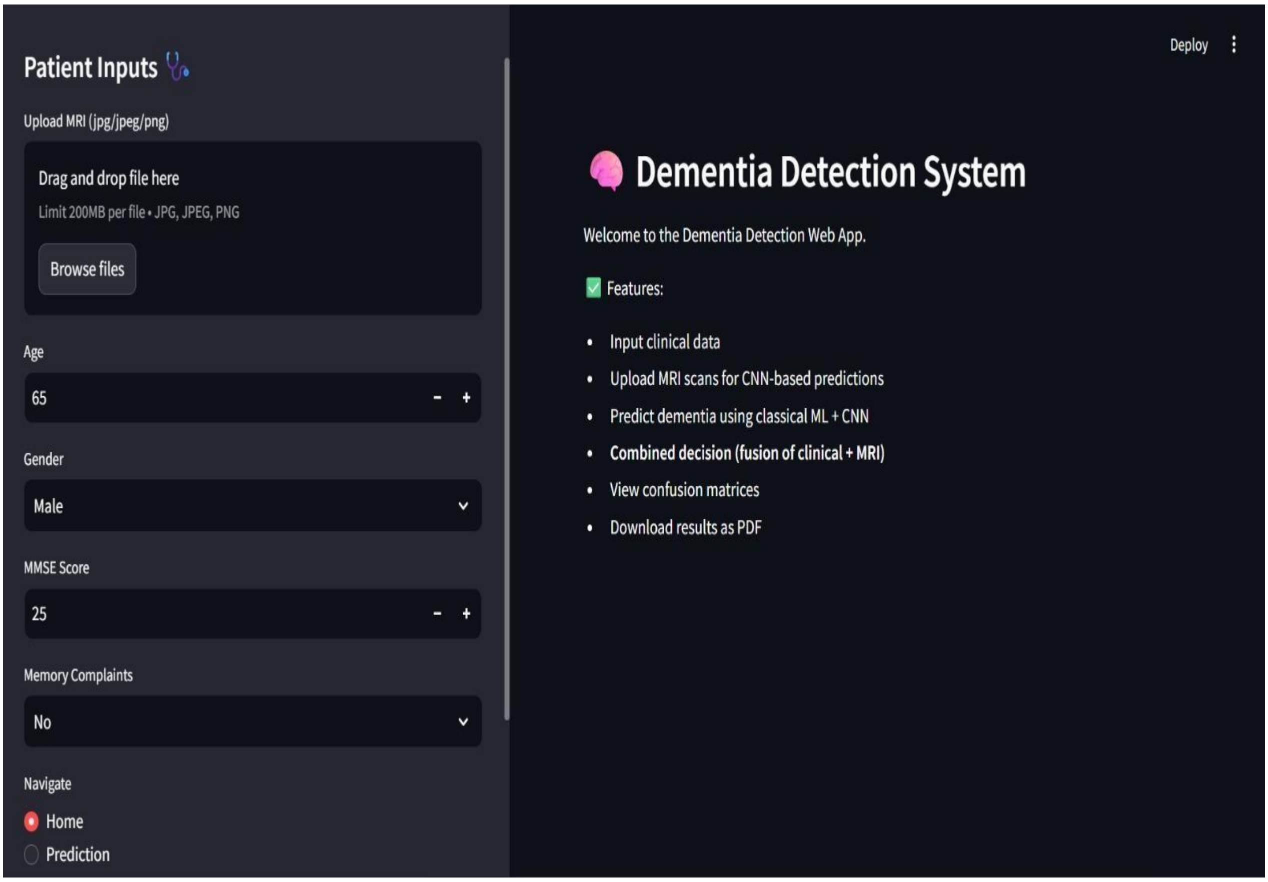


Figure 3

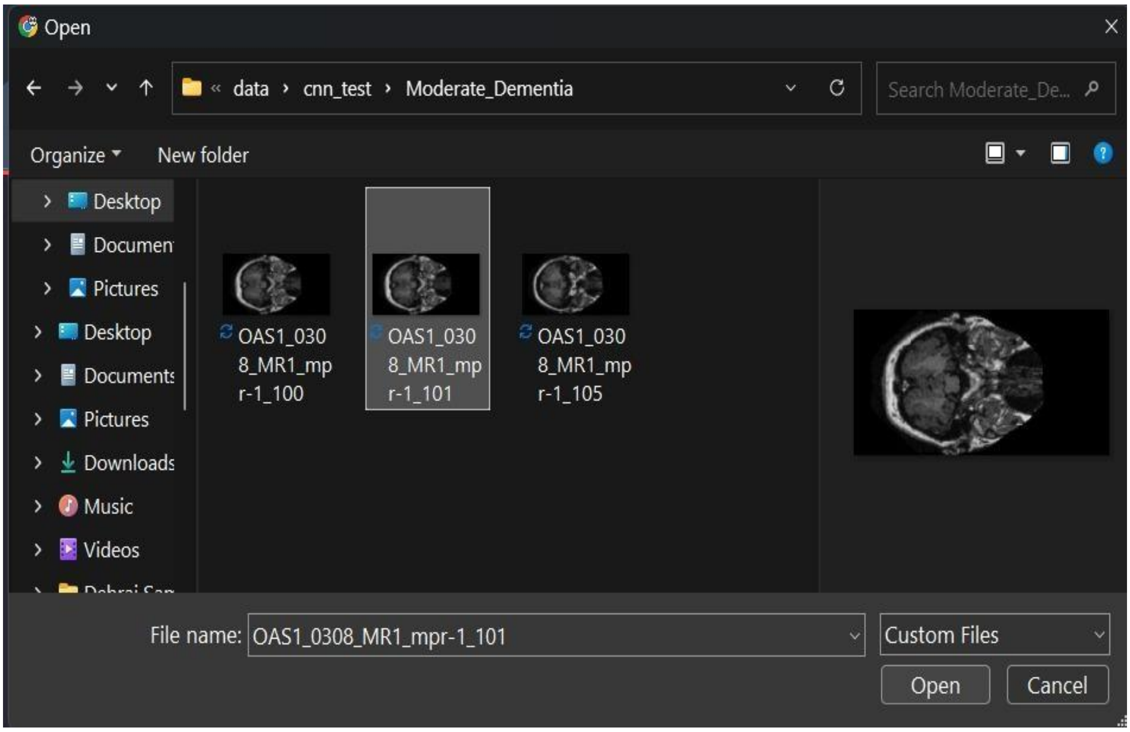


Figure 4

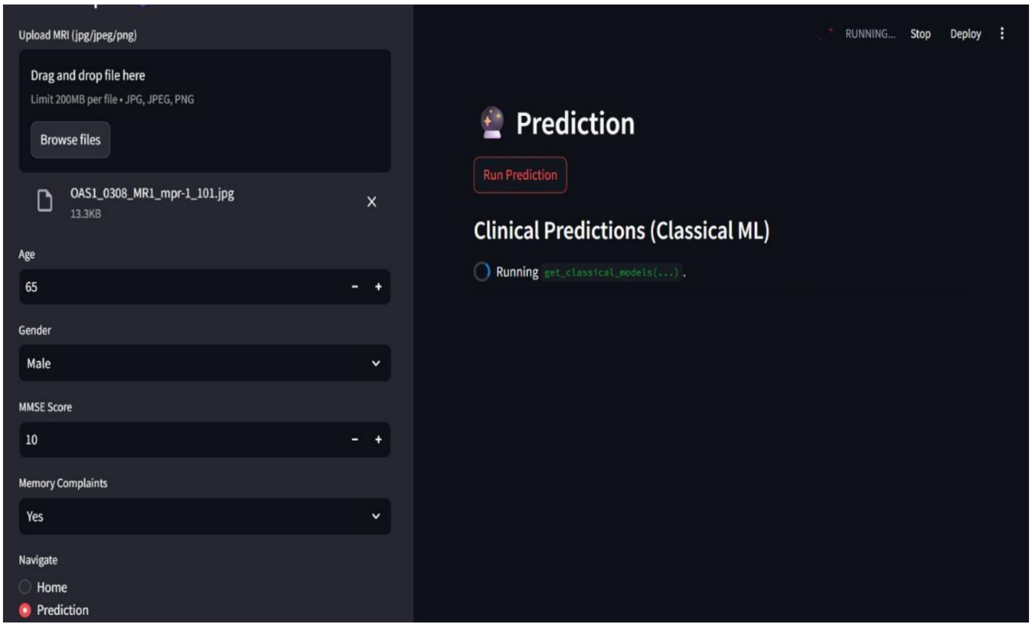


Figure 5

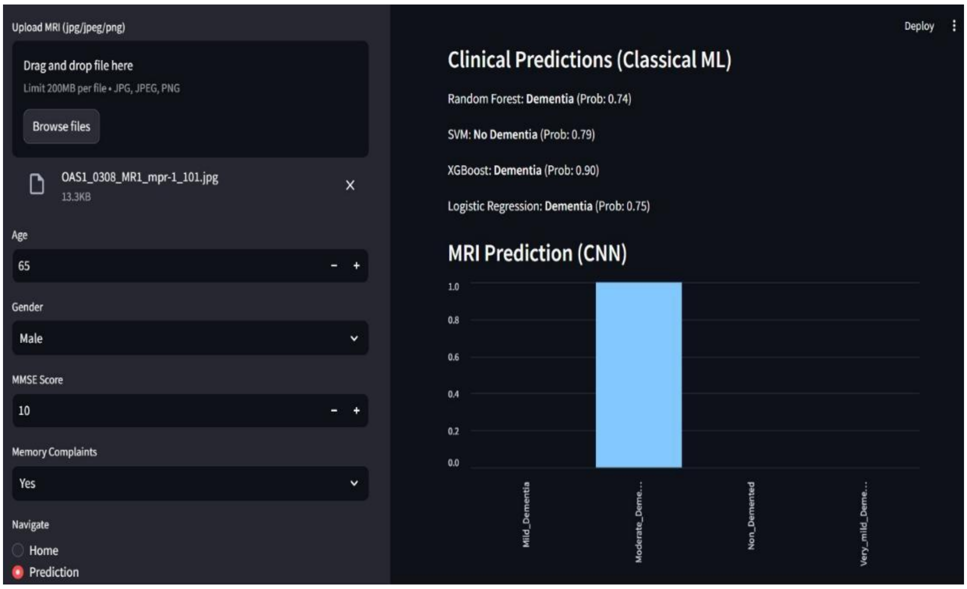


Figure 6

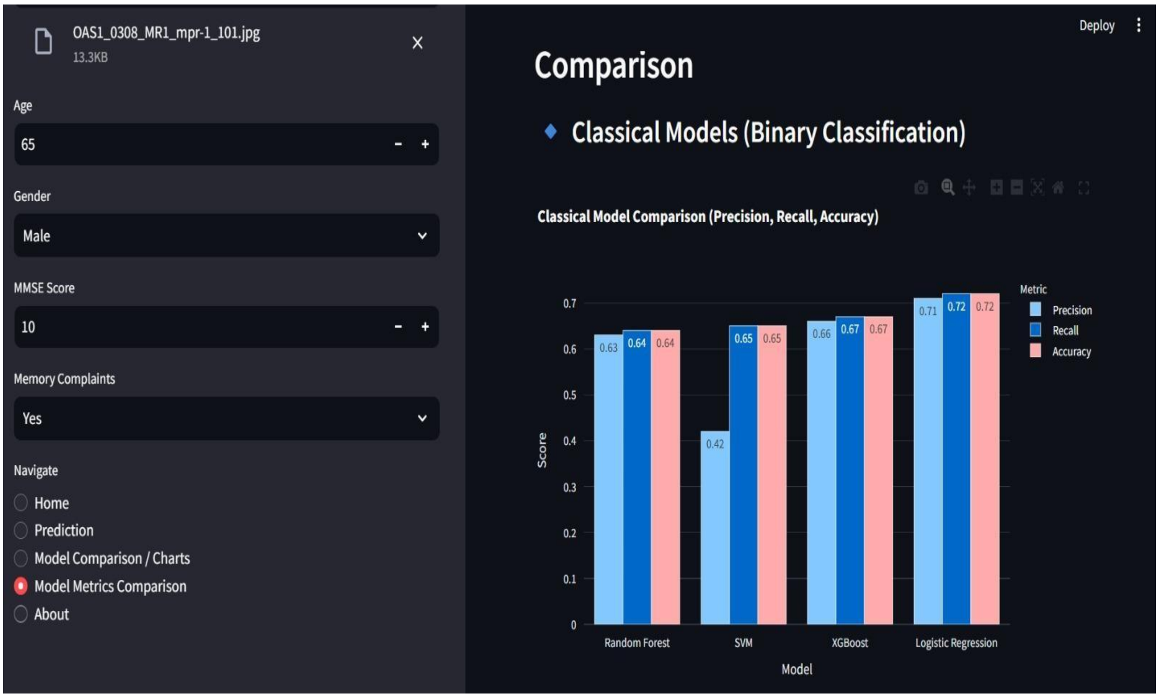


Figure 7

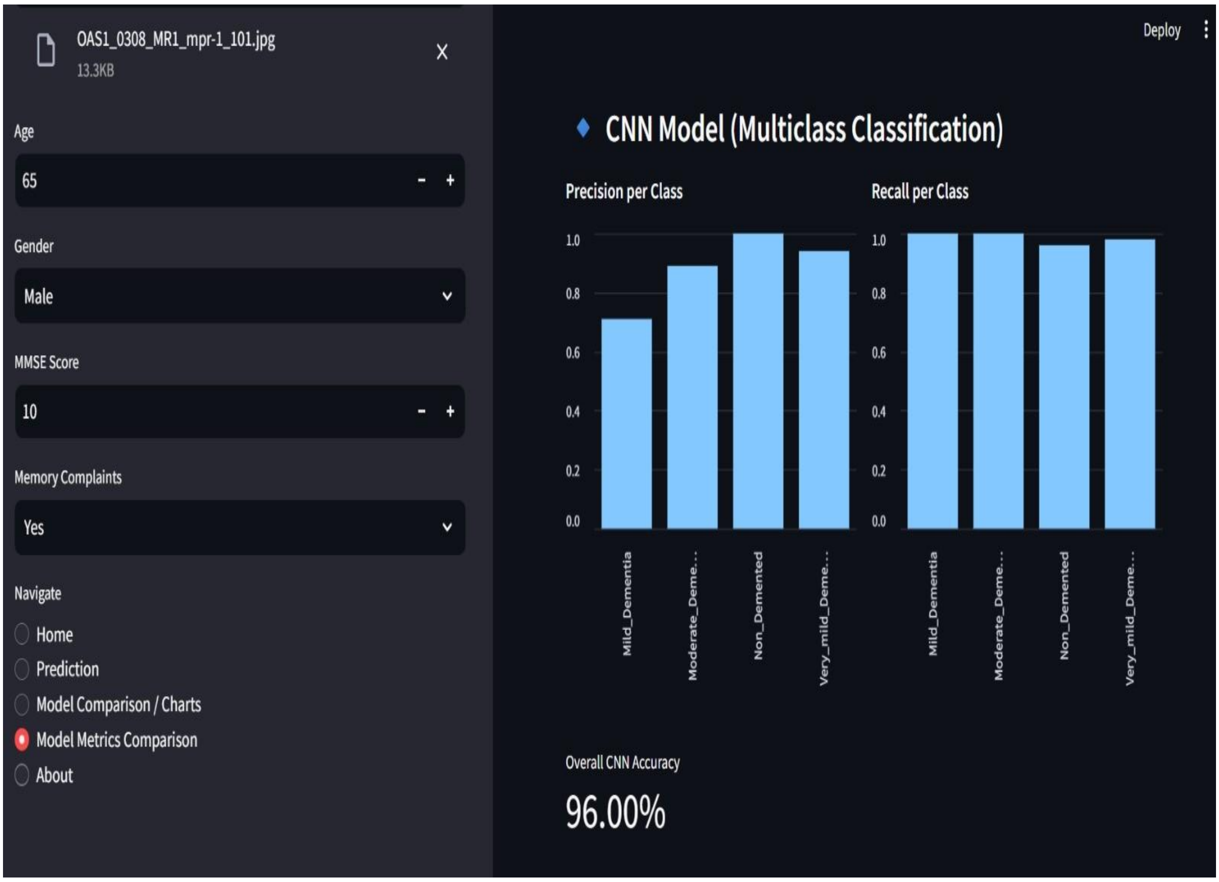
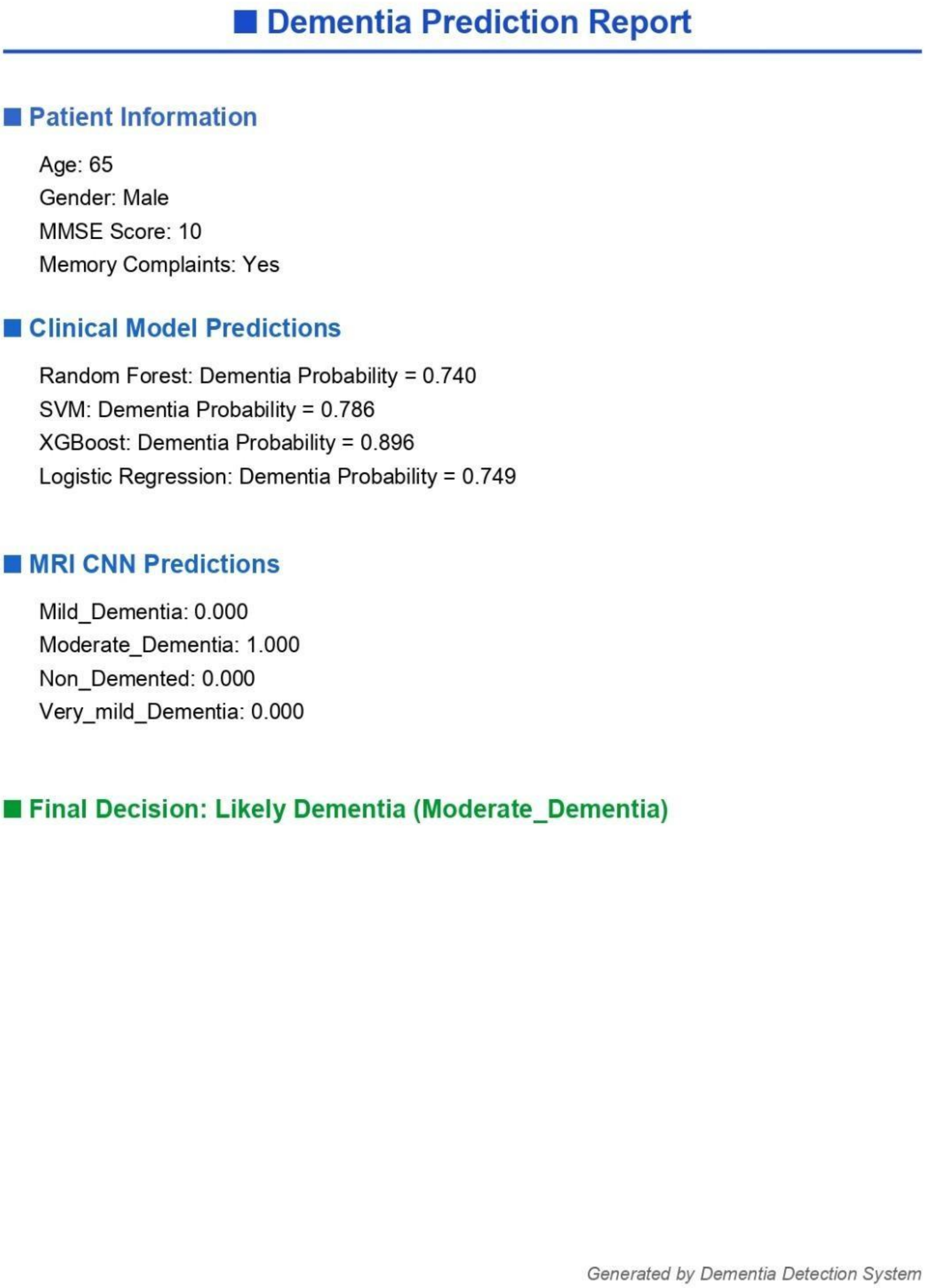

OAS1_0308_MR1_mpr-1_101.jpg
13.3KB
Age
65
Gender
Male
MMSE Score
10
Memory Complaints
Yes
Navigate
Home
Prediction
Model Comparison / Charts
Model Metrics Comparison
About
Deploy
CNN Model (Multiclass Classification)
Precision per Class
Recall per Class
1.0
0.8
0.6
0.4
0.2
0.0
Mild_Dementia
Moderate_Deme...
Non_Demented
Very_mild_Deme...
Overall CNN Accuracy
96.00%

Figure 8



■ Dementia Prediction Report

■ Patient Information

Age: 65
Gender: Male
MMSE Score: 10
Memory Complaints: Yes

■ Clinical Model Predictions

Random Forest: Dementia Probability = 0.740
SVM: Dementia Probability = 0.786
XGBoost: Dementia Probability = 0.896
Logistic Regression: Dementia Probability = 0.749

■ MRI CNN Predictions

Mild_Dementia: 0.000
Moderate_Dementia: 1.000
Non_Demented: 0.000
Very_mild_Dementia: 0.000

■ Final Decision: Likely Dementia (Moderate_Dementia)

Generated by Dementia Detection System

Figure 9