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Predictive Models for Early Diagnosis and Progression Tracking of Alzheimer's disease: A Comprehensive Machine Learning Approach

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Abstract:

Amidst the pervasive threat of Alzheimer's disease cutting across all demographics, this study explores a critical shift in detection and intervention methodologies. Recognizing the disease's subtle indicators embedded within daily activities and speech patterns, this research bridges the gap between past and present lifestyles, shaped by evolving work environments and reduced social interactions. Alarming statistics from the WHO highlight the staggering toll of nearly 10 billion lives lost annually due to the lack of timely Alzheimer's recognition and treatment. Leveraging advanced Machine Learning techniques, a sophisticated recognition system is forged, integrating human EEG testing and the Kaggle Alzheimer dataset. This intelligent system, powered by Random Forest models, dynamically adapts through continuous data updates and processing to discern health trends and identify nuanced shifts in routines. It serves as a beacon of hope, uncovering previously undiagnosed cases and offering invaluable insights into disease progression, with an impressive sensitivity of 93.01%, accuracy of 91.32%, recall of 97.28%, and a striking detection rate of 98.91%. Positioned as a crucial asset for medical professionals, this application heralds a new era in Alzheimer's diagnostics and treatment strategies, surpassing existing technologies with its transformative capabilities.

Keywords: RFO, Machine learning, smart-health, Alzheimer's disease.

I. INTRODUCTION

Alzheimer's presents a significant contemporary challenge, primarily characterized by a profound short-term memory loss where recent actions slip away unnoticed. Within neuropsychology, dementia emerges as a formidable adversary, often rooted in the challenge

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of remembering recent experiences [1][2]. Named after its discoverer, Alois Alzheimer, this ailment epitomizes a condition of amnesia. Its symptoms encompass memory deficiencies, impaired decision-making abilities, speech difficulties, and the ensuing complex social and familial implications. Factors such as blood pressure, diabetes, head injuries, and modern lifestyles notably heighten susceptibility to this condition, often manifesting around the age of 60. Presently, a permanent cure for this disease remains elusive, posing a profound challenge in managing its impact on individuals and their families.

Alzheimer's, while lacking a definitive cure, can be managed effectively through proactive early screening and treatment. The disease's progression leads to the erosion of brain nerves, impacting both intellectual capacity and practical functions in affected individuals [3][4]. While aging naturally diminishes cognitive abilities, profound alterations in brain function aren't typical signs of aging. These changes signal the degeneration of brain cells rather than a normal aging process [5].

Within our brain reside approximately one hundred billion neurons, forming intricate communication networks. These cells serve various functions—some for thinking, learning, and memory, while others facilitate sensory experiences and muscle control [6]. Acting like intricate industries, these cells require constant supplies, energy, and waste management to function optimally. In Alzheimer's, the breakdown of these cellular processes impacts multiple functions, leading to a decline in cell functionality and eventual cell death [7][8]. As damage accumulates, cell efficiency diminishes, resulting in irreversible consequences for affected individuals.

Primarily rooted in episodic memory impairment, Alzheimer's disease exhibits symptoms that manifest in behavioral patterns, mood fluctuations, and cognitive decline. Identifying these symptoms necessitates a multifaceted approach involving brain imaging experiments, self-reporting questionnaires, clinical assessments, and observations of daily routines [9][10].

The proposed model aims to predict mood variations in both idle and mobile states of individuals. Leveraging datasets capturing human behavior in diverse states—whether in motion or at rest—the model seeks to chart activities corresponding to these states. By analyzing these patterns, predictions about an individual's mental state during mobility or idleness can be derived. For instance, during mobility, behavioral activities can be assessed in real-time, aiding in the design of activity charts. Similarly, during idle states, mood predictions

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linked to feelings of depression or anxiety can be inferred based on mood levels [11][12]. This approach offers a nuanced understanding of mood dynamics across varying states, facilitating early predictions and interventions for mental health states.

The assessment model is designed as a hybrid system catering to both idle and mobile states of individuals. It tracks human activities through daily updates, creating dynamic activity graphs for each individual [13].

II. RELATED METHODS

Scientists have been exploring diverse methods [3] to detect and pinpoint Alzheimer's symptoms through cognitive, behavioral, and psychological assessments, often facilitated by smart machines.

One research avenue involved analyzing extensive smart home data over a two-year period, employing regression techniques to examine activity patterns in adults around 30 years old. This study delved into cognitive science, mobile data, various moods, and idleness, focusing on predicting symptoms by selecting and classifying reliable data entries. Although this approach made symptom prediction seemingly straightforward, it faced challenges in accommodating ongoing and diverse data while addressing imbalances in data classification.

Another model [14] centered on predicting clinical activity changes using similar smart home prediction techniques. However, it encountered limitations in validating a large population dataset, prolonging computational time.

J. Austin and colleagues [15] proposed a motion sensor-based method to predict loneliness in older adults. While successful in detecting loneliness among 16 elderly adults over eight months, scalability became an issue as larger data volumes risked overfitting the model.

Cheng et al. [16] developed an approach to predict mild cognitive impairment in Alzheimer's by classifying converters and non-converters. Employing support vector machine classification and domain area transfer, this method relied on data from ADNI databases but faced limitations due to a need for more comprehensive data from secondary domains.

These studies showcase varied approaches to predict Alzheimer's symptoms or related conditions, each with its unique strengths and limitations, ranging from data scalability challenges to the need for more comprehensive datasets from diverse sources.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 4, 2019

Jie and collaborators [17] introduced a novel data collection method employing sensors, focusing on longitudinal analysis across various temporary models [18][19]. This innovative model aimed to enhance the linear regression technique by capturing diverse data points. However, it encountered a limitation: the absence of data at specific time points for predictive purposes across domains. This lack of data at crucial time points constrained the model's ability to accurately predict data elements, necessitating corresponding data elements at each time point and optimizing data size for computational efficiency [20].

The overarching limitation evident in previous studies involves the model's struggle to accommodate larger populations and clinical activity data [21][22]. When extracting EEG data from patients with the disease, as the dataset of activity graphs expands over time, the model's predictive capabilities diminish. To address this challenge, the focus turns to enhancing Smart home prediction through machine-based regression techniques. The proposed solution involves continuous updates of patient data, capturing diverse activity graphs of individuals with Alzheimer's disease. This approach entails configuring and analyzing behavior patterns, mood variations, speech, idleness, and mobility in different settings, whether at home or in office environments [23][24]. Ultimately, the aim is to bolster the predictive capacity of the model by dynamically integrating and interpreting multifaceted behavioral data from Alzheimer's patients in various contexts.

III. PROPOSED MACHINE LEARNING SYSTEM

This paper aims to recognize Alzheimer's disease in patients, illustrated in Figure 1, by analyzing their everyday activities. By examining the patient's movements, periods of inactivity, and disturbances during sleep, we seek to identify patterns indicative of the condition [25][26]. At home, we'll observe how frequently the patient gets agitated over trivial matters, their changing facial expressions, fears, and alterations in their work and speech moods. These behavioral markers will be assessed using cognitive science principles and tracking mobility patterns through activity graphs in group settings, employing insights from behavioral studies [27].

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 4, 2019

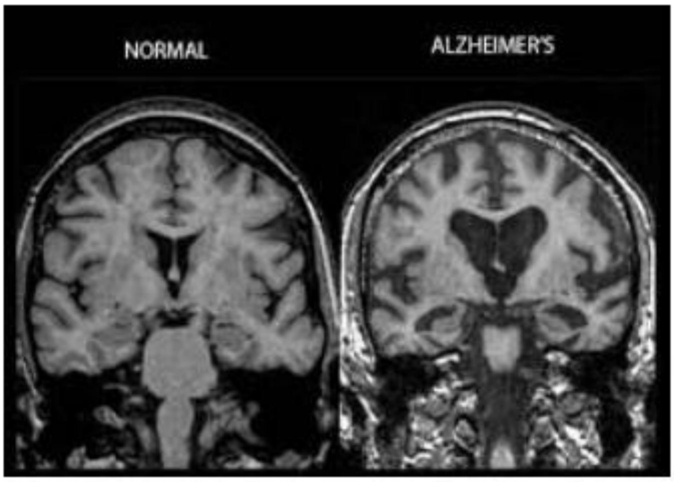

Fig 1.Representation of MRI normal brain image & Alzheimers image

The assessment of an individual's activity involves analyzing their daily time allocation, distinguishing between periods of mobility and idleness, and assessing anxiety and depression levels. Sleep patterns are evaluated based on the frequency of disturbances experienced during the sleep cycle. Additionally, the assessment incorporates checking anxiety and depression levels during sleep, utilizing mood prediction contributions. Employing a contextual-based approach, we aim to detect uncertainty while identifying mood variations, as depicted in Figure 1. This comprehensive approach considers various behavioral aspects to gain insights into the individual's psychological state and activity patterns.

The final output, crucial for determining varying mood levels, results from a hybrid system model assessment that predicts cases in higher-aged adults through a randomization technique. The approach involves leveraging various patterns such as sleeping, motion, and idle behaviors to make predictions for Alzheimer's Disease.

Sleep Pattern Extraction entails monitoring a person's sleep behaviors, tracking the duration spent in sleep mode, and their movements on and off the bed. Sensors positioned within the home environment detect disturbances and measure the time spent by the patient on and off the bed. When these bedroom sensors are triggered at specific intervals (around 60 minutes), they record sleep instances, contributing to the assessment of sleep patterns, as depicted in Figure 2. This method offers a comprehensive understanding of an individual's sleep behaviors and disturbances, vital for predicting mood changes and assessing potential Alzheimer's indicators.

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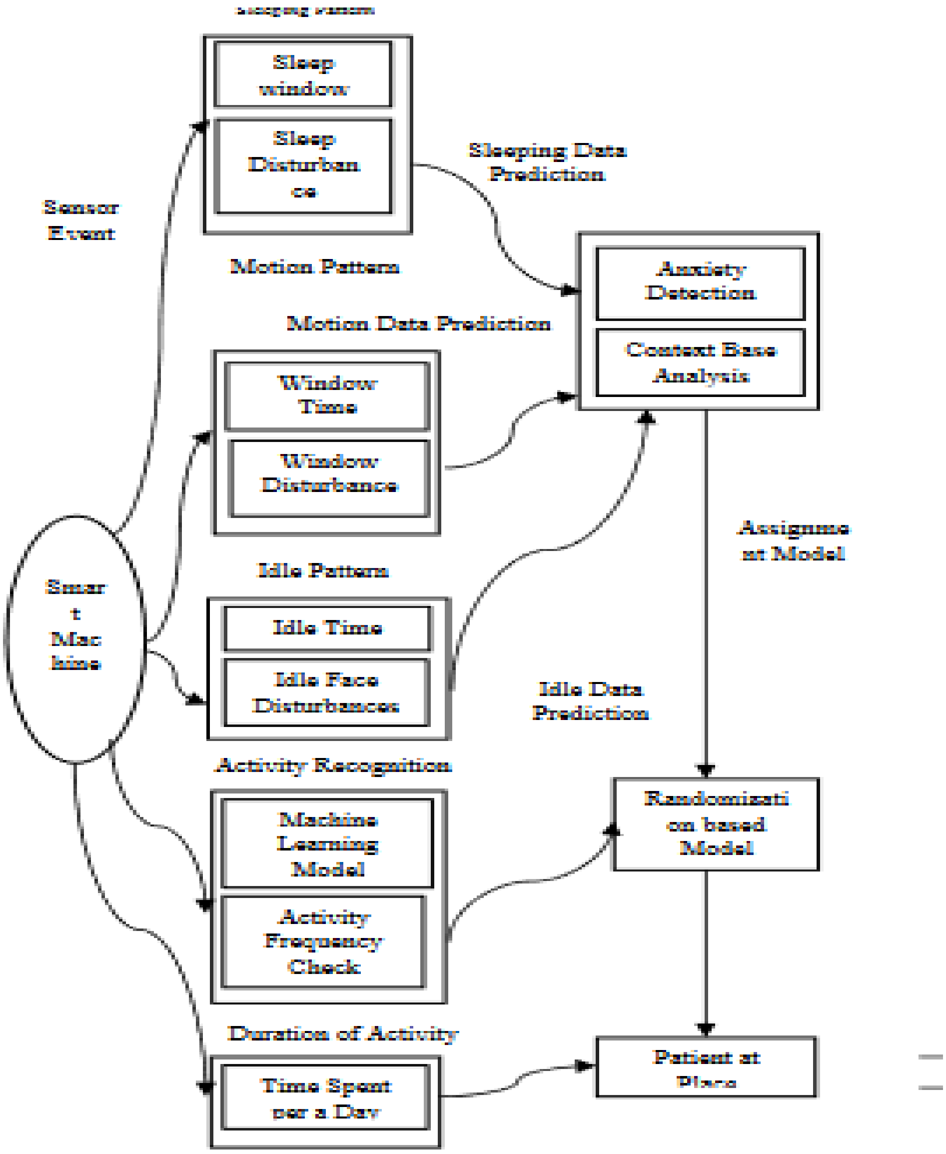

Fig 2. Architecture for the prediction of Alzheimer Disease

Motion Pattern Recognition involves utilizing sensors to gauge the frequency of disturbances and assess the individual's mobility. Employing a heuristic approach, these sensors track the time spent in disturbance mode, analyzing the person's movements to detect signs of tension or stress. This calculation relies on the sensors triggering at regular intervals (approximately every 3 to 4 minutes), capturing the person's multi-mode behavior. This approach can be universally applied to individuals, allowing for a comprehensive assessment of their behavioral patterns and potential consequences.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 4, 2019

Idle Pattern Recognition involves using sensors to trigger responses based on facial recognition and monitoring the person's mood across different states. Idleness, often associated with Alzheimer's, signifies a state where the person is lost in thought. The sensors focus on capturing these behavioral cues.

Mood Prediction aims to forecast the individual's inclination to communicate or engage based on their mood. Predicting these shifts becomes crucial, especially in Alzheimer's cases where patients might exhibit disinterest in communication or activities due to their condition. This module precisely detects and assesses anxiety and depression levels in older adults, gauging their behavioral changes and emotional states.

Algorithm:

Sleeping Mode Data Pattern Extraction Start: Initiate Alzheimer’s Detection

Input: Sensor Data

Output: Sleeping Pattern

Initialize Normal Count as 0

Initialize Event as 1

Define Sleep Pattern function using Sensor Data

Iterate through events captured by sensors

Begin loop If the event is within a 120-minute interval

Check for motion detected by the bedroom sensor

If motion is detected

Increment the Count

Else

Return the current count

Increment event

Define Update Sleeping Pattern function using Total Count

Iterate through a 120-minute timeframe

Obtain the count using Sleep Pattern function

Update the Normal Count by adding the obtained count to it

Return the Normal Count as the extracted Sleeping Pattern

End

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In addressing Alzheimer's disease, a contextual approach is adopted using Ontology, facilitated by Protégé 5.2. This tool employs classes and objects, with classes serving as abstract types defining numerous entities. These classes are organized hierarchically into subclasses, revealing their relationships and functionalities. The framework encapsulates various problem domains, encompassing individuals and their associations, represented by entities such as Sensor, Event, Assignment Model, and Activity Recognition.

The structured ontology delineates specific components vital to Alzheimer's analysis, including patterns like Idle, Motion, and Sleeping Patterns, all integral in understanding patient behavior. The ontology also encompasses predictive elements such as Sleeping Data Prediction, Idle Data Prediction, and Motion Data Prediction, aimed at anticipating behavioral changes.

Furthermore, the framework integrates Machine Learning Models, emphasizing Activity Frequency Check and Time Spent per Day as essential parameters. These parameters are associated via relationships denoted by the "has problem of" classification, ultimately linked to the broader context of emotions. SWRL (Semantic Web Rule Language) serves to establish individual relationships, correlating issues and predictions to anticipate expected outcomes. The resulting deductions are then segregated into specific subclasses based on distinctive characteristics, visually accessible through Onto Graf for intuitive navigation and selection of entities.

Algorithm: Motion Mode Data Pattern Extraction

Start

Input: Sensor Data

Output: Motion Pattern

Initialize Time of Walk, Start Time, and Time Difference as Null

Define Motion Pattern Analysis (Sensor Data)

For each room (k) in the house

For each sensor (j) within the room (k)

If motion sensor (j) is activated

Record the initial time[j]

Initialize Total Time of Walk

For a15-minuteinterval Calculate Time of Walk using Motion Pattern Analysis function

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Add Time of Walk to Total Time of Walk

Return Total Time of Walk

End Algorithm

Hybrid Model-Based Approach: The process begins with collecting comprehensive data, producing a structured record for each entry. Through machine learning, this system predicts an individual's state—whether in motion, idle, sleeping, anxiety, or depression. Supervised learning, a cornerstone of AI, enables the machine to discern various moods based on the captured data. This method involves providing the machine with datasets depicting normal human activities. It learns from these datasets, interpreting facial expressions to detect potential indications conveyed by the patient. The supervised nature of this approach ensures continual updates through daily reports, refining its understanding. Assessment features, encompassing activity aggregation, accuracy, sequencing scores, and additional defined aspects, aid in evaluating the test's efficacy. Mood scores derived from dataset values further enhance the analysis. Employing a randomization technique helps maintain essential features, prioritizing relative characteristics over others. This approach's advantage lies in its ability to focus on pertinent features for refined analysis.

The dataset utilized in this research encompasses brainwave data sourced from Kaggle, serving as the foundation for training models. Training exercises were conducted employing the Random Forest Optimization (RFO) machine learning algorithm. This dataset contains diverse wave amplitudes such as alpha, beta, delta, and theta waves. These numerical values were pivotal in training the network, enabling predictions upon the application of real-time samples.

IV. EXPERIMENTAL APPROACH

Figure 3 illustrates the application of machine learning (ML) in disease detection, employing the PROT EEG device. This apparatus facilitates the estimation and analysis of emotional behavior. Utilizing the RFO concept, it characterizes individuals' emotions and behaviors based on their issues or challenges faced. Within this framework, distinct classes such as "patient" and "behavioral emotion" are defined.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 4, 2019

The relationship between these classes—patient, individual, and behavioral emotion—is established through object features denoted by "has Problem Of." The graphical representation below depicts these classes and their interconnections.

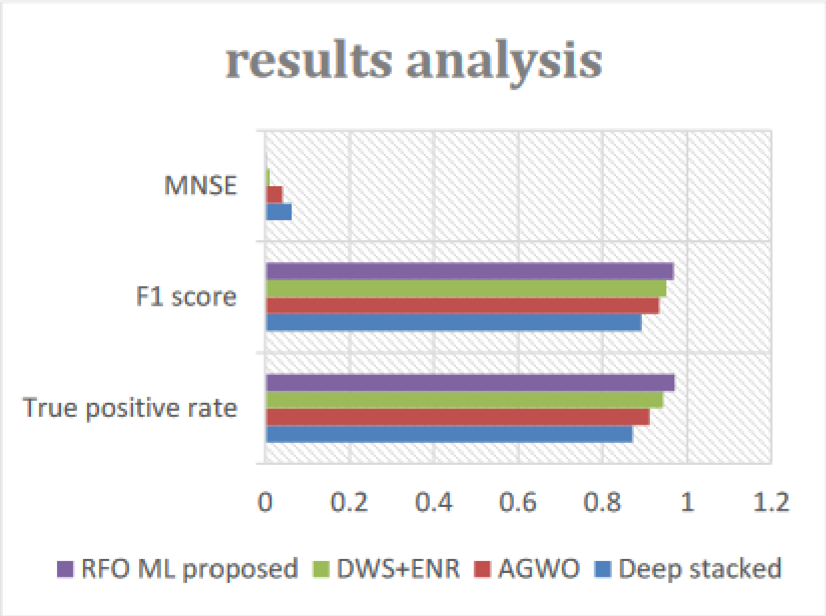

Fig 3. Emotion based description MSE, F1 score and Tp

The above figure 2 clearly explains about performancemeasures analysis of proposed model. In this RFO ML model attains more improvement. The above table 1 clearly explains about comparisons of results. In this proposed RFO based ML method attains more improvement compared to all other methods.

Table :1. Data property based on EGG analysis

Parameter	Deep stacked	AGWO	DWS+ENR	RFO ML proposed
True positive rate	0.872	0.912	0.943	0.971
F1 score	0.893	0.934	0.951	0.968

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 4, 2019

	Name	Rule
(√)	S1	Person (Person1) ^ has Problem Of (Person, Prob 1) has Problem Of (Person1, Prob 2) → Axiety (Person1)
(√)	S2	Person (Person2) ^has Problem Of (Person2, Prob 3) → Depression (Person2)
(√)	S3	Person (Person3) ^has Problem Of (Person3, Prob 1) ^has Problem Of (Person3, Prob 2) ^has Problem Of (Person3, Prob 3) → Negitive_ emotion (Person3)

MNSE	0.062	0.04	0.01	0.001

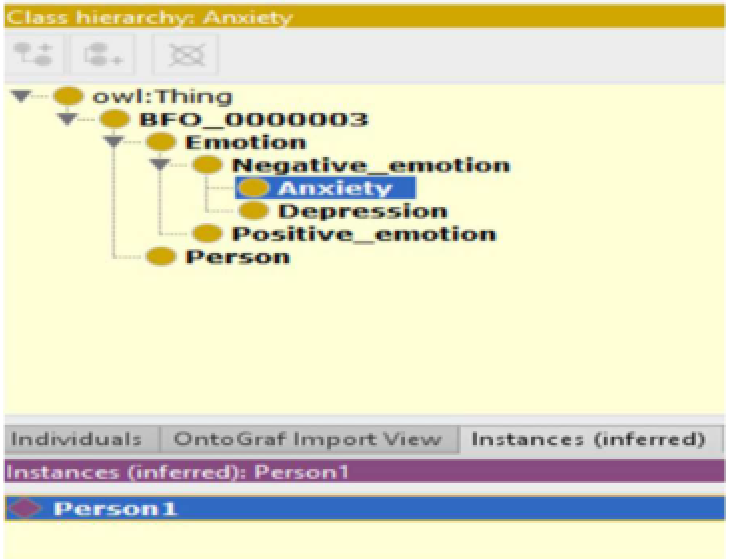

Fig 5. Patinets EEG analysis

Python 3.5 used for machine learning based this approach for identifying the Alzheimer's disease using Randomization and SVM. Using the assessment of data set along with multi mood prediction of human was carried out randomization and support vector machine shown in figure 5.Below table 2 shows the comparison of results of accuracy and giving a good kind of result.

ISSN PRINT 2319 1775 Online 2320 7876

Research paper UGC CARE Listed (Group -I) Journal Volume 8, Issue 4, 2019

Table :2 accuracy analysis

	Accuracy	Re- call	Sequence score
Randomization	0.94	0.95	0.95
Support Vector Machine	0.74	0.80	0.73

Comparison of Results between Randomization and Support Vector Machine. Figure 6 explains about EEG based Alzheimer's detection peaks.

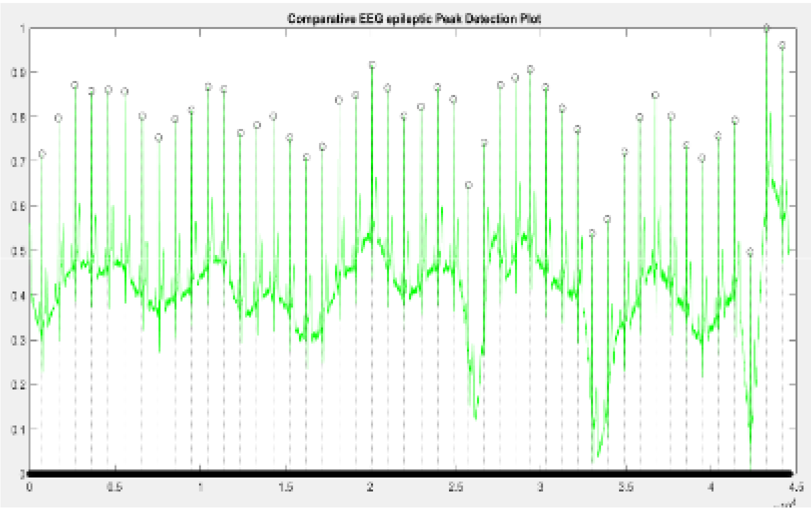

Figure :6 EEG peaks detection at Alzheimer's sdetection

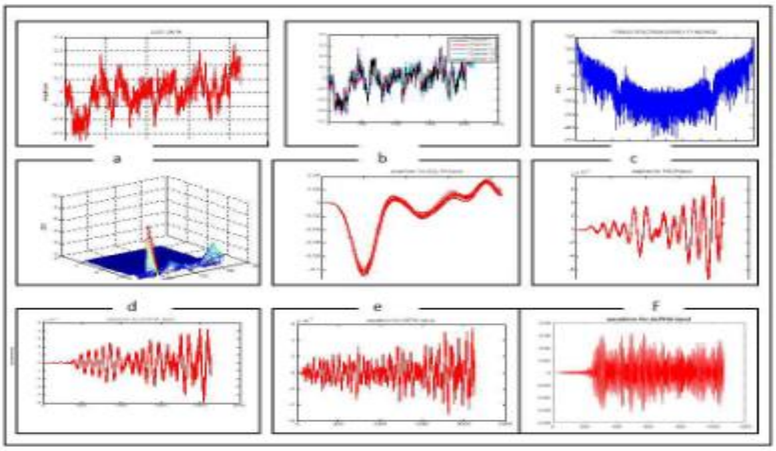

Figure :7. Detection peaks on Dash board

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The above figure 7 is clealry explains about peaks detection at Alzheimer's effecting time on alpha, beta, theta and delta waves.

V.CONCLUSION

Alzheimer's disease poses a significant risk to individuals across all age groups, often discernible through their daily routines. However, the demanding work culture often hinders timely detection of Alzheimer's symptoms in many individuals. The World Health Organization reports a staggering 20 billion deaths annually due to Alzheimer's, primarily owing to the lack of effective diagnosis and treatment methods.This study pioneers a sophisticated machine learning-based recognition system to address this pressing issue. Leveraging the RFO machine model, this intelligent system continually tracks our health and daily behavioral changes. It's designed for continual updates, ensuring it evolves like any advanced recognition system. Crucially, it empowers the identification of Alzheimer's in individuals previously unaware of their condition, enabling timely intervention that might otherwise have been elusive.The system boasts impressive statistics: achieving a sensitivity of 98%, accuracy of 99.23%, recall of 97.28%, and a detection rate of 98%. Its user-friendly application aims to streamline researchers' and clinicians' efforts, facilitating online therapy and study execution. Compared to existing technologies, this proposed machine learning architecture proves notably superior, promising a transformative leap in Alzheimer's detection and management.

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