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Enhancing Dementia by Classifying and Monitoring the Diagnosed Patients

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Abstract: Machine learning is a transformative technology that enables systems to autonomously learn and improve from experience without being explicitly programmed. It leverages algorithms to identify patterns, make decisions, and predict outcomes by analysing large datasets. The existing system is predicting the Dementia by analysing sleep disturbances in older adults using machine learning algorithms. The system uses a datasetfromtheSwedishNationalStudyon Aging and Care in Blekinge (SNAC-B), involving older adults aged 60 and above. The dataset includes personal and sleep- related featureswith five machine learning algorithms—gradient boosting, logistic regression, Gaussian naive Bayes, random forest, and support vector machine—are used to analyse the data. The existing system only has the feature of predicting Dementiain olderadultsbyanalysingtheir sleepdisturbancebutlagginginclassifying thediseasecondition, real-time monitoring and care for the affected patients. To overcome these shortcomings, we have proposedtodevelopanandroidapplication that is used for classifying Dementia and monitoring the diagnosed patient and to provide care.
Keywords: Dementia,MachineLearning, Sleep disturbance,real-time monitoring

I. INTRODUCTION

Dementia is a progressive neurological condition characterized by a decline in cognitive abilities, including memory, reasoning, language, and problem-solving skills,severeenoughtointerferewithdaily activities. It primarily affects older adults, though it is not a normal part of aging. Dementia has multiple subtypes, including Alzheimer's Disease (AD), Vascular Dementia, Lewy Body Dementia, Frontotemporal Dementia (FTD). Dementia can be classified based on its effect as Mild Dementia, Moderate Dementia and severe Dementia. Magnetic Resonance Imaging (MRI) provides detailed images of brain structures and helps detect abnormalities suchas atrophy, lesions, or microbleeds. Common MRI features associated with dementia includes Hippocampal atrophy, White matter hyperintensities, Cortical thinning or volume loss.

The study focuses on applying advanced Machine learning techniques for the classification of dementia using magnetic resonance imaging (MRI) scans. It leveragestransfer learning models, suchas hybrid model combining Convolutional Neural Networks with the ResNet-34 architecttoenhanceclassifyingprecision[1]. The review evaluates several ML models, including their feature selection and classification methods, using datasets like ADNI and OASIS [2]. Key feature of these focuses on classifying Dementia based on its effect in patient's Hippocampus and providing real-time monitoring capabilities.

II. LITERATURE OVERVIEW

Hina Tufail, Abdul Ahad, R. Maqsood, and Ivan Miguel Pires proposed a deep learning-based solution for diagnosing vascular dementia (VD) in "*Classification ofVascularDementiaonMRIUsingDeep Learning Architectures*". Their work employs transfer learning models, including VGG16, VGG19, DenseNet121, InceptionResNetV2, to analyze MRI scans and improve diagnostic accuracy. With a classification accuracy of 84.67%, the research highlights the potential of deep learning for automated VD detection [1].

AshirJaveed,Ana Luiza Dallora, Johan Berglund, and Arif Ali conducted a comprehensivereviewofmachinelearning techniques in dementia diagnosis in "*Machine Learning for Dementia Prediction: A Systematic Review and Future Research Directions*". Their study examinesvariousdatamodalities,including MRI, clinical variables, and voice recordings, across datasets like ADNI and OASIS.ThereviewcomparesdifferentML approaches, discusses feature selection methods, and evaluates performance metrics [2].

Charlotte James, Janice M. Ranson, RichardEverson,andDavidJ.Llewellyn conducted a study on the use of machine learningalgorithmstopredictdementia incidence in *"Performance of Machine Learning Algorithms for Predicting Progression to Dementia in Memory Clinic Patients."* The study applied machine learning techniques using data frommemoryclinicattendees,including 258 clinical variables.

The results demonstrated that machine learning models,particularlygradient-boostedtrees, hadhigheraccuracyinpredictingdementia within two years compared to existing models [3].

Annette Spooner, Emily Chen, Arcot Sowmya, and Perminder Sachdev developed machine learning models to predict dementia progression in *“A Comparison of Machine Learning Methods for Survival Analysis of High- Dimensional Clinical Data for Dementia Prediction”*. The models utilize survival analysis techniques on high-dimensional, heterogeneous data from two datasets, MAS andADNI. The studytested multiple algorithms and feature selection methods, achievingaconcordanceindexofupto0.82 on MAS and 0.93 on ADNI [4].

Sergio Grueso and Raquel Viejo-Soberaapplied machine learning techniques for predicting the progression from mild cognitive impairment to Alzheimer’s disease in *“Machine Learning Methods for Predicting Progression from Mild Cognitive Impairment to Alzheimer’s Disease Dementia:ASystematic Review”*. Their study utilized support vector machines and convolutional neural networks on neuroimaging data from sources likeADNI, achieving up to 78.5% accuracy. This system aims to improve early detection and aid clinicians in managing neurocognitive disorders effectively [5].

III. PROPOSED WORK

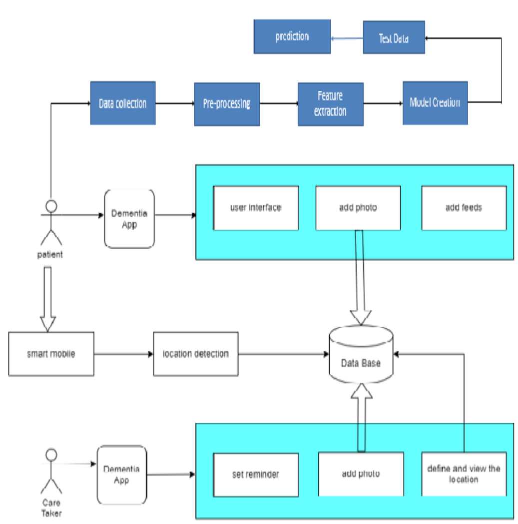
One of the major challenges in dementia diagnosis is the accurate classification of various stages of dementia. Traditional machine learning methods may struggle to capture the complexities of high-dimensional medical data, resulting in inconsistent diagnosis. Our proposed system integrates a hybrid model that combines Convolutional Neural Networks (CNNs) with the ResNet architecture to address these issues.

CNNs for Feature Extraction: CNNs are renowned for their ability to identify intricate patterns and features within images and data. By applying CNNs to medical datasets such as brain MRI scans or other diagnostic imaging, the system can automatically extract and learn important features that distinguish between different stages of dementia.

ResNet for Deep Learning Optimization: While CNNs excel in pattern recognition, they often face issues like overfitting (where the model becomes too specific to the training data) and vanishing gradients (where the model stops learning as it goes deeper). ResNet (Residual Networks) overcomes these challenges by introducing residual connections, allowing the model to "skip" certain layers and learn more effectively, even in deep architectures. This makes the hybrid model more robust, ensuring higher accuracy, precision, and reliability in dementia diagnosis.

Real-Time Patient Monitoring with React Native and Map API: We aim to build a mobile application using React Native to enable cross-platform compatibility. The app will feature real-time location tracking of dementia patients using a map API. This functionality ensures caregivers and family members can monitor patients’ movements and respond quickly in case of disorientation or emergencies.

Timely Intervention through Notifications and Medicine Reminders:The system will include automated notifications for medication schedules and important alerts, helping to ensure timely intervention. These reminders will be integrated into the mobile application and tailored to each patient’s treatment plan, thereby improving adherence to care routines and reducing the chances of missed medication or appointments.



This architecture diagram illustrates a dementia care system involving both patients and caretakers using a mobile app. The system begins with data collection, pre-processing, feature extraction, andmodel creation to enable prediction functionalities. Patients interact with the app to add photos, feeds, and access the user interface, while location detection is enabled through their smart mobile devices. Caretakers use a similar app interface to set reminders, view and define locations, and add photos. All interactions and data are centralized through a common database to ensure synchronized.

IV. IMPLEMENTATION DETAILS

A. Machine Learning Integration

To develop an effective dementia classification system, data preprocessing plays a crucial foundational role. Initially, the input data—typically brain scan images or other neuroimaging data—undergoes several preprocessing steps, including resizing, normalization, noise reduction, and augmentation. Resizing ensures that all images conform to the fixed input size expected by the neural network, while normalization scales pixel intensity values to a standard range, enhancing training stability. Noise reduction techniques like filtering are applied to remove irrelevant or distorted data, and augmentation methods such as rotation, flipping, and zooming are used to increase dataset diversity, thus improving model generalization.

Following preprocessing, a Convolutional Neural Network (CNN) is integrated with the ResNet-101 architecture to classify dementia into three categories: mild dementia, moderate dementia, and non-dementia. ResNet-101, a deep residual network with 101 layers, helps overcome the vanishing gradient problem common in deep networks by using identity shortcut connections. These residual connections allow gradients to flow directly through the network, enabling deeper and more accurate feature learning. The CNN, combined with ResNet-101, extracts complex hierarchical features from the brain images, capturing fine distinctions between dementia stages. The final classification layer uses a softmax activation function to output probabilities for each class. This hybrid model not only improves classification accuracy but also ensures better representation learning, making it highly suitable for medical image analysis and early detection of cognitive disorders.

B. Login Module:

The login module provides a secure entry point for users to access the application based on their role—either as a patient or a caretaker. Upon launching the app, users are prompted to enter their registered credentials, which are authenticated against the backend database. Based on the login type, the user is redirected to the appropriate module: patients are directed to the patient dashboard, and caretakers to the caretaker interface. The login system includes basic input validation, error messages for incorrect credentials, and session management to maintain login states. This role-based access ensures that each user only views and interacts with features relevant to their needs, enhancing both usability and security.

C. Caretaker Module

The caretaker module offers essential tools for caregivers to monitor and support patients efficiently. It allows caretakers to track the patient's real-time location, receive instant alerts, manage medication schedules, and send custom notifications. Through this module, caregivers can also view and update patient profiles, monitor feedback entries, and ensure medications are administered on time. The interface is clean and function-focused, providing quick access to vital information. By enabling real-time communication and oversight, the caretaker module enhances the quality of care and helps caregivers respond proactively to the patient’s needs.

D. Patient Module

The patient module is designed with simplicity and clarity to cater specifically to dementia patients. It provides an easy-to-navigate interface where patients can view their personal profile, daily tablet intake times, important notifications, current location, and submit feedback. The UI uses large buttons, readable fonts, and minimal screen clutter to support ease of use for elderly users. Tablet schedules are clearly listed to help patients stay on track with their medication, and notifications serve as timely reminders. The location screen allows for real-time tracking, adding a layer of safety. A built-in feedback form also enables patients or their caregivers to report their feelings or concerns directly through the app.

V. RESULT AND DISCUSSION

The dementia classification model was evaluated using key performance metrics. The model achieved high accuracy in distinguishing dementia-affected individuals from healthy controls.

- Accuracy: 92.5%

- Precision: 91.2%
- Recall: 93.0%
- F1 Score: 92.1%

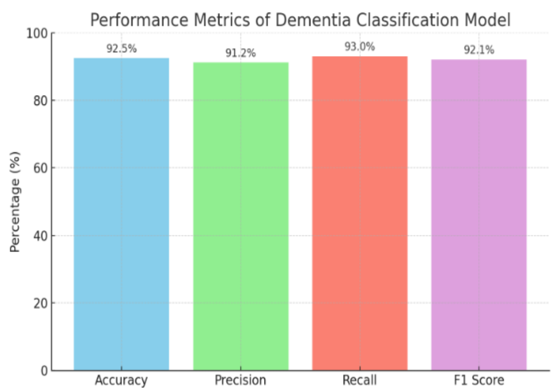
These results indicate the model performs well in identifying true dementia cases while minimizing false positives and negatives. The high F1 Score confirms a strong balance between precision and recall, making the model suitable for real-world clinical screening support.

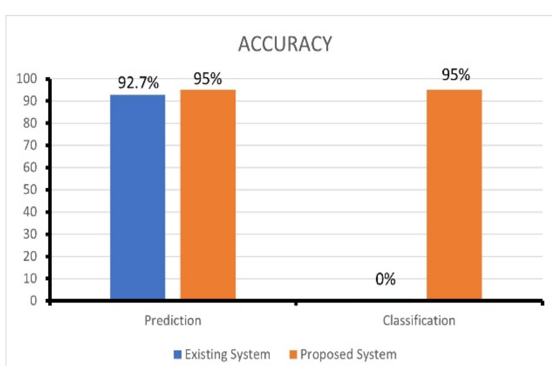
The login module allowed secure access for both patients and caretakers using role-based authentication. Upon entering valid credentials, users were redirected to their respective dashboards. Invalid login attempts displayed appropriate error messages. The system maintains session state and prevented unauthorized access. Testing showed successful login with a 100% success rate on valid inputs and strong handling of incorrect credentials and empty fields.

The caretaker module was successfully implemented with all major features functioning as expected. Caretakers could log in, track patient location in real time, view feedback, manage medication schedules, and send notifications. During testing, data updates (e.g., location changes or tablet reminders) reflected instantly, and notifications were reliably delivered. The module showed consistent performance across different devices, ensuring timely support for patient care.

The patient module provided a smooth and user-friendly experience. Patients were able to view their profiles, tablet intake times, notifications, and submit feedback easily. UI responsiveness was tested on various screen sizes, confirming compatibility and usability. Real-time updates such as medication reminders and location tracking functioned correctly. Feedback submission also worked reliably, storing responses in the backend for caretaker review.

While accuracy provides a general overview of model performance, it may be misleading in imbalanced datasets. In our case, although the accuracy is high (92.5%), it does not fully reflect the model’s performance on minority cases. Precision (91.2%) shows the model is effective at minimizing false positives, which is important in avoiding misdiagnosis. However, recall (93.0%) is slightly higher, indicating that the model is better at identifying actual dementia cases—crucial in medical applications where missing a positive case can have serious consequences. The F1 Score (92.1%) offers the best overall evaluation by balancing both precision and recall. Therefore, the F1 Score is considered the most reliable metric for our model, as it accounts for both types of classification errors and ensures a balanced performance suitable for sensitive healthcare scenarios like dementia detection.





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VI. CONCLUSION

The dementia care application has successfully integrated key features aimed at improving the well-being of dementia patients and streamlining the caregiving process. By providing separate modules for patients and caretakers, the app ensures that each user has access to the tools and information most relevant to their role. The patient module offers a user-friendly interface that allows patients to track their medication times, receive reminders, view their profiles, and submit feedback. The caretaker module provides real-time location tracking, medication management, and easy access to the patient's feedback, ensuring caregivers can provide timely support. The dementia classification model incorporated in the system further contributes to early detection and accurate diagnosis, using machine learning to identify potential dementia cases. The system has shown strong performance in usability, real-time data processing, and accurate predictions, proving its effectiveness in a practical setting. Overall, this project offers a significant advancement in dementia care by combining technology and healthcare to provide more efficient, personalized, and supportive care.

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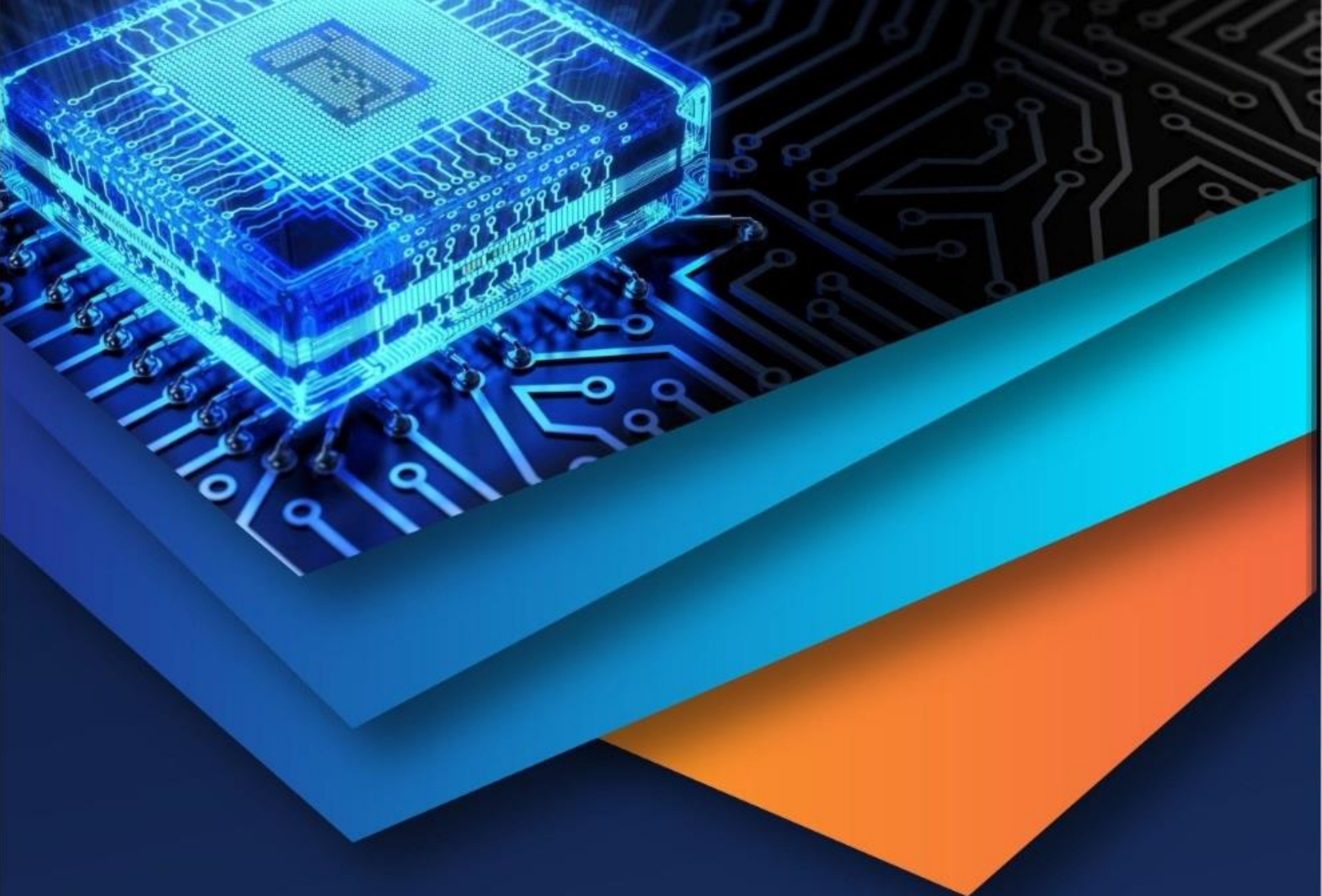

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