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Full Length Research Article

A KNOWLEDGE-DRIVEN EXPERT SYSTEM FOR EARLY DEMENTIA SCREENING AND DIAGNOSIS

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ABSRACT
Dementia is a neurological disorder that progresses and has a significant impact on memory, cognitive functions, and daily activities. Early detection is essential for enhancing patient outcomes and optimizing care strategies. Nevertheless, traditional diagnostic methods can be lengthy, require specialized knowledge, and often miss crucial early indicators. This research introduces a knowledge-driven expert system aimed at facilitating the early screening and diagnosis of dementia. The objective of this study is to enhance access to early screening, support healthcare professionals in their decision-making processes, and ultimately improve patient management and overall quality of life. The system uses a meticulously organized knowledge-base and inference mechanisms to emulate expert reasoning, which enables it to assess patient symptoms and provide initial evaluations. Comprehensive validation against real-world clinical datasets showcases the system's impressive performance, with the interactive expert system achieving a peak accuracy of 93%, and a precision of 0.97 surpassing the traditional statistical models. The system's rule-based architecture is not only a step towards improving diagnostic accuracy, but it also enables critical interpretability, fostering trust among clinicians, and allowing for smooth integration into current healthcare practices.

Keywords: Dementia, Memory loss, Expert reasoning, Knowledge-base, Expert system, Models

INTRODUCTION

Dementia is still a significant challenge for humanity, despite the remarkable progress made in modern medicine. Early diagnosis can make a profound difference, helping individuals maintain a better quality of life (Shree, 2016). Dementia is an umbrella term for a range of cognitive disorders that disrupt daily functioning. It is not just one illness, but rather a syndrome that influences memory, reasoning, and social behavior. Early detection of dementia is crucial for effective management, as it enables patients and caregivers to access treatment options and support systems that can improve their well-being and slow down its progression. Unfortunately, the early symptoms are often subtle and easily missed, making accurate and timely diagnosis difficult.

Expert systems is a branch of artificial intelligence and have shown great promise in replicating the reasoning abilities of human specialists to address complex problems, especially in healthcare. By leveraging structured knowledge bases and logical reasoning techniques, these systems can evaluate symptoms, recognize patterns, and support clinical decision-making with greater precision.

Since dementia imposes significant clinical, societal, financial, and psychological consequences on patients, families, and caregivers, early detection is critical. Furthermore, early identification facilitates management strategies; caregivers can initiate health-promoting behaviors, such as exercise, as well as legal and financial planning while the individual remains competent. However, persons with early dementia seldom come to clinical attention, as both patients and caregivers often overlook subtle early changes as normal or attribute them to stress. Cognitive difficulties are frequently concealed from others. Thus, general practitioners, the initial contact for most patients with early dementia routinely overlook the early diagnosis. Diagnosis is hardest at the earliest stage, during which cognitive impairment may be nondisabling and performance on diagnostic tests may be normal (Panegyres et al., 2016). Quality of life is improved and institutionalization delayed by early diagnosis. Hence, early detection has become a public health imperative and should precede formal diagnosis (Vyas et al., 2022).

The focus of this research is on the development of a rule-based expert system designed to assist in the early detection and diagnosis of dementia. Such a system is able to mimic human reasoning and decision-making within a specialized domain by relying on a set of if-then rules. The system was developed by combining established medical knowledge and clinical guidelines to aid healthcare practitioners in recognizing dementia at its early stages.

The central goal of this study is to provide a diagnostic tool that is not only consistent and reliable but also efficient in supporting timely clinical decisions.

A RULE-BASED EXPERT SYSTEM

Rule-based systems represent a fundamental type of expert system consisting of a set of "if-then" statements. Typically, the statements have the form if <condition> then <consequence>. The condition is a statement that can be either true or false when evaluated, while the consequence suggests an action, a conclusion, or a next condition to be evaluated (Fernandino & Bisheh, 2024). The fundamental elements that constitute a rule-based system include the working memory, rule base, and inference engine. The working memory stores the known facts that are known to be true at a given moment. The rule base contains the set of condition-action pairs that are to be applied in the reasoning process. The inference engine determines which rules to apply at a given moment and can maintain or modify the facts in the working memory depending on the conclusions or actions specified by the consequences of the rules (Vyas et al., 2022).

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Rule-based expert systems used for medical diagnosis are typically designed with a single focal problem to be addressed and do not possess intelligence that goes beyond what the expert knowledge describes. From the medical point of view, the only suitable strategy when applying rule-based expert systems to diagnosis is to determine individual, standalone diagnostic systems for typical illnesses. Complexity emerges when confronted with individual structures combined with other diagnostic systems or when accompanied by other reasoning strategies.

Expert systems simulate the decision-making skills of a human expert to solve complex real-world problems. They emerged in the 1950s with pioneers like Newell, Simon, and Shaw developing the Logic Theorist, the first AI program, aiming to mimic human problem-solving strategies. Medical diagnosis was a driving application for expert systems, with early examples including MYCIN for blood infections, INTERNIST-1 for internal diseases, and CADUCEUS for cardiovascular diagnosis (Edgar, 1991; Fernandino & Bisheh, 2024). Since then, expert systems have been applied in diverse fields such as agriculture, business, finance, and education (Wang et al., 2021)

An Expert System (ES), sometimes called a Knowledge Base System (KBS) is a computer program that contains some of the subject-specific knowledge of one or more human experts. Expert System automates expert's tasks, which require specialized skills and training. The components of a rule-based expert system include the knowledge base, inference engine, knowledge acquisition component, and explanation system.(Hole & Gulhane, 2014). Expert Systems are a special type of software whose main components are a knowledge base and an inference engine. The system uses these rules together with a reasoning engine to look at the facts it's given, apply the relevant rules, and then suggest conclusions or recommendations. Think of it as having a conversation with an expert who goes through their mental checklist step by step. This makes rule-based expert systems very good at solving well-defined problems where the knowledge can be clearly expressed in rules.

A rule-based system is made up of several essential parts that work together to simulate expert decision-making:

i. ***Rules:*** These are the heart of the system. Each rule is a conditional statement that tells the system what to do when certain conditions are met, usually in the format *IF condition THEN action*. For instance, in a medical diagnosis system, one rule might be: *IF the patient has a fever AND a cough THEN suspect flu.*
ii. ***Knowledge Base****:* This is where all the system's rules and facts are stored. It's built from specialized knowledge in a particular field, often gathered from experts, research, or real-world experience.
iii. ***Inference Engine:*** This is the "thinking" part of the system. It takes the rules from the knowledge base, compares them against the facts at hand, and works out the logical conclusions or recommendations.
iv. ***Working Memory****:* This holds the information the system is currently working with. As the inference engine applies rules and learns new facts, the working memory updates in real time.
v. ***User Interface*****:** This is how people interact with the system. It allows users to enter information, ask questions, and receive advice or recommendations based on the system's reasoning.

A typical diagnostic process commences when a user input the observed symptoms into the system through the interactive interface. The inference engine receives the inputted data, processes these inputs against the knowledge base, producing a diagnostic recommendation and explanation. Figure 1 illustrate a rule-based expert system.

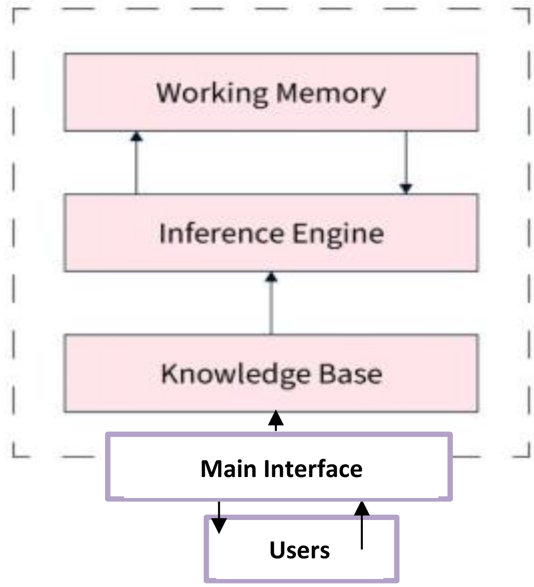

Figure. 1. A chart showing a typical rule-based expert system .

LITERATURE REVIEW

Dementia is a clinical syndrome characterized by acquired losses of cognitive and emotional abilities severe enough to interfere with daily functioning and the quality of life. The early detection and diagnosis of dementia diseases, particularly Alzheimer's disease, is a critical area of research and clinical practice, given the increasing prevalence of these conditions in aging populations worldwide.

According to Alzheimer Disease International, around two-thirds of people with dementia suffer from Alzheimer's disease, yet only about 10% of them are diagnosed in time. This highlights the critical importance of early detection, not only for clinical management but also for long-term planning and improved outcomes (Shree, 2016). Early diagnosis enables families and healthcare systems to prepare adequately, and technology now plays a central role in making this possible. For example, Ford et al. (2020) found that automated systems using primary care records were more effective at identifying dementia early compared to traditional physician-led methods. This shows how combining data-driven models with expert rule-based systems can significantly improve diagnostic timeliness.

One of the persistent obstacles to early detection is the insufficient training of frontline healthcare providers. Raphael (2022) pointed out that knowledge gaps and outdated attitudes towards dementia often hinder diagnosis. Some professionals even question the value of diagnosing an incurable disease, a mindset that delays

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care and support. To counter this, Butler et al. (2012) suggested models of care that automatically refer patients with suspected cognitive impairment to specialists, ensuring that proper evaluations happen without unnecessary delay.

Policies that link health and social services also strengthen dementia care. Tang (2024), for instance, describes the Macao Dementia Policy, which focuses on prevention, detection, diagnosis, treatment, and long-term support. Such a structured, comprehensive approach offers a blueprint for other regions aiming to improve dementia services. In primary care, Eichler et al. (2015) demonstrated that incorporating dementia screening into routine wellness checks improved detection rates. Still, they caution that screening must be followed by detailed diagnostic procedures to avoid misdiagnosis and the associated distress. Technology can add further value here; behaviour-monitoring tools, such as those proposed by Abe et al. (2013), can detect subtle changes that signal cognitive decline, especially useful for older adults living alone. Lin and Cheng's work, as noted by Aravena (2024), reinforces that identifying dementia early not only improves care planning but also helps manage risk factors and encourages adherence to treatment. A systematic review by Lang et al. (2017) underscores the urgency of such efforts, revealing that many dementia cases remain undiagnosed worldwide.

The role of multidisciplinary collaboration is also essential. Chen (2024) showed that case manager-centered models, which bring together different healthcare professionals, improve both diagnosis rates and quality of care. Mata (2023) added that systemic barriers—such as poor clinician training and public misconceptions—must be addressed through targeted education to close existing gaps. Couch (2024) further emphasized the value of involving patients and caregivers in the diagnostic process. Early diagnosis, according to this study, empowers families by giving them resources and a sense of direction, suggesting that expert systems should integrate not just clinical data but also caregiver perspectives for greater impact.

On the technical side, advances in expert systems have shown promise for supporting early detection. Methods like the Dempster-Shafer theory and Certainty Factors offer structured ways of handling uncertainty in medical data. Aldjawad et al. (2021), for example, developed a web-based expert system that achieved diagnostic accuracy with a Certainty Factor of 56% in detecting Alzheimer's disease. While not perfect, such tools demonstrate how rule-based systems can help clinicians weigh symptoms and risk factors more effectively, ultimately supporting informed, timely decisions in dementia care.

General practitioners (GPs) play a pivotal role in the early recognition of cognitive impairments. Studies by Kaduszkiewicz et al. (2010), reported the need for improved training and awareness among the GPs regarding mild cognitive impairment (MCI) and dementia. They argue that while there is a growing public awareness of dementia, GPs often struggle to identify early signs of cognitive decline, which underscores the need for expert systems that can assist in this process. Similarly, Luck et al. (2012) found that GPs face challenges in recognizing pre-dementia cognitive deficits, indicating a gap that rule-based systems could help bridge (Luck et al., 2012).

The implementation of electronic health record (EHR)-based tools, such as the eRADAR developed by Barnes et al., (2019) represents a promising approach to facilitate early detection of dementia (Barnes et al., 2019). This tool utilizes existing patient data to identify individuals at risk of undiagnosed dementia, thereby allowing for timely intervention. The study indicates that nearly half of dementia cases remain undiagnosed, highlighting the urgent need for such innovative solutions (Barnes et al., 2019).

The implementation of screening tools is another critical component in the early detection of dementia. The Early Dementia Questionnaire (EDQ) developed by Zurraini et al. (2013) provides a structured method for screening in primary care settings, facilitating earlier recognition of dementia symptoms. This aligns with the findings of Lin et al., (2016) who highlight that early diagnosis can lead to better management of dementia-related symptoms and improve the quality of life for patients and caregivers. Moreover, the use of computerized cognitive test batteries, as discussed by Ye et al., (2022) can enhance the accuracy of early dementia detection by providing standardized assessments that can be easily administered in clinical settings.

In conclusion, the integration of rule-based expert systems into the diagnostic process for dementia can significantly enhance early detection and management. By addressing the educational gaps among healthcare providers, implementing effective screening protocols, and utilizing advanced technologies, we can improve the overall quality of care for individuals with dementia. Continued research and development in this field are essential to refine these systems and ensure they meet the diverse needs of patients and caregivers.

Key gaps in the existing Systems

Although several diagnostic approaches are currently in use, significant challenges remain within the process:

i. *Early Detection Difficulties*: Many existing systems have limitations in recognizing the subtle, initial signs of dementia. As a result, diagnoses are often made only when symptoms become more pronounced, which reduces the potential benefits of early interventions.
ii. *Resource Limitations:* Advanced diagnostic methods, such as neuroimaging, are costly and not always readily available. This creates accessibility issues, especially in primary care settings or in rural areas where specialized resources are scarce.
iii. *Variability in Expertise*: Diagnostic accuracy can vary significantly between healthcare providers, especially when dementia symptoms overlap with other cognitive or mental health conditions.

The proposed rule-based expert system designed for early detection and diagnosis of dementia aim at addressing the challenges of delayed and inconsistent diagnoses in the current system. This system integrates predefined medical rules and logical reasoning

MATERIALS AND METHODS

Knowledge representation

In a system that relies on rules, acquired knowledge is organized into 'if-then' rules, which are the system's foundation and also facilitate logical reasoning within it. The process of knowledge

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representation entails developing a knowledge base that categorizes symptoms, risk factors, and clinical observations as rules. For instance:
Rule illustration:
"IF a patient presents with frequent short-term memory loss and confusion in familiar settings,
OR
IF a patient has a family history of dementia; AND shows signs of cognitive decline;
THEN the system flags a high probability of early-stage dementia."

Each rule was carefully structured to follow clinical patterns, allowing the system to cover a wide range of symptoms and scenarios typical in early dementia cases. By adopting a rule-based approach, the system can reason through various symptom combinations to support accurate and contextually relevant diagnoses.
A typical diagnostic process starts when a user enters observed symptoms into the interface. The proposed diagnosis system is represented in Figure 2. The inference engine then processes these inputs against the knowledge base, producing a diagnostic recommendation and explanation.

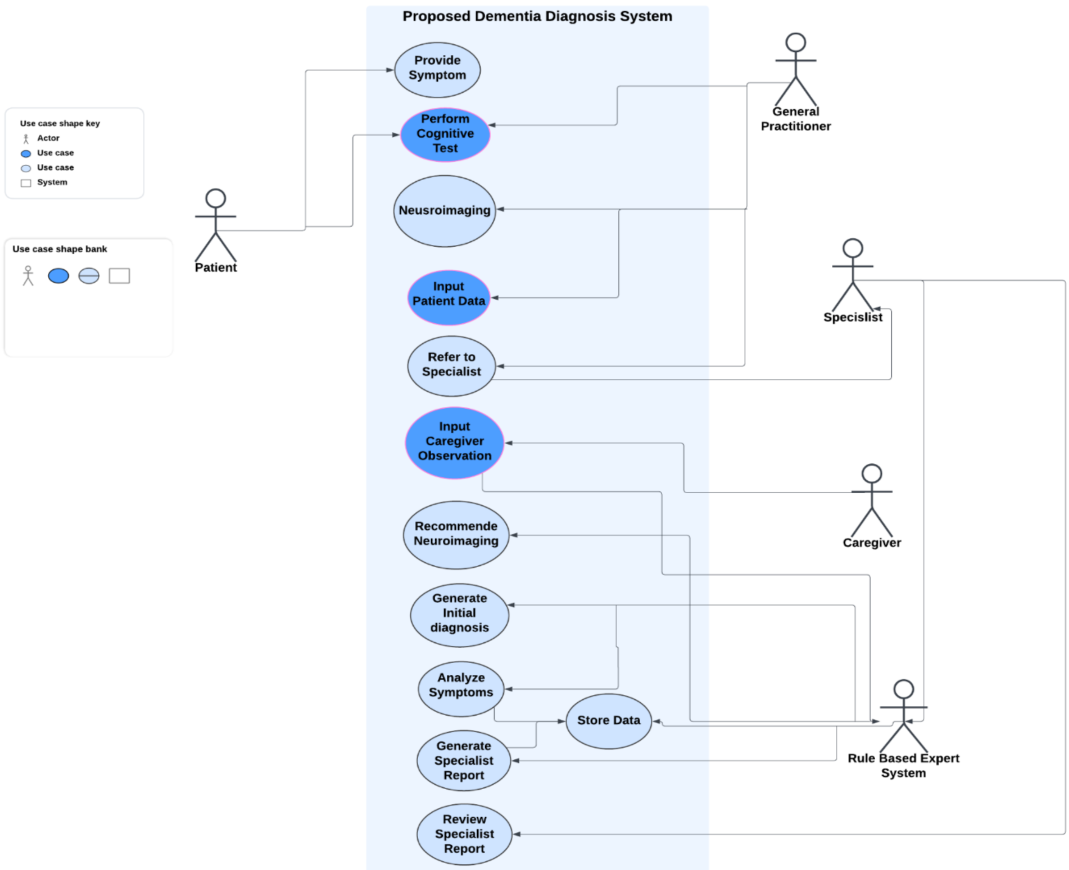

Figure. 2. Use case for the proposed system

Data collection
The knowledge acquisition phase involves collecting critical data related to dementia diagnosis, specifically focusing on early symptoms and indicators that medical experts use in practice. Rules were formulated based on the insights gained from the literature reviews and interviews with experts. Some of the reviewed literature through which relevant data was retrieved includes: Academic articles, textbooks, and other sources such as the Alzheimer's Association that serve as primary references. These materials provide established diagnostic criteria and symptom classifications for various types of dementia. Book reviews and online resources also provided foundational knowledge on dementia types, symptoms, and diagnostic criteria.

Data description
This research utilizes the OASIS Longitudinal database from (Battineni et al., 2019), which is a well-known source for neuroimaging and clinical data about cognitive health and dementia.

Acronyms used:
MMSE - Mini-Mental State Examination
eTIV - Estimated Total Intracranial Volume
nWBV - Normalized Whole Brain Volume
ASF - Atlas Scaling Factor
CDR - Clinical Dementia Rating
EDUC - Years of Education
SES - Socioeconomic Status

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Group - Demented, Non-Demented, or Converted
Key features from the dataset include:

i. Demographic Variables: Age, gender, education level, SES.
ii. Cognitive Assessments: MMSE, CDR.
iii. Brain Metrics: eTIV, nWBV, ASF.

The dataset is valuable for this study because it provides both clinical and structural brain data, enabling the design of rules that integrate cognitive scores with physical brain changes indicative of dementia progression.

The rule-based inference score function is represented in equation 1.

$$S(k) = \sum_{i=1}^{n} w_i \cdot r_i\,(k)) \qquad (1)$$

The equation in (1) aggregates all the fired rules (those matching patient symptoms) and combines them using their assigned weights.

The resulting value S(k) represents the overall likelihood or severity score for dementia for that patient. Application of threshold, T classify the result:

The score function S(k), computes the dementia risk score for a particular patient *k*, based on a set of inference rules in a knowledge-driven expert system.

where: k denotes a patient's data such as age, memory loss, test results, language skills and so on.

$r_i\,(k) \in \{0,1\}$ is the output of the i^{th} rule applied to patient k, which gives:

1 if the condition is met.
0 otherwise.

$$\text{Diagnosis}(k) = \begin{cases} \text{Dementia suspected, if } S(k) \geq T \\ \text{Dementia ruled out, if } S(k) < T \end{cases} \qquad \text{Equation (2)}$$

Where T is the threshold, equation 2 forms the core diagnostic logic for screening in the expert system. Each rule might represent a known symptom or test result indicator, e.g.:

i. Rule 1: IF memory loss AND confusion → dementia score increases
ii. Rule 2: IF poor spatial awareness → dementia score increases

The weights w_i reflect how important each rule is in early dementia detection.

$w_i \in R$: which represents the weight or confidence of the i^{th} rule based on expert knowledge

n: The total number of rules in the system

reliable the system is when it indicates dementia. Recall, on the other hand, measures how many of the actual dementia cases the system is able to correctly detect, demonstrating its sensitivity to true cases. The F1-score combines both measures into a single value by utilizing their harmonic mean, providing a balanced perspective that takes into account both accuracy and sensitivity in decision-making.

$$Precision = \frac{TP}{TP+FP} \qquad (3)$$

Implementation

Software and Tools : Python was used as the primary programming language, leveraging some libraries such as:

i. Pandas – library for data manipulation and pre-processing.
ii. Scikit-learn contain suite of algorithms for decision tree analysis and cross-validation.
iii. Matplotlib and Seaborn library for visualizations during exploratory data analysis.
iv. A Jupyter Notebook which serves as the interactive environment for data analysis, rule formulation, and iterative refinement.

Rule-based system structure: The system have a modular structure which comprised of:

i. Data Input Module: Handles raw data entry, pre-processing, and normalization.
ii. Rule Engine Module: Executes the predefined diagnostic rules and outputs predictions.
iii. Evaluation Module: Calculates performance metrics and presents diagnostic results.

System Validation

The process focuses on ensuring that a system performs exactly as intended—essentially asking, did we build the right system? Dementia refers to a group of neurological disorders marked by progressive memory loss and cognitive decline. Diagnosing dementia at an early stage is often difficult because symptoms vary widely and may not present in a typical way (Yin et al., 2015; Braun et al., 2022). Although early detection enables timely intervention, there are still no effective treatments to completely stop or reverse the progression of the disease.

To help address this gap, a knowledge-driven expert system was developed to support early dementia screening and diagnosis. The system applies rules drawn from both medical experts and current dementia research, implemented using the Java Expert System Shell (Jess). It features user-friendly graphical interfaces that make it easier to input patient data and view diagnostic results, medical insights, and preventive recommendations. This tool not only provides valuable decision support for specialists but also empowers non-specialists to carry out preliminary self-screening.

Model evaluation

The evaluation process makes use of well-chosen performance metrics to provide a comprehensive picture of the system's diagnostic ability. Key measures include precision, recall, and the F1-score, each highlighting a different aspect of how effectively the expert system performs. Precision reflects the proportion of correct positive predictions out of all positive cases identified, essentially showing how

$$Recall = \frac{TP}{TP+FN} \qquad (4)$$

$$F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \qquad (5)$$

Where TP represent the True Positive, TN represent the True Negative, FN is the number of False Negative and FP represents False Positive.

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RESULTS AND DISCUSSION

Tables 1 and 2 demonstrate the importance of early detection of dementia in terms of clinical significance. Identifying the condition early and making an accurate diagnosis are key to providing timely care, helping patients and their families prepare for the future, access the right support, and take advantage of new treatment options as they become available. The expert system's transparent, rule-based design also makes it easier for clinicians to understand and apply its insights in real-world medical settings. Clinicians can examine and understand the system's diagnostic logic, fostering trust and facilitating integration into clinical workflows.

Table 1. Performance Metrics of Baseline Logistic Regression Model for Group Classification

Metric	Class 0	Class 1	Macro Avg	Weighted Avg
Precision	0.73	0.77	0.75	0.75
Recall	0.81	0.68	0.74	0.75
F1-Score	0.77	0.72	0.74	0.75
Support	37	34	71	71

The high accuracy achieved, especially when incorporating interaction features, suggests that this expert system has the potential to serve as a valuable aid tool for clinicians, aiding in the often complex and time-consuming process of dementia diagnosis. Furthermore, the rule-based nature of the system allows for potential adaptation and refinement as new clinical knowledge emerges and diagnostic criteria evolve. The system could be updated and expanded to incorporate new biomarkers, genetic risk factors, or refined cognitive assessments, maintaining its clinical relevance and enhancing its diagnostic capabilities over time.

Table 2. The system performance based on several models.

Model	Precision (Non-Demented)	Recall (Non-Demented)	F1-Score (Non-Demented)	Precision (Demented)	Recall (Demented)	F1-Score (Demented)	Accuracy	ROC-AUC
Baseline Model	0.73	0.81	0.77	0.77	0.68	0.72	0.75	0.8
Model with Interaction Features	0.82	0.84	0.83	0.82	0.79	0.81	0.82	0.9
Expert System (Baseline)	0.78	0.84	0.81	0.81	0.74	0.77	0.79	-
Expert System (Interaction)	0.9	0.97	0.94	0.97	0.88	0.92	0.93	-

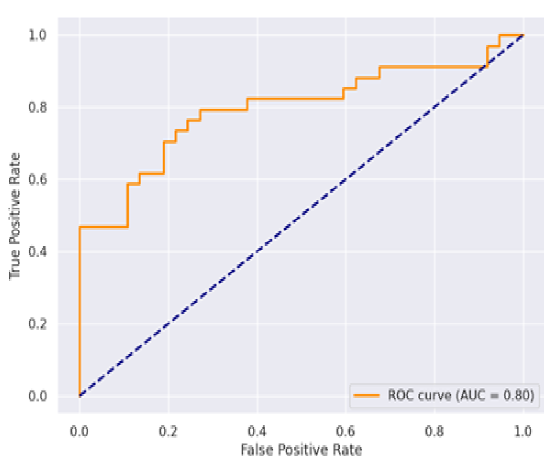

Figure. 3. ROC curve baseline model (before feature interaction) distribution of mini mental state examination of people with respect to their age is represented in Figure. 4, the figure show that demented people are concentrated between the age of 70 and 90; while figure 5 which illustrate how the whole brain volume decreases with age. The cognitive assessment i.e. mini mental state examination carried out is illustrated in Figure 4, it represents the proportion as affected by the three groups.

Also, figure 4 shows large numbers of people converted and free from demented as a result of early screening and diagnosis, while figure 5 illustrates Normalized whole Brain Volume with respect to Age.

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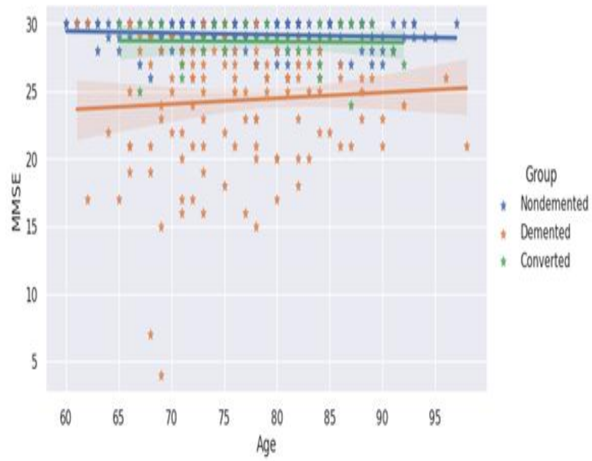

Figure 4. Scatter plot of Age vs MMSE

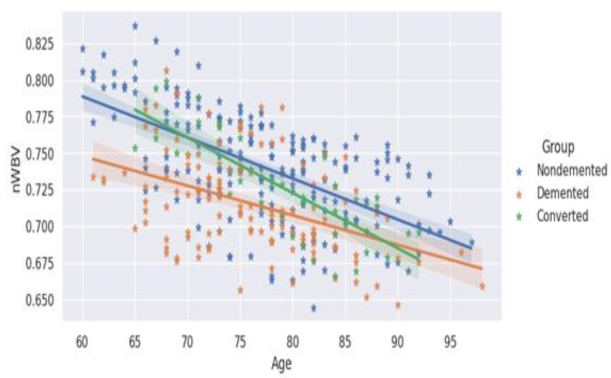

Figure 5. Scatter plot of Age vs nWBV

Conclusion

To tackle the increasing challenge of detecting dementia quickly and accurately, a practical way to tackle the growing challenge of detecting dementia is provided by creating a knowledge-driven expert system for early dementia screening and diagnosis. This not only improve the accuracy of diagnosis but also cuts down the delays often seen with traditional methods, giving patients the chance to get timely treatment and better care. In the end, the system brings together medical knowledge and modern technology, opening the door to faster, more accessible, and more reliable dementia diagnosis in hospitals as well as in remote areas.

This study recommends an enhancement with machine learning and a comprehensive knowledge-based expansion. Although, rule-based systems provide clear decision logic, combining them with machine learning techniques could improve adaptability and accuracy as more patient data becomes available. To keep the system up-to-date and reliable, it is recommended to update the knowledge base, which should include new clinical research findings and guidelines on dementia diagnosis.

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