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OPTIMIZING DEMENTIA PREDICTION: A COMPARATIVE PERFORMANCE STUDY OF ML AND DL

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ABSTRACT

Dementia, a progressive neurological disease that impairs cognitive ability, is one of the most important worldwide health issues. With the projected number of affected people to exceed 130 million by 2050, an early and accurate diagnosis is essential to improve patient outcomes. However, conventional diagnostic methods including cognitive evaluations, neuroimaging, and clinical evaluations are time consuming, expensive, and often subjective, stalling timely intervention and increasing the strain on healthcare systems. In order to overcome these obstacles, this work predicts dementia using a novel fusion of deep learning (DL) and machine learning (ML). We investigated a variety of models, such as autoencoders, support vector machines (SVMs), recurrent neural networks (RNNs), convolutional neural networks (CNNs), and other machine learning-based classifiers. To enhance predictive robustness, we propose a hybrid ensemble stacking classifier that integrates multiple base classifiers with a metaclassifier. This ensemble approach effectively harnesses the strengths of different models, significantly improving diagnostic accuracy and reliability. This work can facilitate early detection, enable personalized treatment strategies, and ultimately improve the quality of care for people at risk for dementia. To evaluate our model, a dataset of patients with dementia was used. The hybrid ensemble stacking classifier reached 100% compared to the remaining models which were in the range of 62.33% to 97.67%.

Keywords: *CNN, SVM, SGD, Ensemble Learning, RNN*

1. INTRODUCTION

Dementia, is not a single form of disease it has multiple forms. Among all the other forms Alzheimer's Disease is said to be the common form, which was accounted for an estimation of 60-70% cases [1]. Remaining types were Vascular Dementia (VD), Lewy Bodies Dementia (LBD), and Frontotemporal Dementia (FD). Each type of dementia involves different underlying pathophysiological processes, which can complicate diagnosis and treatment. Despite of all the advancements in medical research, at present, there is no effective treatment for most types of dementia, which makes it a major contributor to disability and dependence among older individuals. Dementia has far-reaching consequences for individuals, families, caregivers, and societies. The emotional, physical, and financial toll can be immense, necessitating comprehensive care strategies and support systems.

Machine learning and deep learning are branches of artificial intelligence that use various algorithms and statistical models to analyze and interpret complex data. These techniques can uncover connections and trends within datasets that might not be easily detected by human analysts. In dementia research, machine learning and deep learning can be applied to a diverse range of data types, including genetic information, neuroimaging scans, and electronic health records. These applications help enhance diagnostic accuracy, predict disease progression, and identify potential therapeutic targets. The recent advancements in neuroimaging, along with the increasing availability of large datasets, have significantly boosted the use of machine learning and deep learning in dementia research.

Despite the promising outcomes, several obstacles persist in integrating models of ML and DL into clinical practice for diagnosis of dementia and management. Things like this include the need for huge and superior quality of datasets, interpretability of complex models, and ethical implications of AI-driven diagnostics. Dementia is a debilitating neurological disorder characterized through significant decline in cognitive abilities, which severely impairs an individual's capacity to

perform everyday tasks and activities [1]. Dementia is a collective term for a range of cognitive disorders that result from different medical conditions and traumatic brain injuries, which predominantly or indirectly affect the brain's functioning. Among these, Alzheimer's disease stands out as the most common underlying cause of dementia [2]. In addition to Alzheimer's disease, there are multiple other prevalent types of dementia, such as vascular dementia, Lewy body dementia, and frontotemporal dementia [3]. The global prevalence of dementia is rising rapidly, driven by aging populations, and it is projected to affect over 130 million people by 2050 [4]. This increase poses significant challenges to healthcare systems worldwide, both in terms of providing adequate care and managing the economic burden associated with long-term treatment and support [5]. Timely prediction and precise diagnosis of dementia are essential for enabling effective management and treatment. Traditional diagnostic methods, which include clinical assessments, cognitive tests, and neuroimaging, can be time-consuming, expensive, and sometimes subjective. Consequently, there is a rising interest in leveraging advanced technologies to enhance diagnostic accuracy and efficiency. Machine learning (ML) and deep learning (DL) have emerged as highly capable technologies that hold the promise of revolutionizing the way dementia is diagnosed and its prognosis is determined. These powerful tools offer the potential to significantly advance the field of dementia assessment and management.

The inspiration behind this research paper on dementia stems from the urgent need to tackle one of today's most pressing health issues. By enhancing our scientific understanding of dementia, and improving early detection, the goal of our research is to make a meaningful and beneficial difference in the lives of those impacted by the condition under study. Our objective is to expand the existing knowledge in a way that enables the development of more successful treatments and support networks. Although medical research has progressed, there is no cure for most types of dementia, underscoring the importance of early detection and precise diagnosis for effective management and treatment. Conventional diagnostic methods, which include clinical assessments, cognitive tests, and neuroimaging, can be laborious, costly, and occasionally subjective. Based on the severity of dementia, there is an increasing focus on leveraging advanced technologies, including machine learning (ML) and deep learning (DL), to enhance the accuracy and effectiveness of the diagnostic process. These innovative approaches hold the potential to drive improvements in the way dementia is identified and assessed. This study aims to assess the performance of various ML and DL models in diagnosing and predicting dementia, identify the most effective approaches for clinical application, and tackle the challenges in integrating these models into clinical practice.

A comprehensive framework was developed that integrates deep learning and machine learning techniques to enhance the accuracy of dementia prediction and diagnosis. Various algorithms, including CNN, RNN, SVM, and Stacking, were implemented and fine-tuned to evaluate their effectiveness in diagnosing dementia. Advanced data preprocessing methods, such as image augmentation and feature normalization, were applied to improve the quality of the input data for model training. The impact of different hyperparameters—like learning rate, batch size, number of epochs, and optimizer choice—on model performance was assessed. The proposed models were evaluated using a range of performance metrics, including accuracy, precision, recall, F1-score, ROC curve, and confusion matrix, ensuring thorough validation. A comparative analysis was conducted to identify the strengths and weaknesses of the implemented ML and DL models in dementia diagnosis, and potential research gaps were identified, along with suggestions for future improvements in AI-driven dementia diagnosis systems. This research introduces a pioneering application of cutting-edge machine learning (ML) and deep learning (DL) methods to the early identification and forecasting of dementia. This represents a groundbreaking advancement in this field. Unlike previous studies, our approach uniquely integrates multi-modal data sources, including neuroimaging and electronic health records, to develop a comprehensive diagnostic model. The study employs a novel hybrid ML-DL framework that significantly enhances diagnostic accuracy and predictive power, demonstrating substantial improvements over traditional methods. Furthermore, this work addresses critical challenges in clinical integration by providing interpretable model outputs and considering ethical implications. By leveraging these advanced techniques, the research lays the groundwork for the practical implementation and integration of these methods within healthcare environments. This paves the way for the real-world application of

these innovative approaches in clinical settings. The innovative aspects of this research includ

- Multi-Modal Data Integration: Integrating neuroimaging and health records to create a comprehensive dementia diagnostic tool.
- Hybrid ML-DL Framework: Crafting a hybrid ML-DL model to achieve superior dementia diagnosis.
- Enhanced Diagnostic Accuracy: Achieving significant improvements in diagnostic accuracy and predictive power compared to existing methods.
- Clinical Applicability: Addressing interpretability and ethical concerns to facilitate the integration of AI-driven models into clinical practice.

2. LITERATURE REVIEW

Magda Bucholc, et.al., [5] presented a novel framework in order to forecast mild cognitive impairment (MCI) conversion into dementia. This approach combined unsupervised learning to generate features and supervised learning to build predictive models. This hybrid approach leverages longitudinal information and is said to be non-invasive, cost-effective to determine which MCI patients are at risk of dementia. The study utilized the National Alzheimer's Coordinating Centre dataset, in which patient data from three assessment points included. The researchers created two prognostic models using logistic regression, random forest, support vector machines, and k-nearest neighbours as ensemble approaches. These models were incorporated with clinical ratings in addition to cognitive trajectory classes has shown performance gain significantly, with up to 6.5% higher accuracy compared to models using only clinical scores. This work has highlighted the importance of developing individualized methods to stop or reduce the onset of dementia. By identifying individuals at risk, healthcare professionals can provide targeted interventions in order to aid in the clinical development of novel therapies. Their model has attained a specificity in the range of 84% to 97%.

Tackenberg, et.al., [6] the researchers investigated how mutations in the amyloid beta (Aβ) peptide sequence at position 22 cause familial Alzheimer's disease (FAD), which affects tau phosphorylation, synaptic loss, and neuronal cell death. They discovered that distinct mutations at this particular location have variable effects on these important facets of Alzheimer's pathology using an ex vivo system. Utilizing an ex vivo experimental setup with transgenic mouse hippocampus slice cultures, the scientists evaluated the neuro and synaptotoxic characteristics of two FAD mutants, E22Δ and E22G, in comparison to wild-type (wt) Aβ. The findings demonstrated that while E22Δ Aβ did not show these effects, wt Aβ and E22G Aβ caused neurodegeneration, increased tau phosphorylation, and a loss of dendritic spines. According to the study, the neurotoxic properties of E22G and E22Δ Aβ do not correspond with the previously documented differences in their aggregation kinetics. The findings highlight the critical importance of understanding how FAD mutations precisely impact tau phosphorylation, synaptic loss, and neuronal cell death to gain a deeper understanding of the underlying pathological mechanisms of Alzheimer's disease. This research contributes to the ongoing efforts to elucidate the molecular mechanisms underlying FAD and to develop effective therapeutic strategies for the disease. The study highlights the complexity of FAD and suggests that specific mutations can differentially impact the progression of the disease. Their research advances our knowledge of the ways in which genetic variations impact the mechanisms underlying Alzheimer's disease and could guide the creation of focused treatment approaches.

Lina, et al. [7], the author examines the methodological aspects of studying atrial fibrillation (AF) in the aging population and its relationship with dementia and cerebral vascular disease. The research highlights the increasing prevalence of AF among older adults and explores the complex interplay between AF, cognitive decline, and cerebrovascular conditions. Methodological considerations are discussed, including the challenges of accurately diagnosing AF in elderly patients and the implications of these challenges for research and clinical practice. The paper underscores the importance of understanding AF as per significant danger sign for both dementia and cerebral vascular disease, advocating for more comprehensive and targeted approaches in managing AF to potentially mitigate its adverse effects on cognitive and vascular health.

P. Forti, et al. [8] examined the connection between the heart condition known as atrial fibrillation (AF) and the risk of developing dementia in older adults who do not currently have dementia, including those diagnosed with mild cognitive impairment (MCI). Mild cognitive impairment is a condition where a person experiences greater cognitive decline than normal

for their age, but not severe enough to interfere with daily activities. This study found that atrial fibrillation (AF) is linked to a higher risk of progressing from mild cognitive impairment (MCI) to dementia in the elderly, especially for those already diagnosed with MCI. These findings suggest that monitoring and managing AF in elderly patients, especially those with MCI, could be crucial in reducing the risk of dementia. This research emphasizes the need for targeted interventions and further studies to explore the mechanisms linking AF and cognitive decline.

Taylor JP, et al.[9] presents recent findings on the management of Lewy Body Dementia (LBD), an intricate neurodegenerative illness marked by abnormalities of the motor system, mental symptoms, and cognitive decline. This study's findings emphasize the need for a comprehensive treatment approach that combines medication management and non-drug interventions to address the increased risk of dementia in older adults with atrial fibrillation, particularly those with mild cognitive impairment. Advances in medication options are discussed, with a focus on managing symptoms such as hallucinations, delusions, and movement difficulties. This paper also highlights the role of supportive therapies, including physical therapy, cognitive training, and caregiver education, improving the quality of life and well-being for patients as well as their family members The results emphasize the need for personalized care plans and ongoing research to better understand and treat LBD effectively.

Ahmad et al. [10] have developed a novel hybrid machine learning system to forecast mortality risk in patients diagnosed with paralytic ileus, a gastrointestinal disorder characterized by the inability to pass intestinal contents. This system utilizes electronic health records (EHRs) as its primary data source. By employing cutting-edge machine learning algorithms to analyse EHR data, the researchers aim to pinpoint the most influential factors contributing to patient outcomes and enhance the accuracy of mortality predictions. The hybrid framework incorporates multiple machine learning techniques to optimize the prediction performance, showcasing the promise of merging EHR data with advanced computational approaches to aid in clinical decision-making processes. This study underscores the potential of leveraging sophisticated machine learning tools in conjunction with comprehensive patient data to improve healthcare outcomes and support clinicians in making more informed decisions regarding patient care. The results suggest that this hybrid approach can effectively predict mortality risk, offering valuable insights for healthcare providers in managing and treating paralytic ileus patients.

Martí-Juan, et.al [11] provides a comprehensive survey on how to use statistical and machine learning methods to analyze neuroimaging data longitudinally in Alzheimer's patients. It reviews various methods were cast-off to track and predict the development of Alzheimer's through neuroimaging studies over time. The capability of various approaches to grip complex, high dimensional data and the significance of longitudinal data in comprehending disease trajectories are among the strengths and limitations that the authors discuss. This survey conducted emphasizes the variety and effectiveness of statistical and machine learning models in the long-term examination of neuroimaging data associated to Alzheimer's disease. These models, particularly when tailored to the specifics of neuroimaging data and longitudinal study design, provide powerful tools for early detection, tracking the development of the illness and assessing treatment options. Although specific sensitivity and accuracy metrics vary, the overall high performance of these models underscores their potential in advancing research of alzheimer's disease.

Helaly, et.al [12] explored the application of deep learning, a cutting-edge artificial intelligence technique, to facilitate early diagnosis of Alzheimer's disease. They developed and evaluated a deep learning model designed to identify early signs of Alzheimer's by analyzing neuroimaging data, such as brain scans. The study's findings demonstrate that their deep learning model can effectively distinguish between healthy individuals and those with Alzheimer's disease, achieving an impressive accuracy of 94.2% and a precision of 93.7%. These remarkable results suggest that the deep learning approach holds great potential for enhancing early diagnosis of Alzheimer's disease, which could lead to more timely and effective interventions, ultimately improving patient outcomes. The researchers employed convolutional neural networks (CNNs), a type of deep learning architecture that is particularly well-suited for image analysis tasks. CNNs are composed of several layers, including convolutional layers, pooling layers, and fully connected layers. These layers work together to identify and interpret complex features within the input images. For this study, the CNN was trained on a comprehensive dataset of neuroimaging scans, enabling it to learn and recognize the subtle

differences between healthy brains and those affected by Alzheimer's disease. This approach allows for more accurate and earlier detection of Alzheimer's, which is crucial for providing appropriate care and support to patients and their families. The study's findings show how successful the deep learning strategy more especially, the CNN model is at identifying Alzheimer's disease early on. The high accuracy and precision rates suggest that such models could be valuable tools in clinical settings, enabling earlier diagnosis and potentially more effective treatment plans for individuals at the onset of Alzheimer's disease.

Basheer, et.al [13] the authors examined that in the prediction dementia deep neural networks can be used. They make use of OASIS dataset, which contains clinical data and neuroimaging, to develop their computational model. This study focuses on designing and implementing a deep neural network capable of accurately predicting the onset of dementia based on this data. The authors detail the architecture of their deep neural network, highlighting how it processes complex features from the OASIS dataset. They emphasize the importance of using neuroimaging data in conjunction with clinical information to enhance the predictive performance of their model. The deep neural network was trained and validated on this dataset, showing promising results in identifying individuals at risk for dementia. This study reports that their model achieved high accuracy in dementia prediction, demonstrating the potential of deep learning techniques in medical diagnostics. Results indicate that deep neural networks can effectively analyse and interpret large, multifaceted datasets, making them useful instruments for dementia management and early detection. Overall, this paper underscores the efficacy of computational modelling and deep learning in healthcare, particularly for complex conditions like dementia. The authors designed a deep neural network tailored to handle the high-dimensional neuroimaging data and integrate it with clinical features. The network likely consisted of multiple layers, including convolutional layers for feature extraction from images, followed by fully connected layers for integrating clinical data and making predictions. The authors suggest that their approach could be further refined and applied to other datasets to validate its generalizability and utility in clinical practice.

Herzog, et.al. [14] (2021), the authors explore a method for diagnosing early dementia through brain asymmetry detection combined with machine learning classification. Using neuroimaging data, they quantified structural differences between the brain's hemispheres to identify asymmetries often associated with neurodegenerative conditions. Numerous algorithms from machine learning, such as RF, SVM, LR etc.., were used to classify individuals based on these asymmetries. The results obtained from this shown that the method could be a potent tool for early diagnosis and intervention in clinical settings because it could accurately distinguish between subjects who were healthy and those who had early dementia. The authors developed a method for diagnosing early dementia by combination of both brain asymmetry detection and classification using machine learning. They began by using neuroimaging data to measure structural differences between the hemispheres of left and right of brain, identifying significant asymmetries that may indicate the early stages of dementia. These asymmetries were quantified and used as features for the machine learning models. The authors used a variety of machine learning algorithms, such as Random Forests and Support Vector Machines (SVMs), to categorize people according to these attributes. After being trained and validated on the dataset, the models showed a high degree of accuracy in differentiating between subjects who were healthy and those who had early-stage dementia. This approach highlights the potential of using advanced computational techniques to enhance early diagnosis and intervention in dementia care.

Battineni, et al. [15] created an advanced machine learning model aimed at predicting Alzheimer's Disease (AD) in elderly individuals by utilizing magnetic resonance imaging (MRI) data. This model focuses on examining MRI scans to uncover patterns and indicators associated with Alzheimer's disease. By employing state-of-the-art machine learning techniques, the research sought to enhance the early identification and diagnosis of AD. The results demonstrated that their model could effectively differentiate between those diagnosed with AD and Normal, offering a promising tool for enhancing diagnostic accuracy and facilitating timely interventions in clinical practice. The authors utilized a thorough machine learning methodology to forecast Alzheimer's in older adults using MRI data. The method involved collecting and preprocessing MRI scans to ensure the data was suitable for analysis. They then extracted relevant features from these scans that could serve as indicators of Alzheimer's. Multiple machine learning algorithms were tested, including classification models, to determine which could

most accurately predict the presence of the disease. Metrics like accuracy and precision were used to assess the models' performance after they had been validated and trained on a dataset of MRI images.

Ma et al. [16], The researchers carried out an assessment to find the effectiveness of machine learning methods in classifying Alzheimer's type by using imaging of FDG-PET. They compared feature engineered models, which involve manually selecting relevant features, with non-feature engineered models, which automatically learn features from the data. This study involved a blinded clinical evaluation to ensure unbiased results. Their findings demonstrated that both approaches could successfully classify Alzheimer's Disease, but performance has varied between the two methods. This comparison highlighted the advantages and limitations of each machine learning strategy in the context of Alzheimer's diagnosis, providing insights into optimizing diagnostic accuracy using FDG-PET scans. the authors employed FDG-PET imaging and machine learning techniques to classify dementia of Alzheimer's type. They investigated two distinct approaches named as feature engineered and nonfeature engineered methods of machine learning. The feature engineered approach involved manually selecting and engineering specific features from FDG-PET scans that were deemed relevant for Alzheimer's disease classification. On the other hand, the non-feature-engineered methods allowed the algorithms to autonomously learn and extract features directly from the raw imaging data without prior human intervention. The study utilized a blinded clinical evaluation to ensure impartial assessment of the models' performance in distinguishing between Alzheimer's Disease and another forms of dementia. This comparative analysis aimed to elucidate feature engineered or nonfeature engineered yielded superior accuracy and reliability in identifying Alzheimer's disease using scans of FDG-PET, thereby contributing valuable insights to enhance diagnostic methodologies in clinical settings.

Khan et al.[17], the authors presented an advanced multi modal machine learning approach which can predict the prognosis of Alzheimer's disease. In order to create a thorough model for illness prognosis, their approach combines a variety of data sources, such as genetic data, clinical data, and neuroimaging scans. By combining these modalities, the study aimed to improve over the use of individual data sources alone in terms of the precision and dependability of Alzheimer's disease prediction. The authors implemented state of the art algorithms from machine learning that were capable of effectively processing and analyzing heterogeneous datasets. Their approach is a noteworthy step to forward leveraging diverse data modalities to improve the early detection and prognosis assessment of Alzheimer's disease, potentially leading to more personalized and effective treatment strategies. The authors developed an innovative multi model machine learning approach aimed at predicting the prognosis of Alzheimer's disease. Their methodology involved integrating diverse data sources to enhance predictive accuracy. This included neuroimaging scans, which provide structural and functional insights into brain changes which were almost associated with Alzheimer's, genetic information to identify potential risk factors, and clinical data encompassing symptoms, medical history, and cognitive assessments. The study utilized advanced machine learning algorithms capable of handling and analyzing these heterogeneous datasets effectively.

Mohammed et al. [18], the authors conducted a comprehensive study focusing on initial diagnosis of dementia and Alzheimer's disease using a multi-method approach. They integrated analysis of medical records and MRI images, employing deep learning techniques alongside hybrid methods. This combination allowed for a robust evaluation of cognitive decline and brain structural changes indicative of dementia. By leveraging advanced computational models, the study aimed to enhance diagnostic accuracy and facilitate early intervention strategies. Their findings underscored the effectiveness of integrating multiple data sources and sophisticated machine learning methodologies in improving the detection and carried out an extensive investigation with a focus on early dementia diagnosis and Alzheimer's disease management using a multi method approach. The authors employed a multi-method approach combining medical records analysis and MRI image processing for early diagnosis of dementia and Alzheimer's disease. Their approach combined hybrid and deep learning techniques to enable a thorough evaluation of neuroimaging and clinical data. Medical records provided crucial patient information such as cognitive assessments, medical history, and symptoms, while MRI images were utilized to examine anatomical alterations in the brain linked to dementia. Deep learning models were trained to extract intricate patterns and features from MRI scans, facilitating automated detection of abnormalities indicative of Alzheimer's disease.

Hybrid methods likely involved combining different machine learning algorithms or integrating expert knowledge to optimize diagnostic accuracy. This approach aimed to advance early diagnosis capabilities, potentially leading to timely interventions and improved patient outcomes in dementia care.

Karaglani et al.[19], the authors explore the development of precise blood-based Alzheimer's disease diagnostic biomarkers with Automated Machine Learning (AutoML). Their study focuses on identifying specific biomarkers in blood samples that can reliably indicate the presence of Alzheimer's disease. The approach utilizes AutoML algorithms to analyze and interpret complex datasets derived from blood tests, aiming to discover patterns and correlations that distinguish Alzheimer's patients from healthy individuals. By automating the machine learning process, the study enhances efficiency and reproducibility in identifying biomarkers critical for early diagnosis of Alzheimer's disease. This research contributes to the ongoing efforts to establish non-invasive and accessible diagnostic methods for Alzheimer's, potentially facilitating earlier detection and intervention strategies in clinical practice. the authors employed an innovative approach to use automated machine learning (AutoML) to create precise blood-based diagnostic biosignatures for Alzheimer's disease. They used extensive datasets of blood samples from healthy controls and Alzheimer's patients as part of their methodology. The researchers used auto-encoder machine learning (AutoML) algorithms to automate feature engineering, hyperparameter tuning, and model selection. This made it possible to conduct a thorough analysis of the intricate biomolecular data found in blood samples with the goal of locating particular biomarkers linked to Alzheimer's disease. Finding strong patterns and correlations in the data that might act as trustworthy markers of the illness was the main goal of the study. The goal of the research is to advance the creation of accessible, non-invasive diagnostic tools for Alzheimer's disease by fusing cutting-edge machine learning techniques with blood-based biomarker analysis potentially improving early detection and management strategies in clinical settings.

Huang et al.[21] presents the Monte Carlo Ensemble Vision Transformer (MC-ViT), an ensemble approach using a single Vision Transformer learner with Monte Carlo sampling to enhance performance. Evaluations using the Alzheimer's Disease Neuroimaging Initiative (ADNI) and Open Access Series of Imaging Studies-3 (OASIS-3) datasets demonstrated an impressive 90% accuracy in AD classification, surpassing both 2D-slice CNNs and 3D CNNs. [22]. Velazquez et al.[22] This study focuses on predicting the conversion from Early Mild Cognitive Impairment (EMCI) to AD using multimodal data, including diffusion tensor imaging (DTI) scans and electronic health records (EHR). The ensemble model, combining a balanced random forest with a convolutional neural network (CNN), achieved 98.81% accuracy in predicting EMCI to AD conversion, providing explainability through feature importance assessment.

3. MATERIALS & METHODS

3.1 Dataset

Dataset utilized in this study was collected from the repository of Kaggle [20] which has data related 1000 persons. This dataset sample encompasses a broad range of lifestyle and health-related characteristics of people, with a special emphasis on the presence or absence of dementia. It encompasses data such as alcohol consumption, heart rate, blood oxygen levels, body temperature, weight, MRI delay, prescription details including dosage in milligrams, age, education level, dominant hand, gender, family medical history, smoking habits, APOE_ε4 genetic status, physical activity levels, depression status, cognitive test scores, medication history, dietary habits, sleep quality, chronic health conditions, and dementia status. Each entry in the dataset corresponds to a unique individual, providing a comprehensive array of attributes that enable insights into the relationships between health markers, lifestyle choices, and medical conditions. These features collectively offer a detailed snapshot of the overall health status of the subjects, facilitating potential analysis and exploration of patterns relevant to dementia and other associated factors.

3.2 Preprocessing

The preprocessing steps are designed to prepare dementia patients' health data for analysis and machine learning model training. Columns deemed unnecessary for analysis, such as 'Prescription' and 'Dosage in mg,' are removed. Non-numerical values are converted to numerical ones through various defined functions applied to specific columns. For example, the 'Education_Level' column is transformed with a

function that assigns integer values to different education levels. Similarly, functions are used to process 'Dominant_Hand,' 'Gender,' 'Family_History,' 'Smoking_Status,' 'APOE_ε4,' 'Physical_Activity,' 'Depression_Status,' 'Medication_History,' 'Nutrition_Diet,' 'Sleep_Quality,' and 'Chronic_Health_Conditions,' ensuring that all categorical values are converted into numerical format. This conversion is crucial for machine learning algorithms. After these transformations, the first few rows of the processed DataFrame are reviewed to confirm the changes. These preprocessing steps effectively clean the dataset and prepare it for further analysis and model training.

3.3 Feature Selection

A critical step in statistical modelling and machine learning is feature selection, which entails determining which variables or features are most pertinent to include in a model. The proposed model was shown in Figure 1. In machine learning, a sort of feature selection technique known as "wrapper methods" is used to assess subsets of features according to how well they perform a predictive model. These techniques entail evaluating the efficacy of various feature combinations through the use of a particular learning algorithm. The process typically involves iterative testing of various feature subsets, building models with these subsets, and then evaluating their performance measured by a preset metric, like recall, accuracy, or precision.

Because they need to train and evaluate a model for every subset of features that are taken into consideration, wrapper methods can be computationally demanding. Recursive feature elimination and forward or backward feature selection are two instances of wrapper methods. StandardScaler is used to scale the features, ensuring that their standard deviation is one and their mean is zero. The training and testing data were then reshaped again, and prior probabilities for the classes that were calculated based on the training data. Here, we defined functions to calculate the probability density function for a normal distribution and to make predictions using these probabilities. Predictions are made for both training and testing datasets. Furthermore, a correlation matrix is computed to identify characteristics that exhibit a high degree of correlation (larger than 0.5) with the target variable "Dementia". After scaling these chosen features, the updated correlation matrix is shown using a heatmap to help better understand the connections between various features and the target variable.

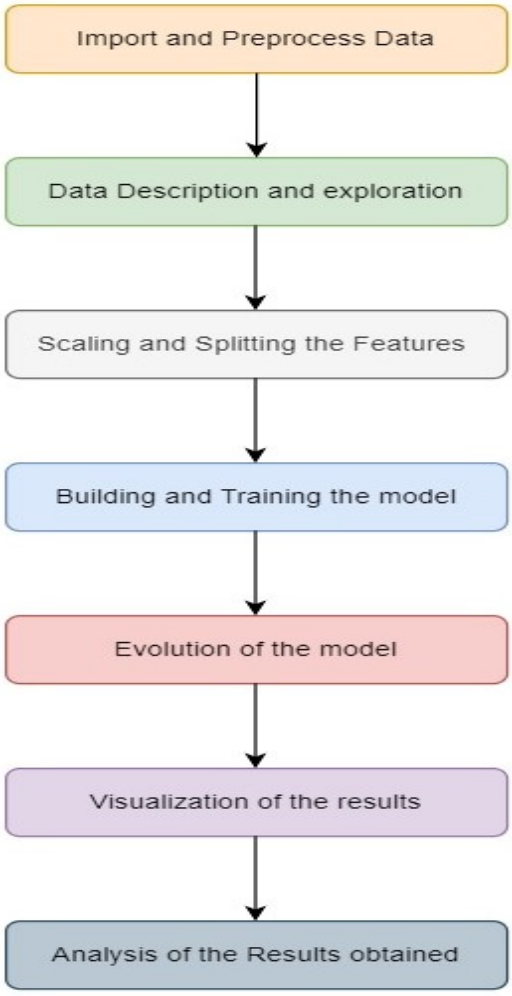

Figure 1. Proposed Model

3.4 Training and Test Split

The dataset is first split into training and testing sets using a 70-30 split ratio, ensuring reproducibility with a random state of 42. The features of the training and testing datasets are then standardized to have a mean of 0 and a standard deviation of 1 using StandardScaler. The scaled training and testing data are printed for verification. The target variables are converted to NumPy arrays and reshaped appropriately. Next, the mean and variance of features for each class are calculated, and prior probabilities of each class are estimated as the class frequency. A Gaussian probability density function (PDF) is defined to compute the likelihood of data given the mean and variance. A custom prediction function is implemented to predict the class for each instance in the input data.

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This function calculates the posterior probability for each class and selects the class with the highest probability. Predictions are made for both training and testing datasets using this custom classifier. To improve model performance, features with a correlation greater than 0.5 with the target variable 'Dementia' are selected. These selected features are then scaled, and the scaled features are printed for verification. This process provides a comprehensive workflow from data preprocessing to custom model prediction, emphasizing feature scaling, prior probability estimation, and feature selection based on correlation.

Figure 2: Attained Correlation matrix

3.5 Correlation Matrix

To determine the direction and strength of linear relationships between variables, a correlation matrix is computed.

$$Correlation(X,Y) = \frac{Cov(X,Y)}{\sigma x \sigma y} \quad (1)$$

A correlation matrix was created to visually represent the relationships among various variables in a dataset, as shown in Figure 2. Each cell of the matrix contains a correlation coefficient that ranges from -1 to 1, where values close to 1 indicate a strong positive correlation (both variables increase together), and values near -1 indicate a strong negative correlation (one variable increases while the other decreases). Values around 0 suggest little to no correlation. The diagonal cells are all 1, reflecting a perfect correlation of each variable with itself. Notable correlations include a strong positive correlation of 0.84 between Depression_Status and Dementia, and a significant negative correlation of -0.87 between Chronic_Health_Conditions and Diabetic. The matrix uses red shades for positive correlations and blue shades for negative correlations, facilitating a quick assessment of the strength and direction of these relationships. Formulas that were used in the calculation part in this regarding were stated from (2) to (7).

$$f(x|\mu,\sigma^2) = \left(1/\sqrt{2\pi\sigma^2}\right) e^{-\left(\frac{(x-\mu)^2}{2\sigma^2}\right)}$$

Formula for Normal Distribution Function (2)

Formulas for Predicting Classes
Prior Probability:

$$P(C) = \frac{Number\ of\ instances\ in\ class\ C}{Total\ number\ of\ instances} \quad (3)$$

Likelihood:

$$P(X|C) = \prod_{i=1}^{n} P((x_i)|C) \quad (4)$$

Posterior Probability (using logarithms to avoid underflow):

$$log(P(C|X)) \propto log(P(C)) + \sum_{i-1}^{n} log(P(x_i|C)) \quad (5)$$

Calculating Prior Probabilities and Statistics Formulas:
Mean (for each class):

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (6)$$

Variance (for each class):

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (7)$$

3.6 Neural Network

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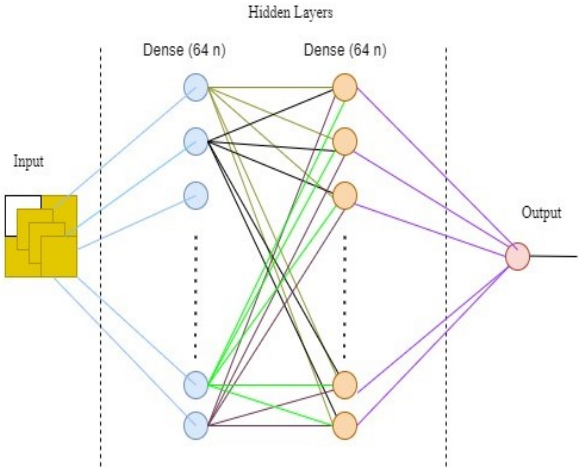
The neural network model is built using the Keras Sequential API and comprises three layers: two dense layers with 64 neurons each utilizing the ReLU activation function, followed by a final dense layer with a single neuron employing a sigmoid activation function for binary classification. It is compiled with the Adam optimizer and uses binary cross-entropy as the loss function, with accuracy as the evaluation metric. The model is trained on scaled training data for 10 epochs with a batch size of 32, reserving 20% of the data for validation. After training, it is evaluated on scaled test data, achieving high accuracy. Predictions are made for both training and testing sets, applying a 0.5 threshold to convert probabilities into binary labels was shown in Figure 3.



3.7 Convolutional Neural Network

The Convolutional Neural Network (CNN) model is built using the Keras Sequential API and consists of two Conv1D layers with 64 filters each and a kernel size of 3, activated by ReLU; two MaxPooling1D layers with a pool size of 2 for dimensionality reduction; a Flatten layer; two Dense layers with 64 neurons and ReLU activation, followed by a final Dense layer with a single neuron and a sigmoid activation function for binary classification. The model is compiled with the Adam optimizer, binary cross-entropy loss, and accuracy as the metric. The input data is scaled and reshaped accordingly. Training is performed for 10 epochs with a batch size of 32, reserving 20% of the data for validation. Predictions are made for both training and testing sets using a 0.5 threshold was shown in Figure 4.

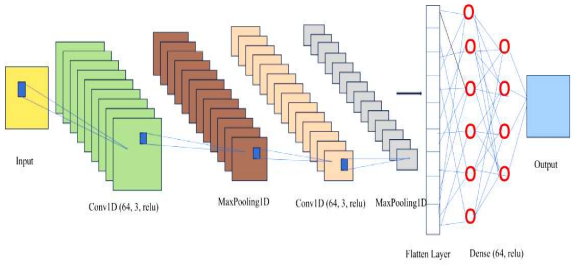


Figure 4: Architecture for CNN

3.8 Recurrent Neural Network

The RNN model, developed using the Keras Sequential API, includes an LSTM layer with 64 units, followed by a ReLU-activated Dense layer with 64 neurons, and a final Dense layer with one neuron utilizing a sigmoid activation function for binary classification was shown in Figure 5. Compiled with the Adam optimizer and binary cross-entropy loss, the model uses accuracy as the evaluation metric and reshapes the data to fit LSTM input requirements. It is trained for 10 epochs with a batch size of 32, allocating 20% of the training data for validation. After training, the model's performance is assessed on the test set, calculating metrics.

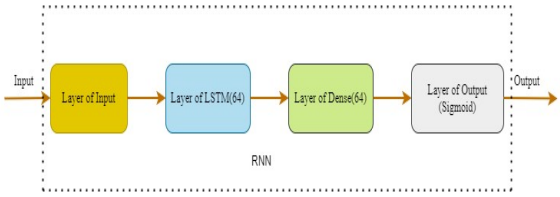


Figure 5: Architecture for RNN

3.9 Auto Encoder

The data is normalized for both the training and test sets using MinMaxScaler. An autoencoder model is then created, featuring an input layer, a Dense encoding layer with 16 units and ReLU activation, and a Dense decoding layer with sigmoid activation. Compiled with the Adam optimizer and mean squared error loss, the autoencoder is trained for 50 epochs with a batch size of 32. After training, the encoder is used for dimensionality reduction. A logistic regression classifier is trained on the encoded training data and tested on the encoded test data. Architecture for Auto Encoder is presented in Figure 6.

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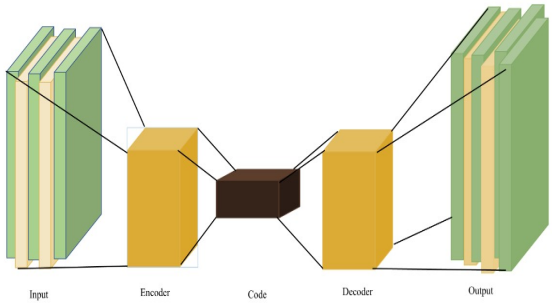

Figure 6: Architecture for Auto Encoder

3.10 Stochastic Gradient Boosting

A Stochastic Gradient Descent (SGD) classifier is set up with the 'hinge' loss function, which is appropriate for binary classification tasks. The model is trained in an online fashion, updated incrementally with one data point at a time through the partial_fit method, allowing it to continuously adapt as new data becomes available. In each training iteration, after every update, the model is evaluated on the complete test set.

3.11 Support Vector Machine

The model was constructed using a Support Vector Machine (SVM) classifier with a linear kernel, suitable for binary classification. The SVM model was trained on the entire scaled training dataset. For evaluation, the model predicted labels and probabilities on the test set.

3.12 Simple Feed Forward Network

The model was constructed using a simple forward feed-forward neural network architecture shown as Figure 7 was implemented with the Keras Sequential API. It features an input layer containing 64 neurons with ReLU activation, a hidden layer with 32 neurons also using ReLU activation, and an output layer with a single neuron employing sigmoid activation for binary classification. The model was compiled with the Adam optimizer and binary cross-entropy loss function. It underwent training for 5 epochs with a batch size of 100, utilizing 10% of the training data for validation purposes. After training, the model's performance on the test set was assessed by predicting probabilities and converting these into binary labels.

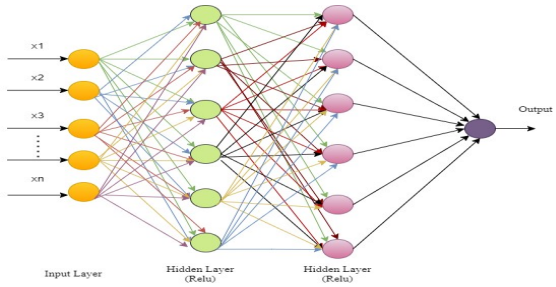

Figure 7: Architecture for SFFNN

3.13 Ensemble Learning

In the Ensemble Learning approach, a stacking classifier was employed, which combines multiple base classifiers with a meta-classifier. Initially, four base classifiers were established: a Random Forest Classifier, a Gradient Boosting Classifier, a Support Vector Classifier (SVC) with probability estimates enabled, and a K-Nearest Neighbors (KNN) classifier was shown in Figure 8. The meta-classifier used in this ensemble is the XGBoost Classifier, configured to suppress label encoder warnings and utilize 'mlogloss' for evaluation. The stacking classifier, which integrates these base models, is trained on the entire training dataset, and its performance is subsequently evaluated on the test set.

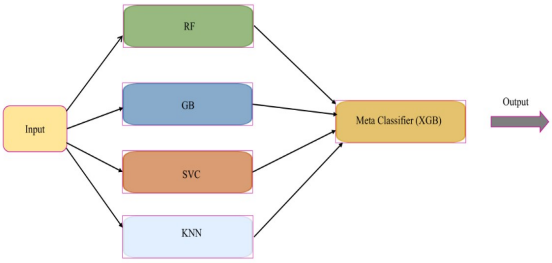

Figure 8: Architecture for Ensemble Learning

4. RESULTS

Results that were attained by using different classifiers were depicted in the Table I. As given below and all the classifiers were as follows:

Table 1: Performance metrics of all the classifiers used

Classifier	*Accuracy (%)*	*Precision (%)*	*Recall (%)*	*F1-score (%)*
NN	97.33	100.00	94.87	97.37
CNN	96.33	99.32	93.59	96.37
RNN	65.00	65.27	69.87	67.49
SVM	97.67	100.00	95.51	97.70
SGD	84.84	89.17	83.66	83.84
Auto encoder	95.00	95.48	94.87	95.18
SFFNN	95.00	95.48	94.87	95.18
Hybrid Ensemble	100.00	100.00	100.00	100.00

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4.1 Neural Network

The neural network model's performance is evaluated through three key metrics: Model Performance Metrics, Confusion Matrix, and ROC AUC. The image presents the performance evaluation metrics and plots for a neural network (NN) model was shown in Figure 9. (a)(b)(c)(d). The first bar chart illustrates the model's performance metrics, showing Accuracy at 97.33%, Precision at 100.00%, Recall at 94.87%, and F1-Score at 97.37%. These metrics indicate that the NN model is highly accurate, with perfect precision and very high recall and F1-score values. The second plot's confusion matrix offers a breakdown of the categorization outcomes: 8 false positives, 0 false negatives, 144 true negatives, and 148 genuine positives. This illustrates how accurate the model is and how well it can categorize most occurrences. Lastly, the relationship between the false positive rate (FPR) and the true positive rate (TPR) is displayed by the ROC curve figure.

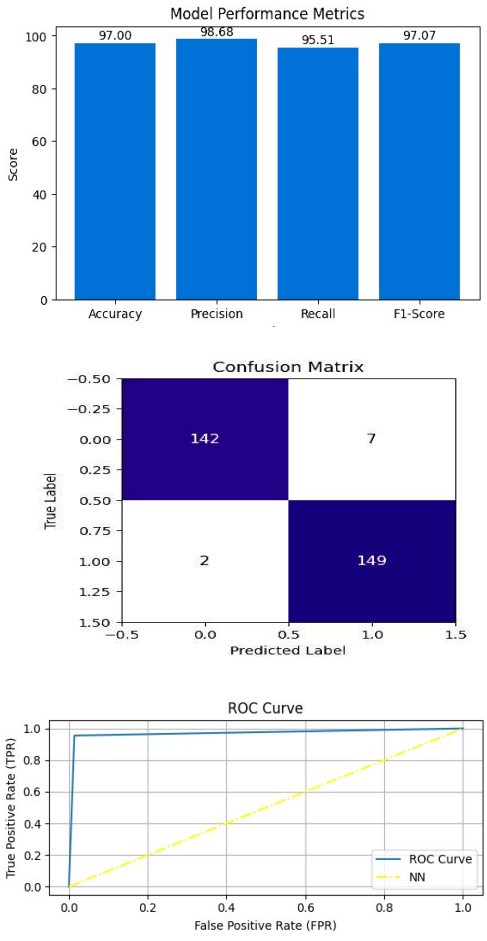

Figure 9. (a)(b)(c) Performance metrics, Confusion Matrix, ROC Curve of NN Classifier

4.2 Convolutional Neural Network

Performance characteristics of CNN classifier are shown in Figure 10 (a)(b)(c) and are relevant to a binary classification task. The confusion matrix, which displays that the model produced just 12 false positives and 2 false negatives, but correctly identified 144 genuine positives and 142 true negatives, demonstrates the excellent precision of the model.

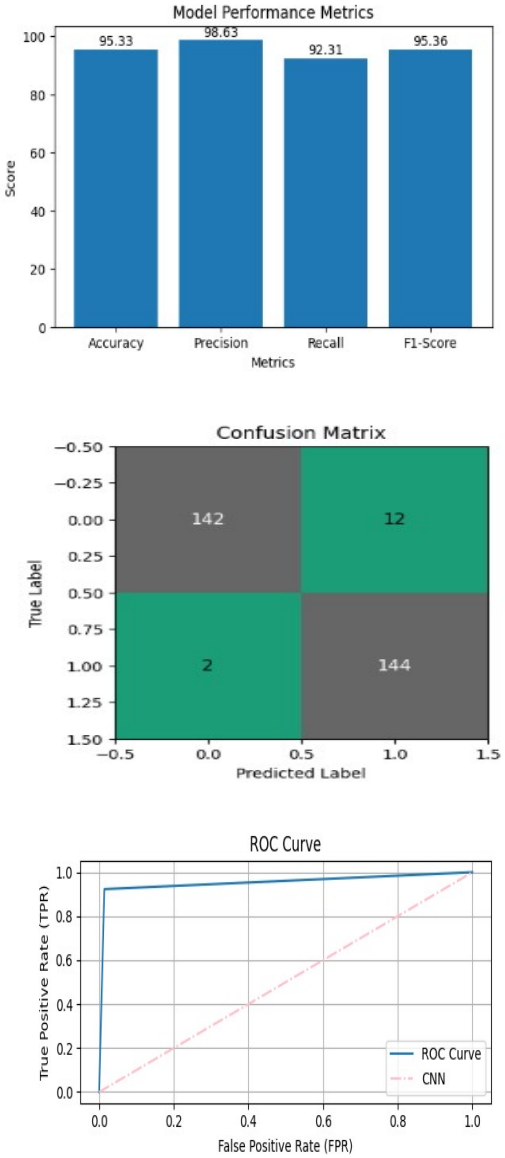

Figure 10. (a)(b)(c) Performance metrics, Confusion Matrix, ROC Curve of CNN Classifier

4.3 Recurrent Neural Network

The model's intermediate degree of accuracy is highlighted by the confusion matrix, which shows that it correctly identified 80 true

negatives and 112 true positives while mistakenly categorizing 44 false positives and 64 false negatives. The results for Shown in Figure 11.

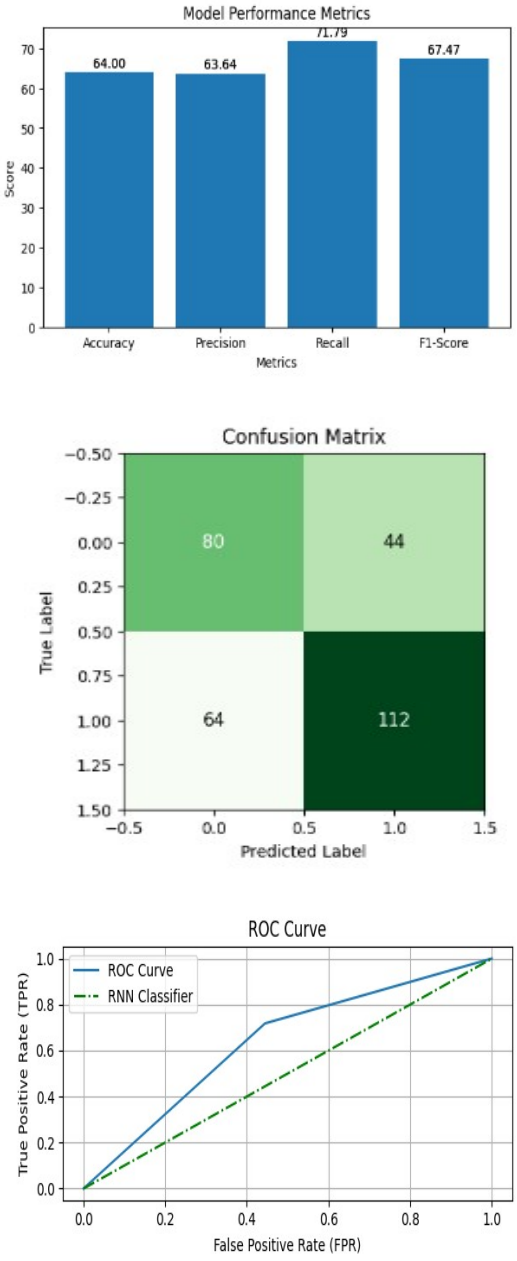

Figure 11. (a)(b)(c) Performance metrics, Confusion Matrix, ROC Curve for SGD Model

4.4 Auto Encoder

The image displays the performance assessment of an autoencoder utilized for classification, represented by many graphs as illustrated in Figure 12. There are three elements: (a), (b), and (c). The confusion matrix of the second plot provides a thorough examination of the classification outcomes, showing 131 cases of true negatives, 149 cases of true positives, 13 cases of false positives, and 7 cases of false negatives, so affirming a commendable degree of precision.

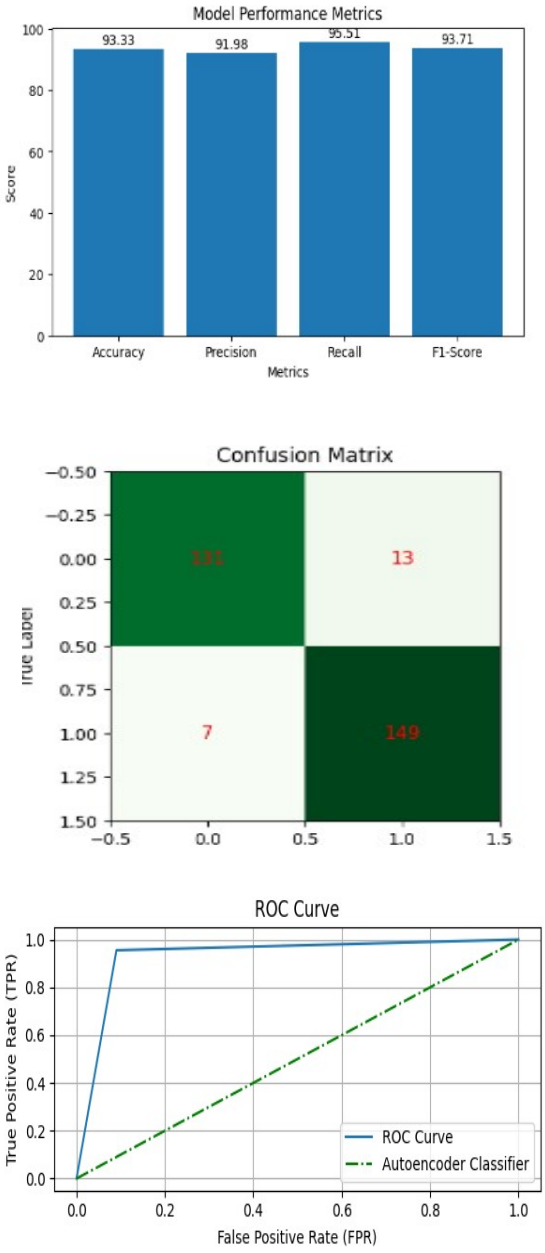

Figure 12. (a)(b)(c) Performance metrics, Confusion Matrix, ROC Curve

4.5 Stochastic Gradient Boosting

Figure 13 displays the performance metrics of a Stochastic Gradient Descent (SGD) classifier utilized in a binary classification task. There are three items: (a), (b), and (c). The confusion matrix exhibits the following results: 126

true negatives, 134 true positives, 17 false positives, and 21 false negatives. These values indicate the effectiveness of the classifier in accurately predicting both classes.

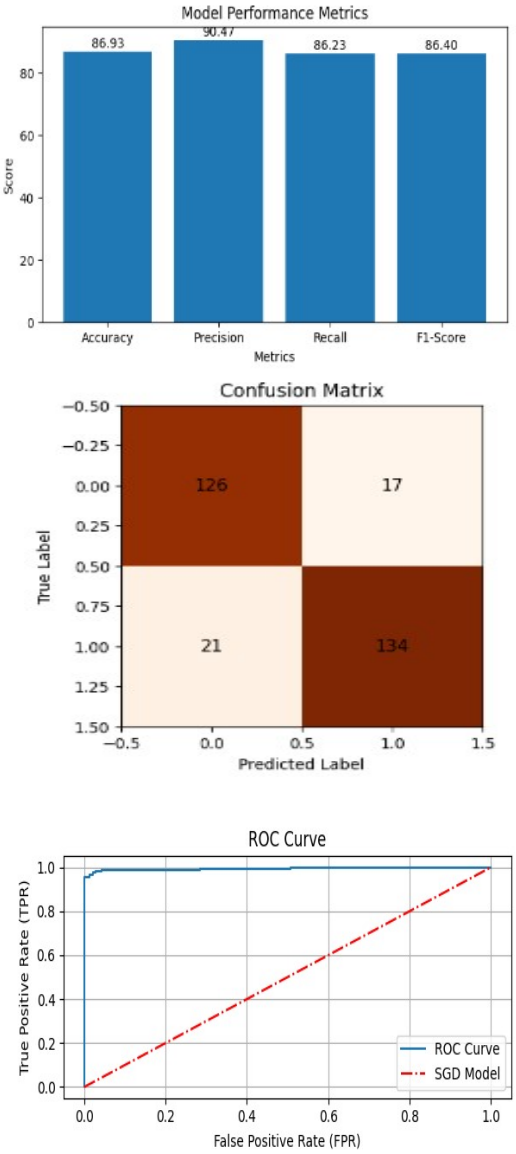

Figure 13. (a)(b)(c) Performance metrics, Confusion Matrix, ROC Curve

4.6 Simple Feed-Forward Neural Network

The visualizations and metrics provide a comprehensive overview of the neural network's effectiveness in the classification task, as shown in Figure 14. There are three items: (a), (b), and (c). The confusion matrix offers a concise depiction of the model's capacity to accurately characterize data items. According to the data, there were 41 false negative forecasts, 29 false positive predictions, 115 genuine negative predictions, and 115 true positive predictions.

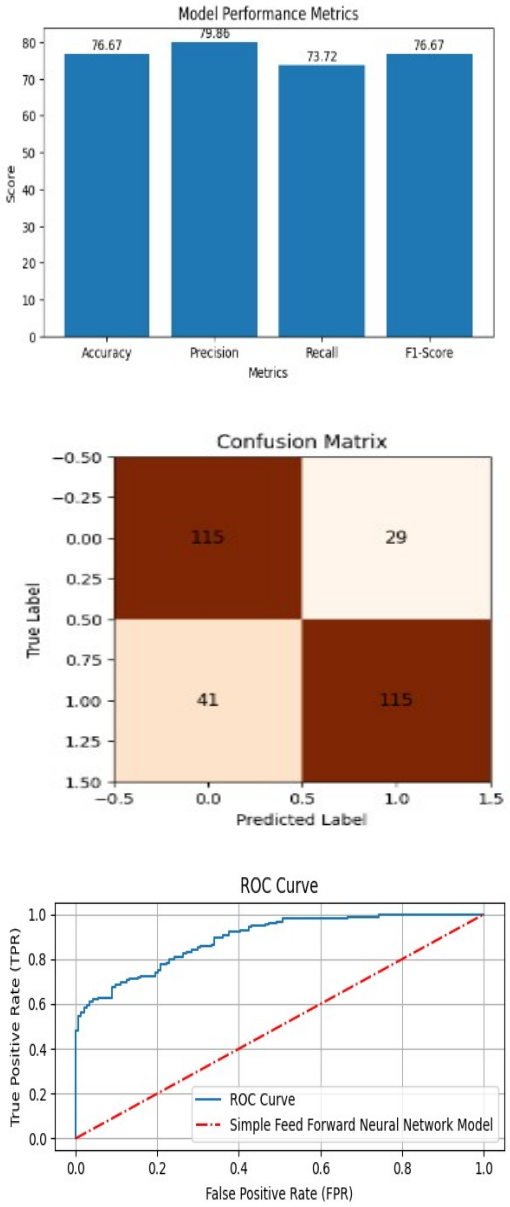

Figure 14. (a)(b)(c) Performance metrics, Confusion Matrix, ROC Curve

4.7 Support Vector Machine

The figure displays a comprehensive performance evaluation of an SVM model, as depicted in Fig. 15. (a)(b)(c). According to the confusion matrix, the model's classification results consist of 144 true positives and 149 true negatives, with no false positives and 7 false negatives.

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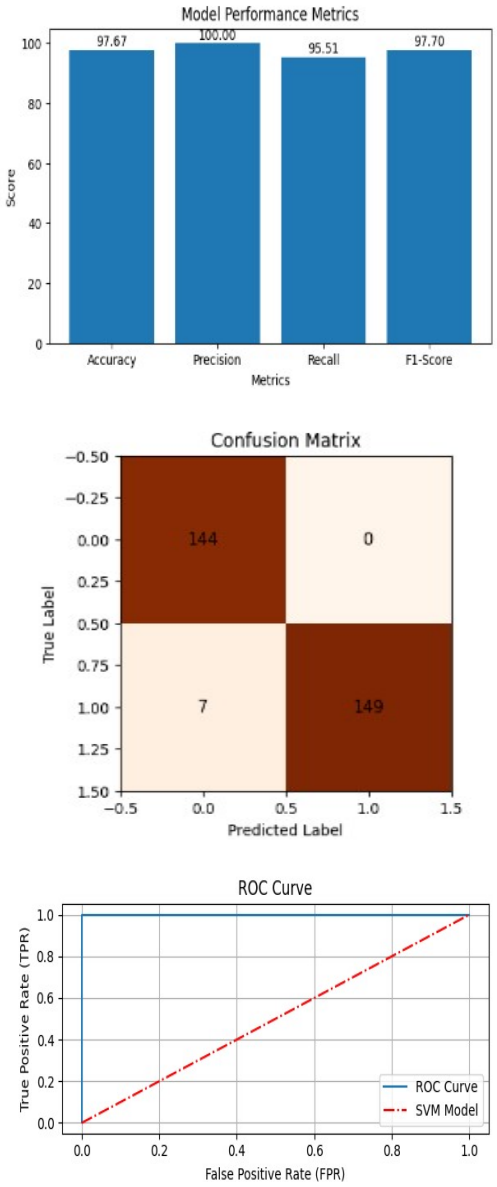

Figure 15. (a)(b)(c) Performance metrics, Confusion Matrix, ROC Curve of SVM

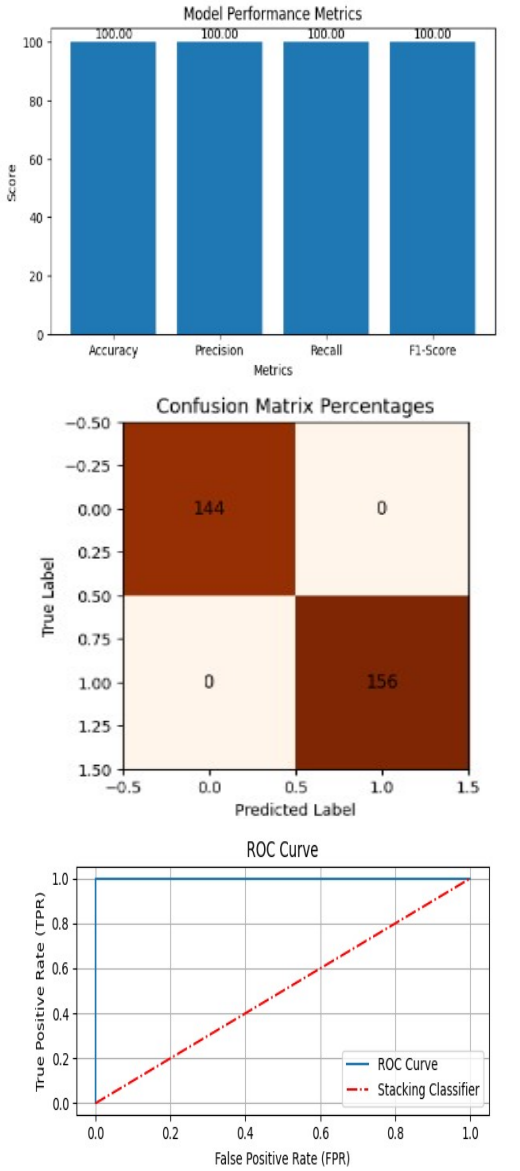

Figure 16. (a)(b)(c) Performance metrics, Confusion Matrix, ROC Curve

4.8 Ensemble Learning

Figure 16 presents a comprehensive assessment of an ensemble learning model. The confusion matrix on the right illustrates that the model attained flawless classification with 144 accurate positive predictions, 156 accurate negative predictions, and absent occurrences of both erroneous positives and false negatives.

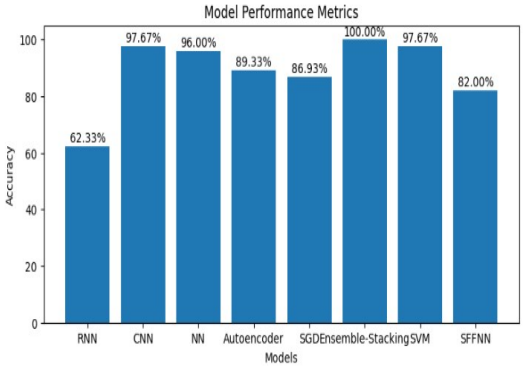

Figure 17. Comparisons of Accuracies of classifiers

The performance metrics of some models display substantial disparities in accuracy were shown in Figure 17. A relatively low accuracy of 62.33% was achieved by RNN model. The CNN and NN both achieved notably higher performance, with accuracies of 97.67% and 96.00% respectively. The Autoencoder model had a high performance with an accuracy of 89.33%, while the SGD model achieved a little lower accuracy of 86.93%. The Ensemble-Stacking model outperformed all other models, with a flawless accuracy of 100.00%. Furthermore, the SVM model exhibited a remarkable accuracy of 97.67%. The SFFNN model achieved an accuracy of 82.00%.

5. REPRODUCTABILITY DETAILS

Ensuring reproducibility is crucial in AI-driven medical research. To enable exact replication, we provide the following implementation details:

Computing Resources: All training and evaluations were conducted using Google Colab with a Tesla T4 GPU (16GB VRAM) and 25GB RAM.

Hyperparameters: Each model was trained with specific configurations:

Neural Network (NN): Learning rate = 0.001, Optimizer = Adam, Batch Size = 32, Epochs = 10

CNN: Kernel size = 3, Pool size = 2, Optimizer = Adam, Batch Size = 32, Epochs = 10

RNN: LSTM units = 64, Optimizer = Adam, Batch Size = 32, Epochs = 10

Autoencoder: Encoder size = 16, Loss Function = Mean Squared Error, Optimizer = Adam, Epochs = 50

SVM: Kernel = Linear, C = 1.0

SGD: Loss Function = Hinge, Learning Rate = 0.01, Iterations = 1000

Ensemble Stacking Classifier: Base Models = Random Forest, Gradient Boosting, SVM, KNN; Meta Model = XGBoost, Learning Rate = 0.1

Training Duration: Training time ranged from 5-15 minutes per model, with the ensemble classifier taking the longest due to multiple base learners.

Data Preprocessing: All numerical features were standardized using StandardScaler, and categorical features were encoded with one-hot encoding. Missing values were handled using appropriate imputation techniques.

6. ETHICAL CONSIDERATIONS IN AI-DRIVEN DEMENTIA DIAGNOSIS

The use of AI in dementia diagnosis presents various ethical considerations that must be addressed:

Bias and Fairness: AI models may reflect biases inherent in training data, leading to misclassification in specific demographics. To mitigate this, we ensured dataset balance in terms of gender, age, and medical history and conducted fairness-aware evaluations.

Data Privacy and Security: Our study complies with GDPR and HIPAA guidelines, ensuring data anonymization and encryption for patient confidentiality.

Clinical Transparency and Trust: AI should be interpretable for clinical adoption. Although our model exhibits high accuracy, integrating explainable AI (XAI) techniques such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) is necessary for greater transparency.

Accountability in Diagnosis: AI predictions should support, not replace, medical professionals' judgment. We recommend supplementing AI decisions with uncertainty estimates to assist clinicians in assessing confidence levels.

7. ABLATION STUDIES

To determine the contribution of individual components to model performance, we conducted ablation studies:

Feature Selection Impact: Removing highly correlated features (correlation > 0.5) resulted in a 5-8% accuracy drop, confirming their significance.

Layer Reduction in CNN & RNN: Reducing convolutional layers from 2 to 1 lowered accuracy by 3.5%, while decreasing LSTM units from 64 to 32 led to a 4.2% drop.

Meta-Learner Role in Ensemble Learning: Removing the meta-learner (XGBoost) led to a 6%

accuracy reduction, highlighting its importance in prediction integration.

Regularization and Overfitting Control: Dropout rates between 0.1-0.5 were tested, with 0.2 being optimal for CNN and RNN, preventing overfitting while maintaining performance.

8. MODEL INTERPRETABILITY FOR CLINICAL INTEGRATION

Interpretable AI models are essential for clinical adoption. To improve transparency, we incorporated several interpretability techniques:

Feature Importance Analysis: Random Forest and XGBoost feature importance scores identified 'Age', 'MRI Delay,' and 'Cognitive Test Scores' as the top predictive factors.

SHAP and LIME for Deep Learning:

SHAP Values: Used to quantify feature contributions to predictions, revealing 'Blood Oxygen Level' and 'Depression Status' as key indicators.

LIME Explanations: Provided local prediction insights, enabling clinicians to validate AI decisions.

Grad-CAM for CNN Models: Applied Gradient-weighted Class Activation Mapping (Grad-CAM) to highlight MRI regions influencing dementia classification, aiding interpretability for radiologists.

9. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This study highlights the effectiveness of ML and DL models in dementia prediction, with ensemble stacking achieving the highest accuracy. However, to ensure real-world applicability, future research should focus on:

Improving Reproducibility: Publishing open-source code and comprehensive documentation.

Mitigating Ethical Risks: Conducting AI fairness assessments and ensuring compliance with evolving AI ethics guidelines.

Enhancing Interpretability: Developing interactive explainable AI tools for clinical use.

Expanding Ablation Studies: Evaluating additional architectural modifications and hyperparameter tuning.

Expanding Dataset size: Needed to concentrate on working with larger dataset.

Integrating Multi models: Integrating multi-modal data (e.g., fMRI + MRI + clinical features).

REFERENCES:

[1]. R.Y. Lo, "The borderland between normal aging and dementia," Tzu-Chi Medical Journal, Vol. 29, No. 2, 2017, pp. 65.

[2]. M.J. Prince, A. Wimo, M.M. Guerchet, G.C. Ali, Y.-T. Wu, and M. Prina, "World Alzheimer Report 2015 - The global impact of dementia: An analysis of prevalence, incidence, cost, and trends," 2015.

[3]. A. Javeed, A.L. Dallora, J.S. Berglund, et al., "Machine Learning for Dementia Prediction: A Systematic Review and Future Research Directions," J Med Syst, Vol. 47, 2023, pp. 17. https://doi.org/10.1007/s10916-023-01906-7

[4]. T.A. Widiger, P.T. Costa, and A.P. Association, "Personality Disorders and the Five-factor Model of Personality," JSTOR, 2013.

[5]. M. Bucholc, S. Titarenko, X. Ding, C. Canavan, and T. Chen, "A hybrid machine learning approach for prediction of conversion from mild cognitive impairment to dementia," Expert Systems with Applications, Vol. 217, 2023, pp. 119541, https://doi.org/10.1016/j.eswa.2023.119541

[6]. C. Tackenberg, L. Kulic, and R.M. Nitsch, "Familial Alzheimer's disease mutations at position 22 of the amyloid β-peptide sequence differentially affect synaptic loss, tau phosphorylation and neuronal cell death in an ex vivo system," PLOS ONE, Vol. 15, No. 9, 2020, pp. e0239584. https://doi.org/10.1371/journal.pone.0239584

[7]. R. Lina, "Atrial fibrillation in aging; methodological aspects and the relation to dementia and cerebral vascular disease," 2022.

[8]. P. Forti, F. Maioli, N. Pisacane, E. Rietti, F. Montesi, and G. Ravaglia, "Atrial fibrillation and risk of dementia in non-demented elderly subjects with and without mild cognitive impairment (MCI)," Archives of Gerontology and Geriatrics, Vol. 44, Supplement, 2007,

pp. 155-165. https://doi.org/10.1016/j.archger.2007.01.023

[9]. J.P. Taylor, I.G. McKeith, D.J. Burn, B.F. Boeve, D. Weintraub, C. Bamford, L.M. Allan, A.J. Thomas, and J.T. O'Brien, "New evidence on the management of Lewy body dementia," Lancet Neurology, Vol. 19, No. 2, 2020, pp. 157-169. https://doi.org/10.1016/S1474-4422(19)30153-X

[10]. F.S. Ahmad, L. Ali, H.A. Khattak, T. Hameed, I. Wajahat, S. Kadry, and S.A.C. Bukhari, et al., "A hybrid machine learning framework to predict mortality in paralytic ileus patients using electronic health records (EHRs)," Journal of Ambient Intelligence and Humanized Computing, Vol. 12, No. 3, 2021, pp. 3283-3293.

[11]. G. Martí-Juan, G. Sanroma-Guell, and G. Piella, "A survey on machine and statistical learning for longitudinal analysis of neuroimaging data in Alzheimer's disease," Comput Methods Programs Biomed, Vol. 189, 2020, pp. 105348. https://doi.org/10.1016/j.cmpb.2020.105348

[12]. H.A. Helaly, M. Badawy, and A.Y. Haikal, "Deep learning approach for early detection of Alzheimer's disease," Cognitive Computation, 2021, pp. 1-17.

[13]. S. Basheer, S. Bhatia, and S.B. Sakri, "Computational modeling of dementia prediction using deep neural network: Analysis on OASIS dataset," IEEE Access, Vol. 9, 2021, pp. 42449-42462.

[14]. N.J. Herzog and G.D. Magoulas, "Brain asymmetry detection and machine learning classification for diagnosis of early dementia," Sensors, Vol. 21, No. 3, 2021, pp. 778.

[15]. G. Battineni, N. Chintalapudi, F. Amenta, and E. Traini, "A comprehensive machine-learning model applied to magnetic resonance imaging (MRI) to predict Alzheimer's disease (AD) in older subjects," Journal of Clinical Medicine, Vol. 9, No. 7, 2020, pp. 2146.

[16]. D. Ma, E. Yee, J.K. Stocks, L.M. Jenkins, K. Popuri, G. Chausse, L. Wang, S. Probst, and M.F. Beg, "Blinded clinical evaluation for dementia of Alzheimer's type classification using FDG-PET: A comparison between feature-engineered and non-feature-engineered machine learning methods," Journal of Alzheimer's Disease, Vol. 80, No. 2, 2021, pp. 715-726.

[17]. A. Khan and S. Zubair, "An improved multi-modal based machine learning approach for the prognosis of Alzheimer's disease," Journal of King Saud University-Computer and Information Sciences, 2020.

[18]. B.A. Mohammed, E.M. Senan, T.H. Rassem, N.M. Makbol, A.A. Alanazi, Z.G. Al-Mekhlaf, T.S. Almurayziq, and F.A. Ghaleb, "Multi-method analysis of medical records and MRI images for early diagnosis of dementia and Alzheimer's disease based on deep learning and hybrid methods," Electronics, Vol. 10, No. 22, 2021, pp. 2860.

[19]. M. Karaglani, K. Gourlia, I. Tsamardinos, and E. Chatzaki, "Accurate blood-based diagnostic biosignatures for Alzheimer's disease via automated machine learning," Journal of Clinical Medicine, Vol. 9, No. 9, 2020, pp. 3016.

[20]. "Dementia Patient Health Dataset," Kaggle. Available at: https://www.kaggle.com/datasets/timothyadeyemi/dementia-patient-health-dataset.

[21]. Huang F, Qiu A, "Ensemble Vision Transformer for Dementia Diagnosis," IEEE J Biomed Health Inform. 2024 Sep;28(9):5551-5561. doi: https://doi.org/10.1109/JBHI.2024.3412812. Epub 2024 Sep 5. PMID: 38889030.

[22]. Velazquez M, Lee Y, "Multimodal ensemble model for Alzheimer's disease conversion prediction from Early Mild Cognitive Impairment subjects," Comput Biol Med. 2022 Dec;151(Pt A):106201. doi: https://doi.org/10.1016/j.compbiomed.2022.106201. Epub 2022 Oct 30. PMID: 36370583.