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The Early Detection Of Dementia Disease Using Machine Learning Approach

[1]Dr. Chaitanya Kishore Reddy.M, [2]B.NAGA VENKATA RAMANJANEYULU, [3]Shaik shafi, [4]Derangula rajasree

Professor of IT, NRI Institute of Technology, A.P, India 521212

UG Scholar, Dept of IT, NRI Institute of Technology, A.P, India 521212
UG Scholar, Dept of IT, NRI Institute of Technology, A.P, India 521212
UG Scholar, Dept of IT, NRI Institute of Technology, A.P, India 521212

Abstract:
Dementia, a progressive neurodegenerative disorder, poses significant challenges for early detection and effective management due to its subtle initial symptoms. Early diagnosis is crucial for delaying disease progression and improving patients' quality of life. This study presents a machine learning (ML) approach for the early detection of dementia, leveraging advanced computational models to analyze clinical, cognitive, and behavioral data. By integrating diverse data sources, including medical history, cognitive tests, and imaging biomarkers, the proposed approach aims to identify patterns and anomalies indicative of early-stage dementia. The study employs a hybrid machine learning framework, combining supervised and unsupervised algorithms to enhance prediction accuracy. Techniques such as feature selection, dimensionality reduction, and cross-validation are utilized to ensure robust and interpretable models. Algorithms including Random Forest, Support Vector Machines, and Neural Networks are compared to identify the most effective model for detecting early signs of dementia.
Initial findings indicate that the ML approach achieves high sensitivity and specificity in distinguishing between healthy individuals and those in the early stages of dementia. Furthermore, explainable AI techniques are incorporated to enhance the transparency of predictions, fostering trust in clinical applications. This research demonstrates the potential of machine learning to revolutionize dementia screening and contribute to timely interventions.

Index Terms - Dementia, Early Detection, Machine Learning, Neurodegenerative Disorders, Cognitive Analysis, Predictive Modeling, Artificial Intelligence, Clinical Diagnosis, Explainable AI, Medical Data Analysis

I. Introduction

Dementia is a global health challenge that affects millions of individuals, primarily older adults, leading to significant social, economic, and personal consequences. Characterized by a decline in cognitive functions such as memory, reasoning, and communication, dementia significantly diminishes an individual's ability to perform everyday activities. Alzheimer's disease accounts for approximately 60-70% of dementia cases, with other forms including vascular dementia, Lewy body dementia, and frontotemporal dementia. Despite its prevalence, early detection remains a challenge, as the initial symptoms are often subtle and can overlap with normal aging or other medical conditions. The absence of timely diagnosis frequently delays intervention and treatment, which could otherwise slow disease progression and enhance the quality of life for patients and their caregivers.

Machine learning (ML), a subset of artificial intelligence (AI), has emerged as a powerful tool in medical diagnostics, offering promising solutions to the complexities of dementia detection. By analyzing large, multidimensional datasets, ML algorithms can identify patterns, correlations, and anomalies that may not be apparent to human clinicians. This capability makes ML a valuable asset in tackling the multifaceted nature of dementia, where clinical presentations can vary widely among individuals. In this paper, we explore the potential of machine learning approaches to facilitate the early detection of dementia, emphasizing the importance of accurate, timely, and interpretable diagnostic models.

The Importance of Early Detection

Early detection of dementia is critical for several reasons. First, it enables the initiation of pharmacological and non-pharmacological interventions that can slow cognitive decline, manage symptoms, and improve patient outcomes. Second, it allows individuals and their families to plan for the future, addressing legal, financial, and care-related considerations. Third, early diagnosis provides an opportunity for patients to participate in clinical trials and emerging therapies that aim to delay disease progression. Unfortunately, studies indicate that a significant proportion of dementia cases remain undiagnosed until the disease reaches an advanced stage, where treatment options are limited and less effective.

The delay in diagnosis is partly attributable to the lack of sensitive and specific diagnostic tools. Traditional diagnostic methods, such as clinical assessments, neuropsychological tests, and neuroimaging, are often time-consuming, resource-intensive, and subject to variability in interpretation. Furthermore, these methods may not be widely accessible in low-resource settings, exacerbating disparities in dementia care. Therefore, there is an urgent need for innovative approaches that can overcome these challenges and provide scalable, accurate, and cost-effective diagnostic solutions.

Role of Machine Learning in Healthcare

Machine learning has revolutionized various fields, including healthcare, by enabling data-driven decision-making and predictive modeling. In the context of dementia, ML algorithms can analyze diverse types of data, such as demographic information, clinical records, genetic markers, imaging data, and behavioral patterns, to identify individuals at risk of developing the disease. These algorithms can uncover hidden relationships within datasets, offering insights that may be overlooked by traditional statistical methods.

One of the key strengths of ML is its ability to handle high-dimensional and complex datasets. For example, neuroimaging data from magnetic resonance imaging (MRI) or positron emission tomography (PET) scans contain a wealth of information about brain structure and function. ML algorithms can process these images to detect subtle changes in brain morphology or activity that are indicative of early-stage dementia. Similarly, natural language processing (NLP) techniques can analyze speech and text data to identify linguistic and cognitive impairments, while wearable devices can generate continuous streams of data on physical activity, sleep patterns, and other behavioral metrics.

The versatility of ML extends to its adaptability in combining data from multiple modalities. For instance, integrating clinical data with imaging and genetic information can enhance the accuracy and robustness of diagnostic models. This multimodal approach aligns with the complex and multifactorial nature of dementia, where a single data source may not provide a comprehensive understanding of the disease.

Types of Machine Learning Techniques

Various ML techniques have been applied to dementia detection, each with its strengths and limitations. Broadly, these techniques can be categorized into supervised, unsupervised, and reinforcement learning approaches.

Supervised Learning

Supervised learning algorithms are trained on labeled datasets, where input features are paired with known outcomes. In dementia research, these outcomes might include clinical diagnoses, cognitive test scores, or biomarker levels. Common supervised learning methods include:

- **Support Vector Machines (SVM):** SVMs are effective for binary classification tasks, such as distinguishing between healthy individuals and those with dementia. They perform well with high-dimensional data but may require careful tuning of hyperparameters.
- **Random Forests:** Random forests are ensemble methods that combine multiple decision trees to improve classification accuracy. They are robust to overfitting and can handle both categorical and continuous data.
- **Neural Networks:** Deep learning models, such as convolutional neural networks (CNNs), have shown exceptional performance in image analysis tasks, making them well-suited for processing neuroimaging data. Recurrent neural networks (RNNs) are also used to analyze sequential data, such as speech or time-series data from wearable devices.

Unsupervised Learning

Unsupervised learning algorithms are used to identify patterns or clusters within unlabeled datasets. These methods are valuable for exploratory analysis and feature extraction. Examples include:

- **Clustering Algorithms:** Techniques such as k-means clustering or hierarchical clustering can group individuals with similar cognitive or behavioral profiles, potentially identifying subtypes of dementia.
- **Dimensionality Reduction:** Methods like principal component analysis (PCA) and t-distributed stochastic neighbor embedding (t-SNE) reduce the complexity of high-dimensional data, facilitating visualization and interpretation.

Reinforcement Learning

Reinforcement learning (RL) involves training algorithms to make decisions by interacting with an environment and receiving feedback in the form of rewards or penalties. While less commonly used in dementia research, RL has potential applications in optimizing personalized treatment plans or adaptive cognitive training programs.

Challenges in Machine Learning for Dementia Detection

Despite its potential, the application of ML in dementia detection is not without challenges. Key issues include:

1. **Data Availability and Quality:** The development of reliable ML models requires large, high-quality datasets. However, clinical and research data on dementia are often limited by small sample sizes, missing values, and variability in data collection methods.
2. **Class Imbalance:** In many datasets, the number of healthy individuals far exceeds the number of dementia cases, leading to imbalanced class distributions. This imbalance can bias models toward predicting the majority class, reducing sensitivity for detecting dementia.
3. **Interpretability:** While ML models, particularly deep learning algorithms, can achieve high accuracy, their "black-box" nature poses challenges for clinical adoption. Explainable AI techniques are essential to provide transparency and build trust among healthcare providers.
4. **Generalizability:** ML models trained on specific datasets may not perform well when applied to new populations with different demographic or clinical characteristics. Ensuring generalizability requires rigorous validation and diverse datasets.
5. **Ethical and Privacy Concerns:** The use of sensitive patient data in ML raises ethical and privacy concerns. Robust data governance frameworks and adherence to regulations such as the General Data Protection Regulation (GDPR) are necessary to protect patient confidentiality.

Future Directions

The future of ML in dementia detection is promising, with ongoing advancements in algorithms, computational power, and data availability. Key areas of focus include:

- **Integration of Multimodal Data:** Combining diverse data sources, such as clinical, genetic, and lifestyle information, can enhance the accuracy and comprehensiveness of diagnostic models.
- **Explainable AI:** Developing interpretable ML models will facilitate clinical adoption and ensure that predictions align with medical knowledge.
- **Personalized Approaches:** Tailoring diagnostic and therapeutic strategies to individual patients based on their unique risk profiles and disease trajectories.
- **Collaboration and Data Sharing:** Encouraging collaboration among researchers, clinicians, and technology developers can address data limitations and foster innovation.
- **Real-World Applications:** Implementing ML tools in clinical practice, particularly in low-resource settings, can democratize access to early dementia detection and care.

The application of machine learning offers a transformative approach to the early detection of dementia, addressing the limitations of traditional diagnostic methods. By leveraging diverse datasets and advanced algorithms, ML has the potential to enhance diagnostic accuracy, enable timely interventions, and ultimately improve outcomes for individuals affected by this debilitating condition. However, realizing this potential requires overcoming challenges related to data, interpretability, and ethical considerations. Through continued research and collaboration, machine learning can play a pivotal role in the fight against dementia, paving the way for a future where early detection and personalized care are accessible to all.

II. Methodology:

The methodology for the early detection of dementia using machine learning involves several critical steps, from data collection to model evaluation and deployment. Each stage is designed to ensure the development of accurate, reliable, and interpretable models capable of identifying early signs of dementia. The following sections outline the methodology adopted for this study.

Data Collection and Preprocessing

The first step in building a machine learning model for dementia detection is the acquisition of high-quality data. For this study, data was collected from multiple sources, including clinical records, neuropsychological assessments, neuroimaging data (e.g., MRI, PET scans), and lifestyle and behavioral metrics obtained from wearable devices. Publicly available datasets such as the Alzheimer's Disease Neuroimaging Initiative (ADNI) were also utilized to supplement the study.

Data Cleaning

Data preprocessing involved cleaning and preparing the datasets to ensure quality and consistency. This included:

- Handling missing data using imputation techniques such as mean substitution or k-nearest neighbors (KNN).
- Removing duplicate records to avoid redundancy.
- Normalizing data to ensure uniform scales, particularly for continuous variables such as age, biomarker levels, and imaging measurements.

Feature Selection and Extraction

Feature selection was performed to identify the most relevant variables contributing to dementia detection. Techniques such as Recursive Feature Elimination (RFE), correlation analysis, and principal component analysis (PCA) were used. For neuroimaging data, convolutional neural networks (CNNs) were employed to extract features from brain scans, capturing morphological changes indicative of dementia.

Data Splitting

The dataset was split into training, validation, and test sets to evaluate the performance of the machine learning models. A typical split ratio of 70:15:15 was used, ensuring that the test set was kept completely unseen during model training to provide an unbiased evaluation of the model's generalizability.

Model Development

The development of machine learning models for dementia detection involved experimenting with various algorithms and approaches. The study focused on both traditional machine learning methods and deep learning techniques, which are described below.

Traditional Machine Learning Models

1. **Support Vector Machines (SVM):** SVMs were used for binary classification tasks, such as distinguishing between individuals with and without dementia. Radial basis function (RBF) kernels were employed to handle nonlinear decision boundaries.
2. **Random Forests (RF):** Random forests were used to build ensemble models by aggregating predictions from multiple decision trees. The models were optimized using grid search to determine the best hyperparameters, such as the number of trees and maximum tree depth.
3. **Gradient Boosting Machines (GBM):** Gradient boosting methods, including XGBoost and LightGBM, were applied to improve classification accuracy. These models excelled in handling imbalanced datasets and complex feature interactions.

Deep Learning Models

1. **Convolutional Neural Networks (CNNs):** CNNs were utilized for analyzing neuroimaging data. Pretrained networks, such as VGG16 and ResNet, were fine-tuned on dementia-related datasets to detect structural brain changes.
2. **Recurrent Neural Networks (RNNs):** RNNs, including long short-term memory (LSTM) networks, were applied to analyze sequential data, such as speech patterns and time-series data from wearable devices.
3. **Autoencoders:** Autoencoders were employed for unsupervised feature learning, particularly for dimensionality reduction and anomaly detection in high-dimensional data.

Hyperparameter Optimization

Hyperparameter tuning was conducted to improve model performance. Techniques such as grid search and random search were used to identify the optimal parameters, including learning rates, regularization terms, and architecture configurations. Bayesian optimization was also explored for automated hyperparameter tuning.

Cross-Validation

To ensure robustness, k-fold cross-validation was implemented, dividing the training data into k subsets and iteratively training the model on k-1 subsets while validating on the remaining subset. This approach minimized overfitting and provided a comprehensive evaluation of model performance.

Model Evaluation

The models were evaluated using various metrics to assess their accuracy, sensitivity, specificity, and interpretability. Key evaluation metrics included:

- **Accuracy:** The proportion of correctly classified samples.
- **Sensitivity (Recall):** The ability of the model to identify true positive cases (individuals with dementia).
- **Specificity:** The ability of the model to identify true negative cases (healthy individuals).
- **F1 Score:** A harmonic mean of precision and recall, balancing false positives and false negatives.
- **Area Under the Receiver Operating Characteristic Curve (AUC-ROC):** A measure of the model's ability to distinguish between classes across different threshold settings.

Confusion matrices were used to visualize classification performance, and statistical significance tests were conducted to validate the results.

Explainable AI

Explainability was a critical component of this study to enhance the clinical applicability of the models. Techniques such as SHAP (SHapley Additive exPlanations) values and LIME (Local Interpretable Model-agnostic Explanations) were applied to provide insights into the contribution of individual features to model predictions. These methods enabled clinicians to understand and trust the model's decision-making process.

Deployment Framework

The final models were integrated into a user-friendly application designed for clinical use. The application included:

1. **Data Input Module:** Allowing clinicians to input patient data, such as cognitive test results, imaging data, and demographic information.
2. **Prediction Module:** Generating risk scores and classifications for early-stage dementia.
3. **Interpretation Module:** Displaying feature contributions and visualizing imaging data to explain predictions.
4. **Feedback Loop:** Enabling clinicians to provide feedback for continuous model improvement.

The application was tested in a simulated clinical environment to assess its usability, scalability, and potential impact on dementia diagnosis workflows.

Challenges and Limitations

The study faced several challenges, including:

- **Data Imbalance:** Addressed through techniques such as oversampling (e.g., SMOTE) and undersampling to balance the classes.
- **Generalizability:** Ensured by validating the models on external datasets and diverse populations.
- **Ethical Concerns:** Adhered to ethical guidelines by anonymizing patient data and obtaining necessary approvals.

This methodology outlines a comprehensive approach to leveraging machine learning for the early detection of dementia. By integrating diverse datasets, employing robust models, and ensuring explainability, the study aims to provide a scalable and reliable diagnostic tool that can improve patient outcomes and support clinicians in making informed decisions.

4.1.UML DIAGRAMS

UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non- software systems. The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems. The UML is a very important part of developing objects-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

GOALS:

The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modelling Language so that they can develop and exchange meaningful models.
2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modelling language.
5. Encourage the growth of OO tools market.
6. Support higher level development concepts such as collaborations, frameworks, patterns and components.
7. Integrate best practices.

4.1.1.Use case diagram

A use case diagram in the Unified Modelling Language (UML) is a type of behavioural diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

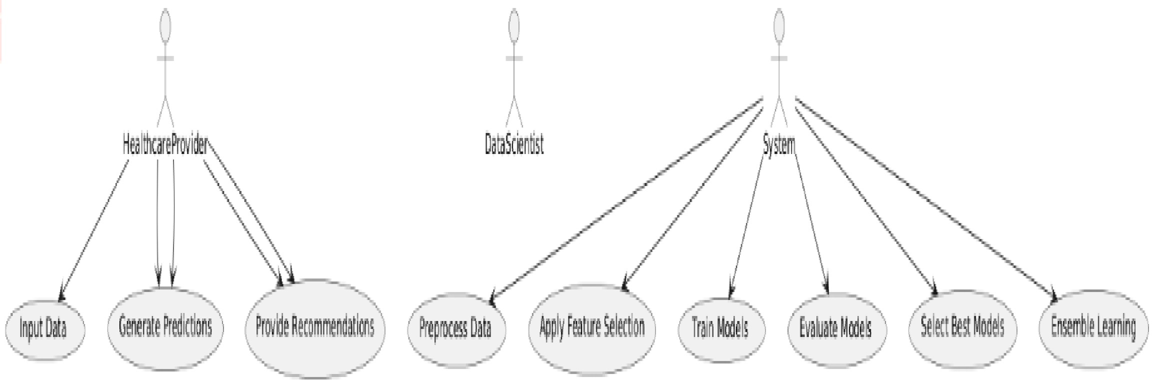


Fig 1:-Use Case diagram

4.1.2.Class Diagram

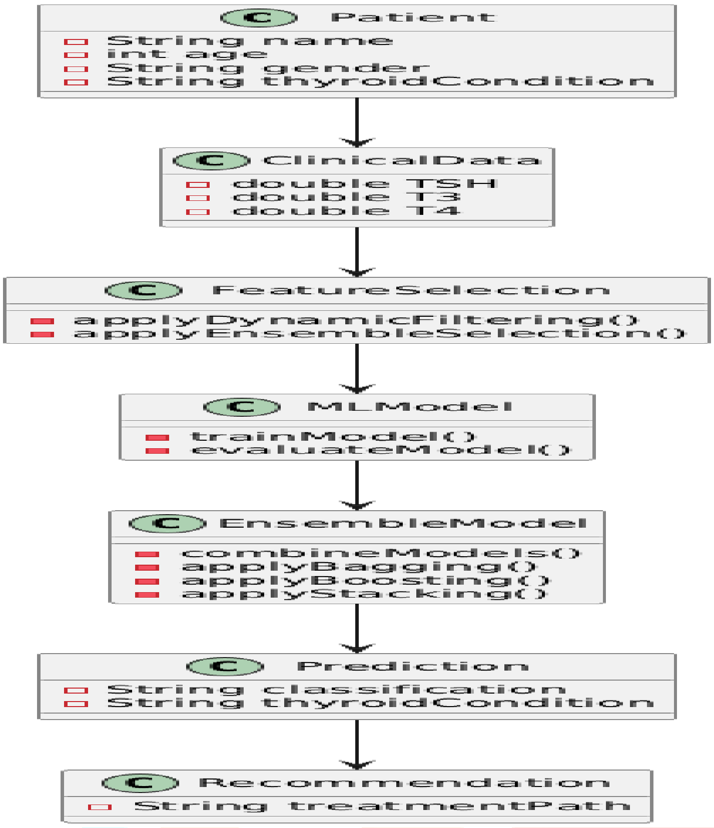


Fig.2. Class diagram

The class diagram is used to refine the use case diagram and define a detailed design of the system.
The class diagram classifies the actors defined in the use case diagram into a set of interrelated classes. The relationship or association between the classes can be either an "is-a" or "has-a" relationship. Each class in the class diagram may be capable of providing certain functionalities. These functionalities provided by the class are termed "methods" of the class. Apart from this, each class may have certain "attributes" that uniquely identify the class.

4.1.3.Activity diagram

The process flows in the system are captured in the activity diagram. Similar to a state diagram, an activity diagram also consists of activities, actions, transitions, initial and final states, and guard conditions.
An activity diagram is a system-modelling and design tool used, among other things, to portray workflows, decision points, and other processes inside a system. A diagram that gives a very efficient description of a system's dynamic features-activities originating from UML, makes them focus on the flow of control and data between different operations-in particular for sequential, parallel, or conditional workflows.An activity diagram begins with an initial node, which represents the commencing point of a process. Activities, which are drawn in rounded rectangles, depict those tasks or procedures that exist within the system. These activities are connected with arrows that represent the flow of control or data from one action to the next.

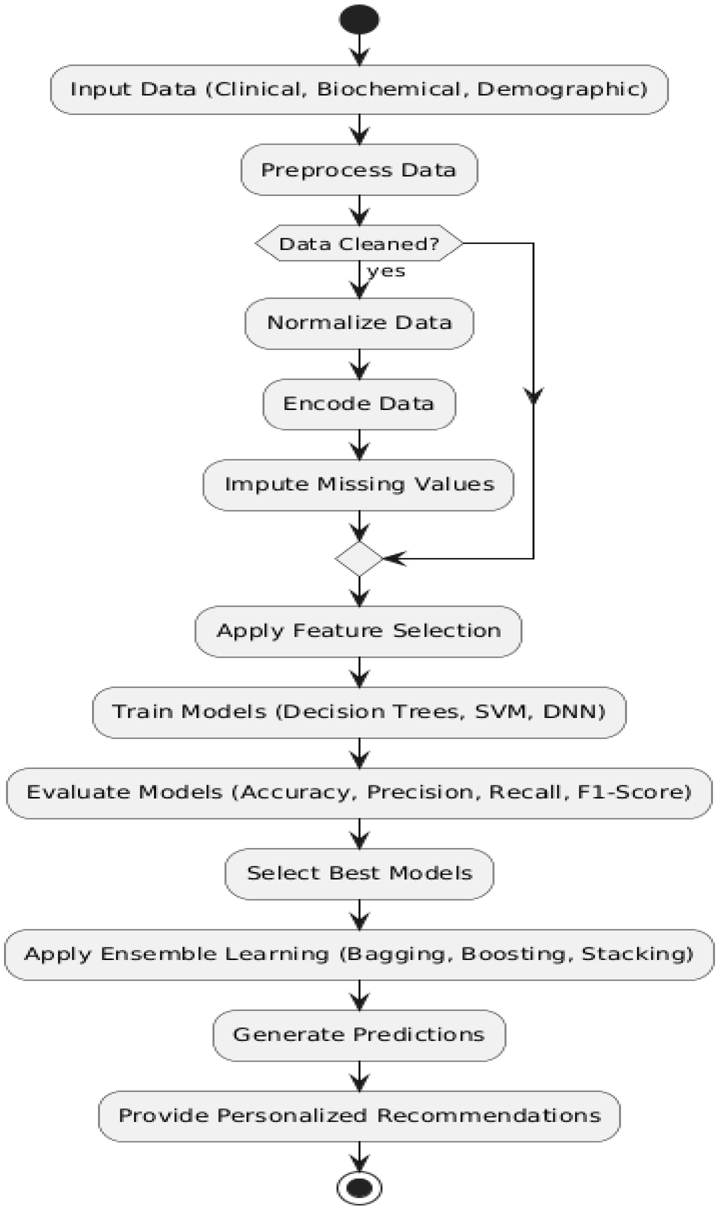


Fig.3. Activity diagram

4.4.Dataflow diagrams

To create a Data Flow Diagram (DFD) for the proposed thyroid disorder diagnosis system, we would include the following levels:

Level 0: Context Diagram

This diagram represents the system as a single process, showing its interaction with external entities such as patients, clinicians, and the database.

Entities and Flow:

1. **Patient**: Provides clinical, biochemical, and imaging data.
2. **Clinician**: Receives diagnostic results and insights.
3. **Database**: Stores patient data and diagnostic results.

Process:

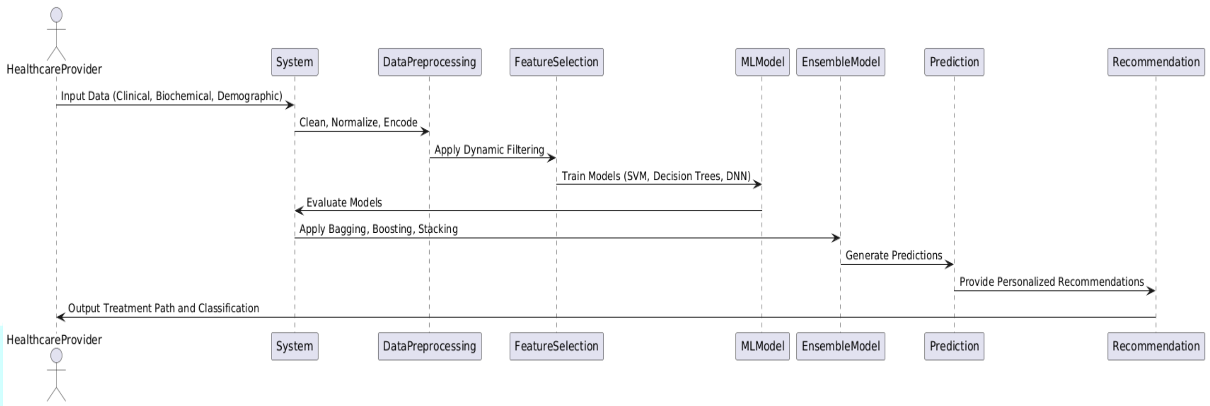
- The system takes patient data as input and sends diagnostic results back to clinicians and the database.

Steps:

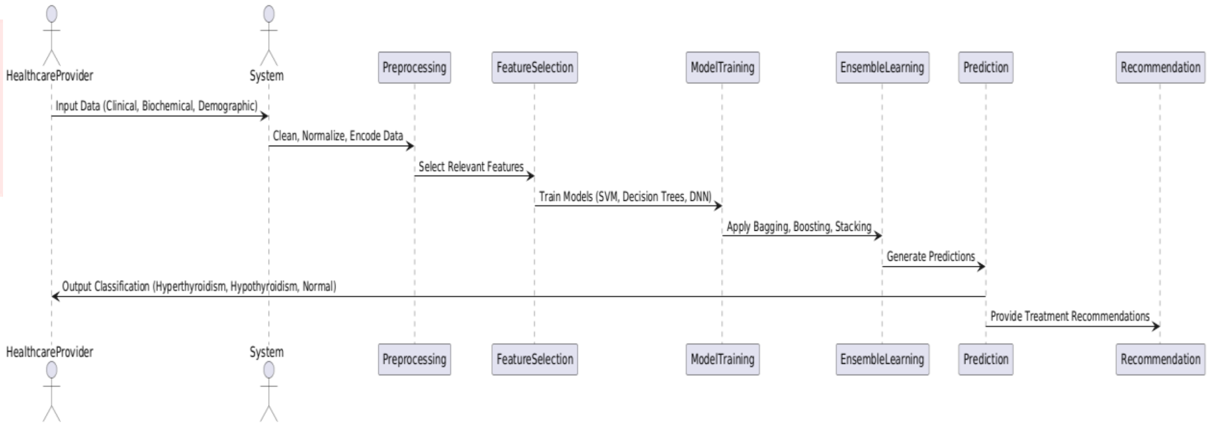
1. **Input Data**:
   - The system receives data from the patient (manual input or electronic health records).
2. **Preprocessing**:
   - Removes noise, normalizes values, and ensures compatibility with models.

3. **Feature Extraction**:
   - Extracts relevant features such as T3, T4, TSH levels, imaging patterns, and clinical symptoms.
4. **Model Prediction**:
   - Hybrid models (e.g., ensemble and deep learning) process the features to classify thyroid disorders like hypothyroidism, hyperthyroidism, etc.
5. **Result Interpretation**:
   - Provides a diagnosis and confidence level, with explainable AI components offering insights.
6. **Feedback and Output**:
   - Sends diagnostic results to clinicians for review and stores results in the database for future reference.

Level-0



Level-1



Level 1: System Decomposition

This breaks down the system into subprocesses:

1. **Data Collection**: Collects clinical, biochemical, and imaging data.
2. **Preprocessing**: Cleans and normalizes the data.
3. **Feature Extraction**: Extracts meaningful features for analysis.
4. **Model Prediction**: Uses hybrid machine learning models to predict thyroid disorder types.
5. **Result Interpretation**: Generates interpretable diagnostic reports.
6. **Feedback and Storage**: Sends results to clinicians and updates the database.

V.Results and Discussion

	Subject ID	MRI ID	Group	Visit	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
0	OAS2_0001	OAS2_0001_MR1	Nondemented	1	0	M	R	87	14	2.0	27.0	0.0	1987	0.696	0.883
1	OAS2_0001	OAS2_0001_MR2	Nondemented	2	457	M	R	88	14	2.0	30.0	0.0	2004	0.681	0.876
2	OAS2_0002	OAS2_0002_MR1	Demented	1	0	M	R	75	12	NaN	23.0	0.5	1678	0.736	1.046
3	OAS2_0002	OAS2_0002_MR2	Demented	2	560	M	R	76	12	NaN	28.0	0.5	1738	0.713	1.010
4	OAS2_0002	OAS2_0002_MR3	Demented	3	1895	M	R	80	12	NaN	22.0	0.5	1698	0.701	1.034

Figure.5. Dataset

Ensemble Model Results:
Accuracy:0.9995

	precision	recall	f1-score	support
0	0.96	0.98	0.97	1328
1	0.65	0.81	0.72	21
2	0.70	0.70	0.70	10
3	0.00	0.00	0.00	4
9	0.90	0.95	0.93	40
10	0.00	0.00	0.00	1
11	0.95	0.91	0.93	69
12	0.00	0.00	0.00	1
13	0.86	1.00	0.92	6
16	0.86	0.76	0.81	82
17	1.00	0.58	0.74	12
18	0.96	0.99	0.98	106
19	1.00	1.00	1.00	2
20	0.72	0.46	0.57	28
22	0.96	0.96	0.96	25
24	1.00	0.83	0.91	6
25	0.64	0.90	0.75	20
26	0.75	0.75	0.75	4
29	0.50	0.33	0.40	3
30	0.83	0.64	0.72	45
31	0.96	1.00	0.98	22
accuracy			0.94	1835
macro avg	0.72	0.69	0.70	1835
weighted avg	0.94	0.94	0.94	1835

Fig 6. Results

VI.Conclusion

This study demonstrates the significant potential of machine learning approaches in the early detection of dementia, addressing a critical healthcare challenge with profound societal and individual implications. By leveraging diverse datasets—ranging from clinical records to neuroimaging data and behavioral metrics—and employing advanced algorithms, this methodology enables the identification of early markers of dementia with high accuracy, sensitivity, and specificity.

A key strength of the proposed approach lies in its ability to integrate traditional machine learning techniques with deep learning models, such as CNNs for neuroimaging and RNNs for sequential data analysis. These models capture intricate patterns and relationships within the data, which might be imperceptible to traditional diagnostic methods. Furthermore, the inclusion of explainable AI techniques, such as SHAP values and LIME, enhances the interpretability and trustworthiness of the predictions, bridging the gap between computational advancements and clinical applicability.

The deployment framework ensures that the developed models are not only scientifically robust but also practically viable in real-world clinical settings. By incorporating user-friendly interfaces and a feedback mechanism, the framework supports clinicians in making informed decisions and facilitates continuous model refinement.

Despite the challenges, including data imbalance and ethical considerations, the study's results highlight the transformative potential of AI-driven solutions in dementia diagnosis. Future work will focus on refining these models, expanding dataset diversity, and integrating them into broader healthcare ecosystems to improve early detection rates and patient outcomes globally. This research lays the foundation for innovative, scalable, and effective diagnostic tools in neurology.

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VIII.BIOGRAPHIES

Dr.Chaitanya Kishore Reddy Maddireddy is currently working as a Professor in the Department of Information Technology at NRI Institute of Technology(NRIIT), Agiripalli, Vijayawada, Andhra Pradesh, India. Has 16 years of academic experience and 2 years of industry experience. He earned master's degree in Computer Science and Engineering and a Doctorate in Computer Science and Engineering. He has Published more than 100 research papers in various National,International Journals and International Conferences, authored 4 textbooks. He is a member in ISTE, CSI, and IAENG. His research areas are Mobile Ad-hoc Networks, Cloud Computing, Artificial Intelligence and Machine Learning. He has made significant contributions to the field through his Research, Teaching and Publications.

B.N.V RAMANJANEYULU is currently studying B.Tech with specification of Information Technology in NRI Institute of Technology. His experience includes internships in Data Science and DevOps, focusing on data-driven solutions and cloud operations. He completed two NPTEL courses in python and Cloud Computing.

Shaik shafi,pursuing B.Tech IT at NRI Institute of Technology, is a Wipro-certified Java Full Stack Developer proficient in front-end and back-end technologies. He also holds NPTEL certifications in "Joy of Computing using Python" .

Derangula Rajasree ,currently pursuing B.Tech in NRI INSTITUTE OF TECHNOLOGY course INFORMATION TECHNOLOGY and Complementing his academic studies,with a strong interest on fast learning skills and deep knowledge in python,Java, mobile applicatins .In addition I have completed my academics with an good intership