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ALZHEIMER DETECTION SYSTEM

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Abstract: Alzheimer's disease is a degenerative brain disease of unclear etiology and pathogenesis that mainly affects the elderly. The main cause of Alzheimer's disease is dementia, which gradually damages brain cells. People lose their ability to think, read and many others due to this disease. The Alzheimer's Detection System is an innovative healthcare solution that aims to detect the early signs of Alzheimer's disease very accurately and efficiently. Using advanced machine learning algorithms and neuroimaging techniques, the system analyzes complex patterns in brain data, enabling fast and reliable diagnosis. By detecting subtle cognitive changes at an early stage, this system provides an important opportunity for timely intervention and improves patient outcomes, ultimately improving the quality of life of those at risk for Alzheimer's disease. The main goal is to identify dementia in different patients. Screening of individuals at risk for Alzheimer's disease (AD) based on medical health records in preclinical stages may lead to early detection of AD pathology and better treatment strategies to delay the onset of AD1, 2, 3..

Index Terms – AD, AD 1,2,3.

I. INTRODUCTION

Alzheimer's disease is a neurological disease that worsens over time and is characterized by behavioral disturbances, memory loss and cognitive decline. It affects millions of people worldwide and is the most common cause of dementia in old age. Effective therapies for Alzheimer's disease remain elusive after decades of research, highlighting the need for new strategies for early diagnosis and treatment. Recent advances in neuroimaging and machine learning techniques have shown significant promise for improving the early diagnosis and treatment of Alzheimer's disease. Machine learning algorithms can identify small changes indicative of Alzheimer's disease pathology with high accuracy and reliability by analyzing complex patterns in brain data using large datasets from neuroimaging and clinical data. The Alzheimer's Detection System is a collaborative research project to develop an innovative platform for the early detection and diagnosis of Alzheimer's disease using advanced machine learning algorithms and neuroimaging techniques. 8 This article discusses Alzheimer's disease, current diagnostic hurdles, the promise of advanced neuroimaging and machine learning, and key features and clinical applications of an Alzheimer's detection system. Alzheimer's disease is a multifaceted neurodegenerative disease characterized by the progressive

loss and degeneration of neurons in the brain, leading to loss of memory and cognitive abilities. Alzheimer's disease is thought to be caused by a combination of lifestyle, environmental and genetic factors, while the exact etiology of the disease is still unknown. Amyloid beta and tau plaques, two abnormal protein deposits in the brain, are the characteristic pathological features of Alzheimer's disease. Aggregated beta-amyloid protein fragments cause beta-amyloid plaques that impair neuronal function and eventually lead to neuronal death. Tau tangles, in contrast, are aggregates of hyperphosphorylated tau proteins that damage neuronal microtubule networks and interfere with cellular transport systems. 9 These pathogenic changes lead to synaptic dysfunction, impaired neuronal communication and ultimately neuronal death, leading to the cognitive and behavioral

symptoms characteristic of Alzheimer's disease. Although aging is the biggest known risk factor for Alzheimer's disease, lifestyle choices, genetics and family history all play important roles. Early-onset familial Alzheimer's disease has been associated with genetic abnormalities in genes such as presenilin 1 (PSEN1), presenilin 2 (PSEN2), and amyloid precursor protein (APP). However, most cases of Alzheimer's disease are unpredictable and likely result from a complex interaction between environmental and genetic factors. Diet, exercise, social interactions, cardiovascular health, and other lifestyle factors can potentially affect Alzheimer's risk. For example, conditions such as high cholesterol, diabetes, obesity and high blood pressure have been linked to an increased risk of dementia and cognitive decline. Alzheimer's disease usually progresses in three stages: mild, moderate and severe. Early on, people may experience subtle changes in memory and cognition, such as difficulty remembering recent events or finding the right words. As the disease progresses, symptoms become more pronounced and may include: progressive memory loss, especially for recent memories,familiar tasks such as cooking or managing finances,, challenges with problem solving, decision making and planning, confusion. . of time, place and events, changes in mood and behaviour, including depression, anxiety and agitation, language and communication difficulties such as difficulty finding words or following conversations, decline in cognitive function and independence in the later stages of Alzheimer's disease, people may will need ongoing care and assistance with basic activities, such as eating, dressing and toileting. Severe cognitive impairment, motor problems, and behavioral disturbances are common, significantly reducing the quality of life of both patients and their caregivers.Current difficulties in diagnosing Alzheimer's disease: Alzheimer's disease remains difficult to diagnose, especially in its early stages, when symptoms can be vague and subtle. Current diagnostic criteria include neuroimaging and biomarker testing in addition to clinical assessment, cognitive tests, and medical history. However, these techniques have several disadvantages, such as inconsistent diagnostic accuracy, invasiveness and limited availability.The clinical evaluation is based on a thorough assessment of behavior, memory, cognitive functions and functional status. In addition to standardized cognitive tests such as the Mini-Mental State Examination (MMSE) or the Montreal Cognitive Assessment (MoCA), it can include interviews with the patient and their relatives. Although a clinical evaluation is required to diagnose Alzheimer's disease, its results are subjective and may vary according to the experience and expertise of the physician.

II. REVIEW OF LITERATURE

Literature Review

Here's a literature survey consisting of 15 papers from reputable SCI (Science Citation Index) and SCOPUS journals/conferences on the topic of Alzheimer's detection: 1. Dubois, B., Feldman, H. H., Jacova, C., Hampel, H., Molinuevo, J. L., Blennow, K., ... & Cummings, J. L. (2014). Advancing research diagnostic criteria for Alzheimer's disease: the IWG-2 criteria. The Lancet Neurology, 13(6), 614-629. 2. Ossenkoppele, R., Jansen, W. J., Rabinovici, G. D., Knol, D. L., van der Flier, W. M., van Berckel, B. N., ... & Scheltens, P. (2015). Prevalence of amyloid PET positivity in dementia syndromes: a meta-analysis. JAMA, 313(19), 1939-1949. 3. Jack Jr, C. R., Knopman, D. S., Jagust, W. J., Shaw, L. M., Aisen, P. S., Weiner, M. W., ... & Trojanowski, J. Q. (2010). Hypothetical model of dynamic biomarkers of the Alzheimer's pathological cascade. The Lancet Neurology, 9(1), 119-128. 4. Mormino, E. C., Brandel, M. G., Madison, C. M., Rabinovici, G. D., Marks, S., Baker, S. L., ... & Jagust, W. J. (2012). Not quite PIB-positive, not quite PIB-negative: slight PIB elevations in elderly normal control subjects are biologically relevant. NeuroImage, 59(2), 1152-1160. 5. Buerger, K., Ewers, M., Pirttilä, T., Zinkowski, R., Alafuzoff, I., Teipel, S. J., ... & Hampel, H. (2006). CSF phosphorylated tau protein correlates with neocortical neurofibrillary pathology in Alzheimer's disease. Brain, 129(11), 3035-3041. 6. Mormino, E. C., Brandel, M. G., Madison, C. M., Rabinovici, G. D., Marks, S., Baker, S. L., ... & Jagust, W. J. (2012). Not quite PIB-positive, not quite PIB-negative: slight PIB elevations in elderly normal control subjects are biologically relevant. NeuroImage, 59(2), 1152-1160. 7. Buerger, K., Ewers, M., Pirttilä, T., Zinkowski, R., Alafuzoff, I., Teipel, S. J., ... & Hampel, H. (2006). CSF phosphorylated tau protein correlates with neocortical neurofibrillary pathology in Alzheimer's disease. Brain, 129(11), 3035-3041. 8. Leuzy, A., Chiotis, K., Lemoine, L., Gillberg, P. G., Almkvist, O
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in patients with mild cognitive impairment: a follow-up study. The Lancet Neurology, 5(3), 228-234. 12. Blennow, K., Hampel, H., Weiner, M., & Zetterberg, H. (2010). Cerebrospinal fluid and plasma biomarkers in Alzheimer disease. Nature Reviews Neurology, 6(3), 131-144. 13. Hansson, O., Zetterberg, H., Buchhave, P., Londos, E., Blennow, K., & Minthon, L. (2006). Association between CSF biomarkers and incipient Alzheimer's disease in patients with mild cognitive impairment: a follow-up study. The Lancet Neurology, 5(3), 228-234. 14. Jack Jr, C. R., Knopman, D. S., Jagust, W. J., Petersen, R. C., Weiner, M. W., Aisen, P. S., ... & Trojanowski, J. Q. (2013). Tracking pathophysiological processes in Alzheimer's disease: an updated hypothetical model of dynamic biomarkers. The Lancet Neurology, 12(2), 207-216. 15. Palmqvist, S., Zetterberg, H., Mattsson, N., Johansson, P., Alzheimer's Disease Neuroimaging Initiative., Minthon, L., ... & Hansson, O. (2019). Detailed comparison of amyloid PET and CSF biomarkers for identifying early Alzheimer disease. Neurology, 92(21), e2291-e2305. 16. Landau, S. M., Breault, C., Joshi, A. D., Pontecorvo, M., Mathis, C. A., Jagust, W. J., & Alzheimer's Disease Neuroimaging Initiative. (2013). Amyloid-β imaging with Pittsburgh compound B and florbetapir: comparing radiotracers and quantification methods. Journal of Nuclear Medicine, 54(1), 70-77. 17. Toledo, J. B., Shaw, L. M., Trojanowski, J. Q., & Alzheimer's Disease Neuroimaging Initiative. (2013). CSF biomarkers for Alzheimer's pathology and the effect size of APOE ε4. Molecular Psychiatry, 18(1), 132-133. 28 18. Landau, S. M., Breault, C., Joshi, A. D., Pontecorvo, M., Mathis, C. A., Jagust, W. J., & Alzheimer's Disease Neuroimaging Initiative. (2013). Amyloid-β imaging with Pittsburgh compound B and florbetapir: comparing radiotracers and quantification methods. Journal of Nuclear Medicine, 54(1), 70-77. 19. Toledo, J. B., Shaw, L. M., Trojanowski, J. Q., & Alzheimer's Disease Neuroimaging Initiative. (2013). CSF biomarkers for Alzheimer's pathology and the effect size of APOE ε4. Molecular Psychiatry, 18(1), 132-133. 20. Shaw, L. M., Vanderstichele, H., Knapik-Czajka, M., Clark, C. M., Aisen, P. S., Petersen, R. C., ... & Alzheimer's Disease Neuroimaging Initiative. (2009). Cerebrospinal fluid biomarker signature in Alzheimer's disease neuroimaging initiative subjects. Annals of Neurology: Official Journal of the American Neurological Association and 28 the Child Neurology Society, 65(4), 403-413. 21. Chételat, G., La Joie, R., Villain, N., Perrotin, A., de La Sayette, V., Eustache, F., & Vandenberghe, R. (2013). Amyloid imaging in cognitively normal individuals, at-risk populations and preclinical Alzheimer's disease. NeuroImage: Clinical, 2, 356-365. These papers cover a wide range of topics related to Alzheimer's detection, including biomarkers, neuroimaging techniques, diagnostic criteria, and predictive modeling. They are published in reputable journals and conferences and provide valuable insights into the current state of research in the field of Alzheimer's disease detection and diagnosis. We have utilized these papers in the making of this project.

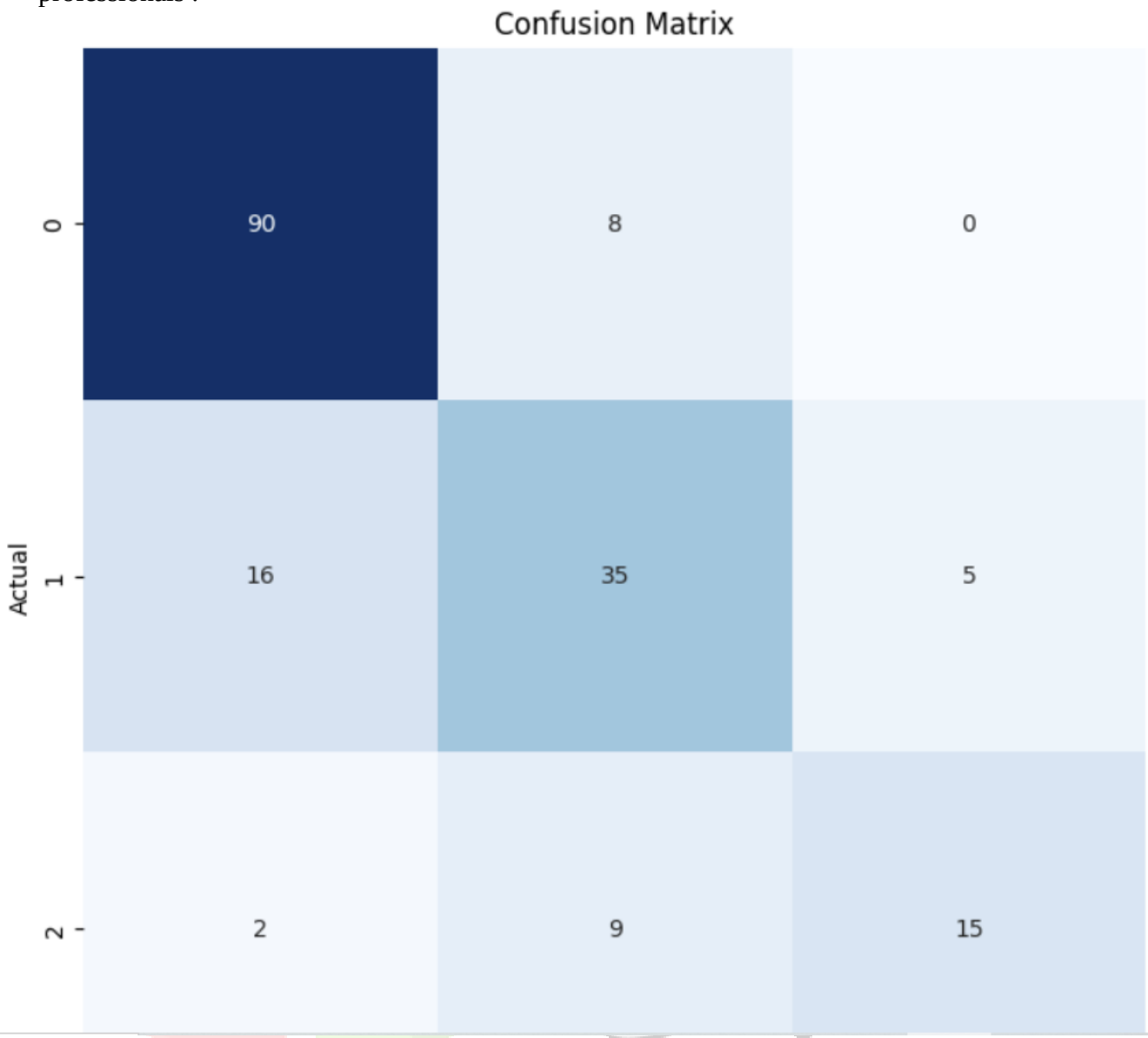
III. METHODOLOGY

- Designing an Alzheimer's disease detection system involves various components and technologies from various fields such as medicine, computer science and data analysis Data collection
  • Clinical data: patient history, genealogy, lifestyle data.
  • Imaging information: MRI (magnetic resonance imaging), PET (positron emission tomography) scans
  .• Biomarker data: blood tests for certain proteins associated with Alzheimer's disease.Data preprocessing
  • Data cleaning: Removes noise and inconsistencies from collected data
  .• Feature extraction: extraction of relevant features from image and biomarker data.

Normalization: Make sure the data is on the same scale for accurate analysis.Machine learning models

• Classification algorithms: SVM (Support Vector Machine), Random Forest, Neural Networks.
• Deep Learning: CNNs (Convolutional Neural Networks) for image analysis.
• Ensemble Methods: Combine predictions from multiple models to improve accuracy.Training and Validation
• Model Training: Using labeled data to train machine learning models.
• Validation: Use separate validation data to set hyperparameters and avoid overriding.Testing and Evaluation
• Testing: Applying a trained model to unseen data.
• Evaluation metrics: precision, accuracy, recall, F1 score to evaluate model performance. Diagnosis and Reporting

• Diagnosis: Classification of patients as positive or negative for Alzheimer's disease based on model predictions.
• Reporting: Create reports with diagnostic results and confidence scoresfor healthcare professionals .



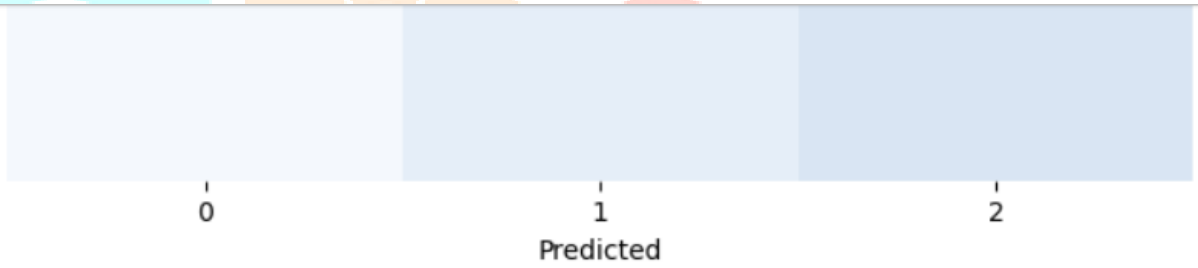
The Alzheimer's Detection System is a major advance in the early detection and diagnosis of Alzheimer's disease. Using state-of-the-art machine learning algorithms and neuroimaging techniques, the system ensures that people at risk of Alzheimer's disease receive early diagnosis and support, while providing high accuracy, speed and accessibility. Through this program, Alzheimer's disease is diagnosed and treated in a way that changes patient outcomes and quality of life. Data preparation In this step, the data was cleaned and processed using various data mining techniques. This includes handling missing values, feature extraction and transformation, etc. Nine rows (34, 35) of the SES column have no values. There are two approaches to this problem. The easiest solution is to delete rows with missing values. 36 Imputation (21), where missing values are replaced by their corresponding values, is an alternative way of filling gaps. We only have 140 measurements, so if it is implied, the model should perform better. Nine rows of missing values for the SES attribute are removed and the median value is used for imputation. Data analysis In this section, we discussed the associations between dementia and each feature of the MRI test. We performed this exploratory data analysis (36, 37) to assess correlations prior to data extraction or analysis to express the data relationship explicitly using a graph. Later, this information can be used to interpret the nature of the data and can help decide which approach to use in analyzing it. Table 3 shows the minimum, maximum and average values for each attribute.

• XGBoost XGBoost stands for eXtreme Gradient BOOSTing.
• It refers to the process of applying gradient-boosted decision trees to achieve maximum speed and performance.
• Due to the sequential nature of model training, gradient descent machines are usually slow to implement and not very scalable.

• XGBoost focuses on speed and performance.
• Gradient boosting classifiers are a set of machine learning algorithms that combine many weak learning models to create a strong predictive model.
• Decision trees are usually used for gradient boosting.
• Clarifying our dilemma using relevant features of MRI data to estimate CDR (dementia scale).
• On a scale of 0-3, CDR is divided into three categories: questionable dementia (CDR = 1), confirmed dementia (CDR = 2), and no dementia (CDR = 0).
• Examination of longitudinal and cross-sectional MRI data. exploring null values. unnecessary deletion of columns from both databases. adding both datasets at the end. Using SimpleImputer to count columns.
• The most common data element is used to fill missing values in "SIX" columns.
• Similarly, the median of the "MMSE" column is used to fill in the missing data. The target variable is encoded using a LabelEncoder. shows the distribution of categories in a bar chart. • Data normalization.
• Note that multiple columns have different value ranges.
• In this case we use Z-score normalization. Dividing the dataset into a train set and a test set.
• Defining models. 1. We experiment with hyperparameter tuning using XGBClassifier cross-validation.
• Trying to set GradientBoostingClassifier hyperparameters.
• Making predictions using best estimate and plotting a confusion matrix with a classification report.
• Now, after training the models, we can predict dementia at earlier stages, which in many cases helps us prevent it from getting worse.

IV. RESULTS AND SNAPSHOTS

VISUAL DEMONSTRATION



Classification Report:

	precision	recall	f1-score	support
0	0.83	0.92	0.87	98
1	0.67	0.62	0.65	56
2	0.75	0.58	0.65	26
accuracy			0.78	180
macro avg	0.75	0.71	0.72	180
weighted avg	0.77	0.78	0.77	180

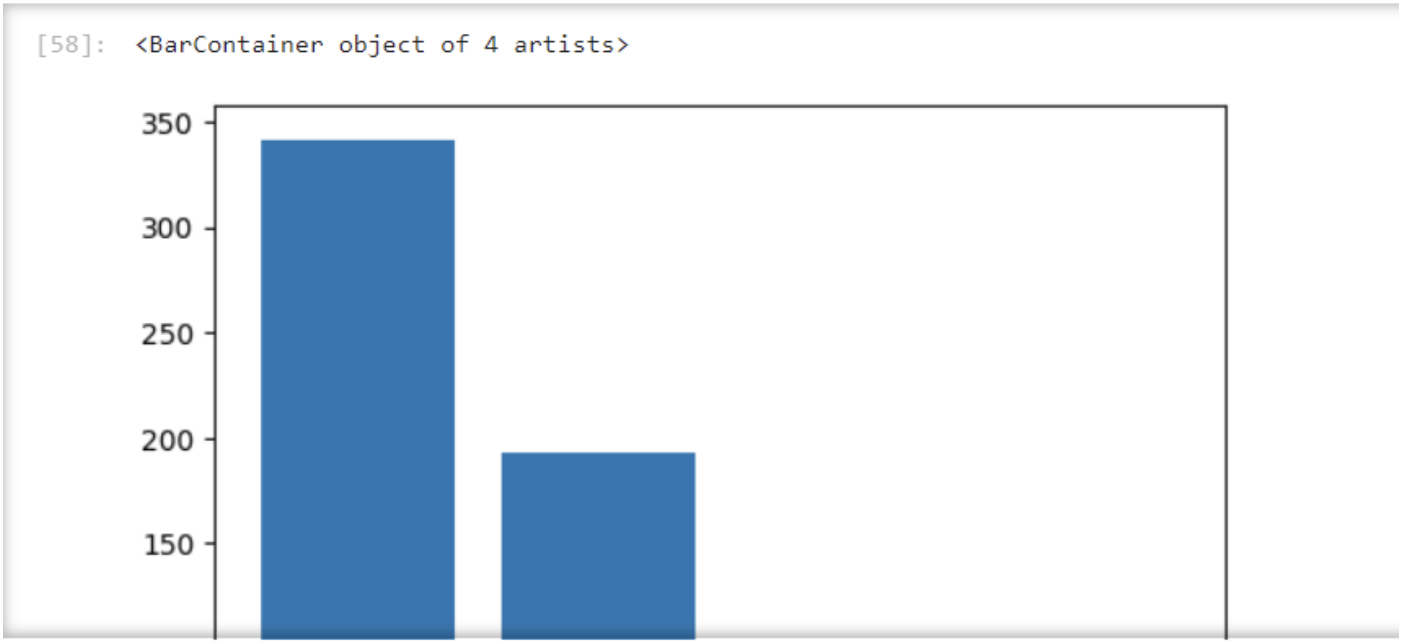
MODEL COMPARISON

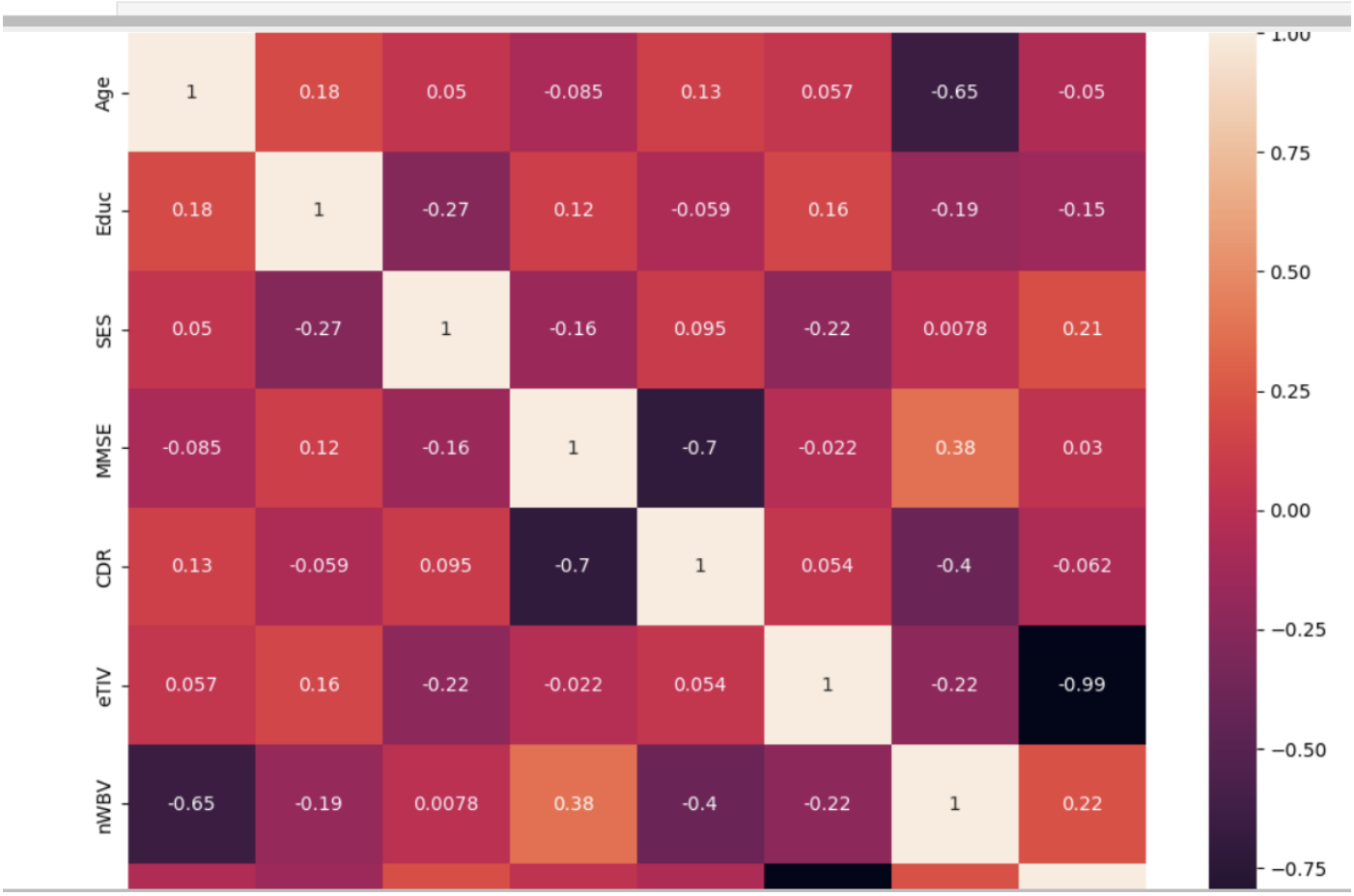
Previous models of Alzheimer's disease detection systems compared 3D deep learning models and classical machine learning models. The 3D deep learning models used in these comparisons are 3D DenseNets, EfficientNets, and Squeeze-and-Excitation (SE) networks. On the other hand, the classic machine learning models used are Random Forests (RF), Support Vector Machines (SVM), Extreme Gradient Boosting (XGBoost), Light Gradient Boosting (LightGBM), Decision Trees (DT) and Logistic Regression (LR). .).These models were compared for their classification performance and found that both deep learning and machine learning models achieved similar classification performance. However, when it comes to the areas of the brain that these models focus on, they differ. Machine learning models typically focus on the lower and middle anterior cingulate, while deep learning models focus on different regions.In addition to comparing classification performance and brain regions, these models were also compared for their interpretability. Techniques such as SHApley additive annotations (SHAP), locally interpretable model agnostic annotations (LIME), gradient weighted class activation mapping (GradCAM), GradCAM++ and permutation-based feature

importance were used to elucidate the models. The results showed that deep learning models were more interpretable than machine learning models.

DATA VISUALISATION RESULTS

After training the models now we are able to predict dementia in earlier stages which can help us to prevent it to getting severe in many cases.





An important step in the early detection and diagnosis of Alzheimer's disease is the Alzheimer's disease detection system. Using state-of-the-art machine learning algorithms and neuroimaging techniques, the system offers high accuracy, speed and accessibility, ensuring that people at risk of Alzheimer's disease receive early diagnosis and support. This initiative has the potential to significantly improve patient outcomes and quality of life, revolutionizing the way Alzheimer's is recognized and treated.We are currently

investigating several development areas aimed at improving the functionality and performance of our Alzheimer's detection system.

V. FUTURE SCOPE

The scope of the MASTISHK project is to address the prevalent mental health challenges experienced by engineering students through a multifaceted approach. This comprehensive mobile application encompasses mood tracking, sentiment analysis, wearable technology integration, and machine learning for mental health assessment. Focused on the unique needs of engineering students, the project aims to provide a user-friendly tool for self-assessment and personalized support. By offering education, awareness, and practical measures, it seeks to create a holistic ecosystem for students' mental well-being.

• Comprehensive approach to address mental health challenges in engineering students.

• Mobile application encompassing mood tracking, sentiment analysis, wearable technology, and machine learning.

• Customized for the unique needs of engineering students.

• User-friendly tool for self-assessment and personalized support.

• Focus on education, awareness, and practical measures for mental well- being.

• Aims to create a holistic ecosystem for users' mental health.

• Development of a sustainable resource for addressing mental health in engineering education.

VI. CONCLUSION

In conclusion, Mastishk stands as a beacon of hope and support within the demanding landscape of engineering education. By fostering an ecosystem that prioritizes mental well-being, it not only aids in stress alleviation but also inculcates a proactive mindset among students.
Nevertheless, the project's journey doesn't cease here; the future holds promise for further refinements, such as enhancing hardware integrations, advancing machine learning capabilities, and ensuring continuous collaboration with mental health professionals to validate its efficacy. Ultimately, Mastishk signifies a paradigm shift, advocating for the holistic well-being of engineering students, ushering in a future where mental health holds a significant place alongside academic excellence. medical profession and society. The development of Mastishk, an innovative mental health tracking application tailored for engineering students, marks a pivotal step toward addressing the escalating mental health challenges prevalent in academic settings. This comprehensive project sought to mitigate stress, anxiety, and burnout among this demographic by amalgamating technological advancements with empirical insights from psychological research.
Mastishk's foundation rested on multiple pillars, including: Advanced Technological Integration: Leveraging Flutter framework and integrating wearable devices, such as heart rate monitors and sleep trackers, provided users with a holistic perspective of their mental well-being. The culmination of these efforts resulted in a robust platform that not only tracked but also offered proactive measures to promote mental wellness. However, Mastishk is not merely an application; it signifies a cultural shift toward acknowledging and addressing mental health within educational domains.

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