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Sensor based EEG Signal based Dementia Disease detection using Artificial Intelligence

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ABSTRACT

Even though it's still unclear how anticholinergic medications and dementia are related, dementia is one of the biggest global health issues. The current study's goal was to conduct a thorough review and meta-analysis of any potential predictive implications anticholinergic medications may have on dementia risk. Dementia has been linked to both low and high anticholinergic medication loading. Additionally, medications and the risk of dementia from anticholinergics were related. Among the anticholinergic drug groups, antiparkinsonian, urological, and antidepressant medications raised the risk for dementia. However, cardiovascular and gastrointestinal medications may have preventive effects. These results highlight the significance of anticholinergic medications as a potentially modifiable dementia risk factor and outline the most effective course of treatment. In this work, Work implemented AI Based algorithms of random forest and XG boost algorithm for predicting sleep disorder and Dementia with a help of sensor.

1. INTRODUCTION

Throughout both dementia illnesses and healthy aging are symptoms of sleep problems. Alzheimer's disease (AD) symptoms include sleep apnea and sundowning, dementia with Lewy bodies (DLB), and persons with DLB frequently exhibit more abnormalities of movement control during sleep. Although though the phenomena of sundowning is not well understood, it frequently manifests as the evening start of disorientation or agitation in dementia patients. The majority of cognitively challenged people, such as those with AD, DLB, and vascular dementia (VD), have irregular sleep-wake patterns. Temporally chaotic and irregular sleeping and waking patterns make up an irregular sleep-wake pattern. Over the course of a day, sleep is divided into multiple brief segments, and the total amount of sleep per day might vary.

To address this issue, a technology that can detect dementia in everyday life (and replace question-naries) is absolutely necessary. Nikamalfard proposed a method based on sleep patterns deduced from bio- vibration data obtained from a mattress sensor for identifying AD, which accounts for 40% of dementia cases. In contrast to non-AD persons, dementia patients usually exhibit increased waking time during sleep and early morning awakenings as a result of shallow sleep, which is how this method precisely assesses AD. Because of this, AD can be identified just by going to bed.

The key instrument for the automatic and semi-automatic diagnosis of dementia disorders in this study's apps is EEG data. The paper is structured as follows: Methods II describes numerous processing and classification techniques for EEG clinical applications. Talks and information analysis are also included in Results III. Conclusions IV provides a summary of the article's contributions and suggestions for additional studies on EEG systems for the automatic diagnosis of dementia disorders with a help of sensor.

AD is the most common type of dementia, accounting for 70% to 80% of cases. A decline in memory, reasoning, planning, comprehending, calculating, learning capacity, language, and judgment are some of its permanent neurological signs. Early detection is crucial because it enables prompt and effective treatment. Preventing the deterioration of higher cognitive skills and the emergence of behavioral issues requires early brain development. It enhances the affected person's and their loved ones' quality of life. Using EEG data, it is possible to recognize, monitor, and even anticipate conditions including dementia, brain tumors, sleep apnea, non-epileptic diseases, encephalopathies, and infections of the central nervous system. One illustration is the central nervous system.

In a group of neurons with a particular spatial distribution Ionic currents both within and outside of neurons create voltage oscillations, which are recorded by the EEG. The EEG records post-synaptic events, and the information it provides helps us understand how the brain functions and dynamics. Neurons transmit and receive information through electrochemical sites called synapses. When recording EEG, anomalies are represented as paroxysms, which are waveforms that do not match the nature of the signals. These waveforms are used to identify abnormalities.

2. RELATED WORK

The extreme learning machine (ELM) approach was used by [1] for categorization. 65 seizure recordings were used to test the classifier after it had been trained on 21 recordings of seizures. The system's recommended course of action had a mean sensitivity, specificity, and accuracy score of 91.92 percent, 94.89 percent, and 94.9 percent, respectively [2].A feature in this paradigm can be any numerical value, and features are crucial for determining classification performance. The five frequency bands that are pertinent to this investigation are the beta band (12–30 hertz), gamma band (30–50 hertz), alpha band (4–8 hertz), and theta band (4–8 hertz). The lower delta band (0-2 Hz) frequencies would only be used in the 2-4 Hz range in this experiment. In the previous round, the sections had been filtered out. In order to eliminate higher frequency information, the framework would also pass all data through a 10th-order low pass Butterworth filter with a cut-off frequency of 50 Hz before features are extracted. component frequencies. Because muscular activity artifacts, which typically have high frequencies up to 300 Hz, can contaminate EEG signals, lowpass filtering was applied. Without finishing this process, it would be difficult to determine whether the effect observed in the high-frequency spectrum is neuronal or muscular in origin.

The system's acquisition stage is crucial in the suggested strategy since it gathers data that is used to identify EEG patterns, also known as biomarkers. A result of inaccurate measurements is a change in the information's dependability, quality, and repeatability, as well as the identification of false patterns or the absence of any patterns at all. It is essential to have a fundamental knowledge of metrology and to apply this knowledge to the project in order to evaluate the veracity of the database being used [3].

Different modes of comparison [4] each article reports sample frequencies from 128 Hz to 1024 Hz, with the maximum repeatability being in the range between 128 and 256 Hz. One of the essential components in identifying which frequency is best for a specific application is the Nyquist theorem. The sampling theorem, also known as the possibility theorem, contends that if a band-limited signal is sampled at a rate greater than twice its bandwidth, it is mathematically feasible to reconstruct a continuous periodic baseband signal from the samples of the signal. The Nyquist theorem can be used to calculate the frequency range's top limit, and this corresponds to 256 Hz being one of the most common frequencies in the normal human body EEG of humans, which shows activity in a frequency range from 1 Hz to 100 Hz with a help of sensor [5] .

Memory loss and personality changes were two of the key Creutzfeldt-Jakob disease symptoms that D. Reddy et al. tried to identify. EEG, MRI, and cerebrospinal fluid analysis are just a few of the methods used to diagnose the disease. The findings show that only within the first 8 to 12 weeks following the beginning of symptoms can excessively frequent slow and sharp waves be seen on the EEG. The EEG alone provided 66% sensitivity and 74.5% specificity. By combining the EEG with additional techniques, the sensitivity was raised to 97% with 100% specificity. This research project demonstrates how employing a variety of detecting approaches, gains of up to 20% can be achieved.

[6] Approximately 92% accuracy is required to distinguish patients with mild cognitive impairment from control cases, according to G. Fiscon et al. With 19 channels and a sampling rate of 256 Hz, they used a monopolar montage EEG. The FFT and the WT were used, and five layers of decomposition were taken into account. Daubechies mother wavelets and Symlets were employed. Combining the two signal processing methods of FFT and WT, which both examine signals in the frequency domain, results in efficiency levels greater than 90%.

Fast Fourier Transform (FFT) analysis of data in the frequency domain for EEG signals is a common practice [7]. Over 90% of the time, this method has been successful in identifying dementia illnesses. The FFT only requires O(nlog2 n) of calculation, as opposed to the DFT, a version of the FFT, which needs O(n2) of effort. A benefit of FFT is its computational process. It produces findings that are strikingly comparable to those from the DFT but with less reliance on processing power, efficiency, and speed.

Over Time-Frequency Representation (TFR), the Synchro Squeezing Transform (SST) is an adaptive, invertible transform that improves quality. Signals spanning the frequency spectrum can be analyzed, and it is noise-resistant. SST is a suitable choice for FT localisation since it concentrates energy content in a certain spectral band. The precise steps for installing this instrument as well as its high levels of reliability and efficacy in processing EEG signals have been documented in the literature [8].

Various types of traumatic brain injuries (TBI), minor to serious systemic diseases, or epilepsy in all its manifestations. The possibility of neurological disorders, including likely psychiatric illnesses that could result in mental deficiencies. Prior to any testing, each participant (patients and carers) signed a detailed consent form outlining the objectives, benefits, and risks of the study [9]. All of the patients also received neuroradiological scans to rule out the possibility of any other cerebral illnesses (such TBI or tumors) that might exhibit symptoms comparable to those of Alzheimer's disease. It is noteworthy to highlight that MCI patients did not receive clinical medicines such Unlike AD patients, who did not receive any medical care, anti-epileptic drugs, anti-psychotics, Memantine, cholinesterase inhibitors (ChEis), and anti-depressants were used. Suggested a strategy based on [10]. The strategy put forth by Fiscon, Giulia, et al. employed data mining as a supervised machine learning method. They used time-frequency changes to preprocess the EEG signal. Despite their limitations, they discovered some good results. Poor methodology. The Fourier transform did not take into account temporal aspects, just providing spectrum information about the signal, therefore their dataset was not significantly enriched. Furthermore, their precision wasn't particularly good.

To early detect Alzheimer's disease, Liu, Siqi, and associates developed a deep learning architecture. The bottleneck was eliminated using softmax output layer and stacked auto-encoders. They claimed that, in contrast to earlier paradigms, this paradigm would allow for the simultaneous analysis of many classes. They also asserted that less labeled training data could be used using their method. Their accuracy wasn't very impressive, though, coming in at only 87.76%. It should significantly improve things [11].

By looking at gene coding data in applied hybrid techniques, Xu, Lei, and colleagues were able to diagnose Alzheimer's disease [12]. The information that was extracted and classified for detection was done so using the k-skip-n-gram model. They argued that their strategy will be less expensive than MRI-based detection. It had an accuracy percentage of 85.50% using its low-cost strategy.

Methods of hybridization were applied [13]. An SVM kernel-based computer-aided diagnostic (CAD) system was created by López, M. M., et al. using kernel principal component analysis (PCA) and linear discriminant analysis (LDA). After removing the data from the image, they applied SVM as a classifier. They only had a small amount of data to work with, and their precision was terribly insufficient.

In their supervised machine learning method, Trambaiolli, Lucas R., et al. used a classifier called the Support Vector Machine (SVM). Using EEG data, they distinguished between AD patients and healthy individuals in the population. The data were essentially categorized using the EEG signal's frequency pattern. Even so, boosting the accuracy parameter of the SVM can help [14]. They brought a mannequin. Entropy is a measure of information uncertainty that has the extended attribute of being dependent on the initial state of the source. Almost all systems react, regardless of the initial conditions. The EEG signal is non-extensive in a manner similar to this, and its higher level of uncertainty is related to the brain's higher level of entropy and chaotic nature. An incomplete The Tsallis entropy, which was introduced by Constantino Tsallis [15], is a generalization of the traditional Boltzmann-Gibbs entropy (BGS).

AI methods improve the performance of dementia screening exams by increasing the number of features that can be extracted from a single test, reducing errors brought about by subjective assessments, and elevating the automation of dementia screening to a new degree. AI-based computerized cognitive tests increase discrimination sensitivity and specificity by approximately 5% and 4%, respectively, when compared to traditional cognitive tests. Combining both linguistic and acoustic features yields the best results, with an accuracy of about 96%, in speech, conversation, and language tests. Two possible future directions that may help distinguish dementia from normal aging are movement tests and smart environment settings that capture everyday behaviours with a help of sensor.

3. PROPOSED WORK

According to Fig. 1, the suggested strategy is broken down into four key steps. EEG data must first be acquired under exact conditions, and then each signal must be cleaned to eliminate any biological and environmental noise and prepare for the next stage. To give a few examples, sinusoidal frequencies are produced by electrical fluctuations, electronic devices, fluorescent lighting, and other outside noise sources like undesirable frequency (more than 65 Hz). The EEG signal was cleaned of outside noise using the bandpass filter and frequency-domain regression technique of the CleanLine application. Eye blink, head jerk, and ECG signals are a few examples of biological noise that can be reduced using the EEGLAB toolbox's independent component analysis (ICA) technique. Informationmax Logistics makes use of the ICA algorithm. White noise in the signal has been removed by wave-based denoising. The signal is compressed into a sparse collection of large wavelet coefficients using the wavelet transform. Small wavelet coefficients are often regarded as noise, therefore removing them won't have a negative impact on the signal's quality. The signal is subsequently reconstructed using the inverse wavelet transform once those coefficients have been eliminated. By combining ICA and wavelet denoising, artifacts in an EEG signal can be eliminated. In the second stage, continuous data is divided into four categories: EO, EC, FTT, and CPT.

Traditionally, Fourier spectrum analysis has been used for signal analysis. Wavelet transform is yet another widely used method. These strategies often work well and have minimal downsides. The main problem with these methods is that they don't react to changing data. Compared to the Fourier and Wavelet transforms, the empirical mode decomposition (EMD) method was created by Norden Huang et al. in 1998. IFD is better than EMD, which was just proposed. IFD is more stable than EMD in the presence of a perturbed non-stationary signal, such as the EEG. The signal is divided into six intrinsic mode functions (IMF) in the third phase, which applies IFD to the segmented EEG data. The sixth IMF was disregarded because it was lacking in information. Four Each IMF contains additional properties, such as PSD, Var, FD.

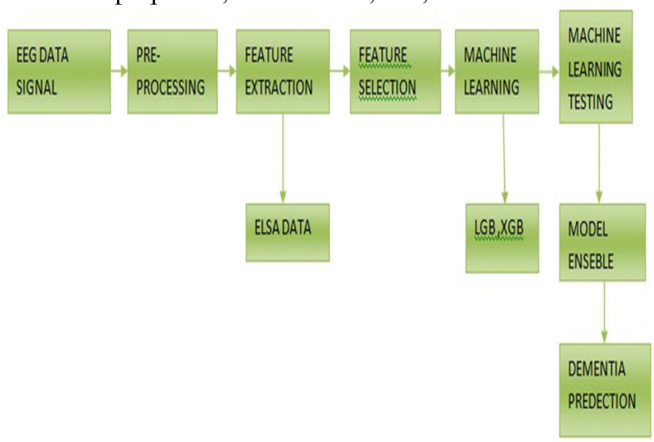

Figure 1. General flowchart steps of the proposed model.

The standard methods for machine learning-based EEG analysis the following: preprocessing, feature extraction, feature selection, model training, and model testing. The proper classification of the data sets using machine learning in general is shown. Signal acquisition is the initial stage. This is essentially unfiltered raw data. Pre-processing includes the inclusion of outliers and other erratic data points. The range of data point groups and their associated properties are established by feature extraction. The process of choosing the essential classifiers to test as part of the machine learning approach's training is known as feature selection. The categorization method is improved by machine learning training, which makes use of training data sets with or without known outputs processing of the actual test with a help of sensor.

For feature selection, regression, and classification issues, the popular machine learning technique Random Forest is used. In order to produce predictions that are more accurate, it uses an ensemble learning technique that combines several decision trees.

Work can use the Random Forest model to filter features and get their correlation with classification. Due to the inherent randomness of Random Forest, the model may give a different weight of importance each time. However, when training the model for several runs, in each run, Work select a certain number of characteristics and retain the intersection between the new feature set and the set of features selected in other runs. After a certain number of runs, Work can finally get a certain amount of features. Then, Work calculate the out-of-bag error rate corresponding to these features and use the feature set with the lowest out-of-bag error rate as the last selected feature set.Random Forest is a method can be used to evaluate huge datasets and spot trends in sleep disorders and dementia that may be challenging to spot using conventional statistical techniques. For instance, using a patient's demographic data, medical history, and sleeping patterns, the Random Forest algorithm can be used to estimate the likelihood that a patient would develop sleep apnea or other sleep disorders.

The probability that someone would develop Alzheimer's disease can also be predicted using the Random Forest algorithm. Using a range of factors, such as age, genetic markers, the results of cognitive tests, and other health indicators. Additionally, it can be used to identify the major dementia risk factors, which will help in the design of effective prevention and treatment plans. In general, the Random Forest algorithm is an effective tool that may be used to assess difficult datasets and produce accurate forecasts in the domains.

It's crucial to remember that the caliber and volume of data utilized to train a random forest model for identifying dementia are crucial, as well as the specific features and parameters selected, will all have an impact on the model's accuracy. The selection, preparation, and tuning of your data, as well as the parameters of the model, are essential for achieving peak performance. The accuracy of dementia diagnosis may be evaluated and relevant risk factors can be found using a well-built and trained random forest model, Work conclude. It ought to be utilized along with clinical examination and other diagnostic techniques to guarantee a precise and trustworthy diagnosis.

The decision tree paradigm is the foundation of the RF algorithm. The RF technique and the decision tree approach are extremely similar. After the data has been preprocessed, a small sample of randomly selected samples is taken from the provided dataset for the training phase. A decision tree is built for each instance. After construction, the arbitrary backwoods system wasn't immediately modified. (En) Only a few boundary blends have been used with network search in conjunction with boundary mixes and 5-overlap cross-approval. These boundary blends comprise the number of trees in the hypothetical forests (n assessors), the number of features to take into account at each branching point, the levels of the tree, and the method for selecting tests to prepare each tree. To analyze the tree's features, the Gini model was used. Additionally, the model has been assessed.

On several subsets of the dataset (processed sensor activations and survey indices), the main analysis was carried out using ML algorithms. Regression forest and regression tree methodology were the two main approaches looked at. This type of analysis' major objective was to identify a multivariate pattern in the sensor data that might be used to predict the users' state of health. User input serves as the models' input, and their output are the responses from users.

The main motivation behind using the RT and RF techniques is the model's interpretability. One of the things the writers wanted to understand was the population's projected self-reported health state, as well as the logic and methodology that went into it. The RT makes it possible to learn a non-linear/complex decision boundary while maintaining interpretability and reasonable processing effort. Even though the RT typically refers to interpretability in terms that are intuitive, the size of the model—specifically, the number of nodes and the depth of the tree—determines how interpretable it is [16]. Work set the grid-search's maximum tree size (or maximum depth) to 10 in order to prevent abuse. Maximum 10 tests during a single estimation phase are needed for every regression rule. The clarity of Improvements are made to the method's discriminative power and efficiency.

Using an artificial dataset created by the RF method, it was shown to be effective at extracting discriminative information from a short dataset. The method's power is more specifically demonstrated by the usage of deep trees, which are randomly constructed from a sample of the data received through via the candidate from the best-performing subset of feature data, a node split is constructed via bootstrapping [17].

In actuality, the tree's size and the number of permitted splits were altered, and the RF approach was developed by choosing features from the observation and feature set (i.e., the number of features to be selected). Using grid search and layered cross-validation, the RT and RF hyper parameters contained in the training set were optimized. Despite losing interpretability, it is commonly known that the RF model performs better in generalization. The relevance of a feature in predicting the self-reported health condition was assessed in order to address this problem using the permutation of feature observations from out-of-bag [18].

The permutation strategy is a good choice when creating a very complicated model (i.e., a large number of ensemble RT) since it allows for the most discriminative properties to be captured. The permutation strategy states that permuting the feature's responses should change the model error. A feature determines the self-reported health status index. As a result, permuting the answers of an unimportant feature shouldn't materially change the model error. The permutation process offers a nearly impartial importance assessment, making it a more trustworthy way than others (like the Gini index). Instead, the significance of a feature in the RT model was determined by adding and then dividing the MSE changes for each split of the predictor that was considered with a help of sensor.

Both RT and RF show that a modest amount of computing was required during the training phase, even for a short tree. In comparison to black-box models like neural-network models, an RT frequently improves performance more quickly. Additionally, the chosen models—the RT and RF models—bested rivals (the linear SVM, the Gaussian SVM, and the Boosting method) in the resolution of this regression work [19].

Data relationships can be described using the independence test. This section introduces the two independence test methodologies used in this investigation. One popular technique for determining independence is the chi-square test, whose statistic is described as

$$X^2 = \frac{\sum (O_i - E_i)^2}{E_i} \tag{1}$$

Where O_i − Observed value and E_i − Expected Value

The relationship strength of the cross tabulations is measured by the Kendall correlation, which is defined as

$$\nabla = \frac{4S}{l(l-1)} - 1 \quad (2)$$

Interregional links were employed in this study as traits and as input into classifiers for further analysis. To gauge the Work employed the directed transfer function (DTF) to model the internal information flow of the brain. The argument for DTF is that sources may have information that can help us predicta better target for behavior. The multivariate autoregressive (MVAR) model, which statistically delineates the emergence and evolution of a signal, is the foundation upon which DTF is built. It is possible to describe the EEG signal from M channels at sampling moment n using the vector X(n)=(X1(S), X2(S),..., XM(n))T, where "T" stands for transposition. The following equations numerically represent a p-order MVAR model.:

$$X(n) = \sum_{K=1}^{Q} Bk\, y(P - K) + x(n) \quad (3)$$

A0′ =I (which denotes an identity matrix with dimensions of M by M) and Ak′ =Ak(k=1, 2,..., p) are used to represent frequency in Hertz (Hz), sampling frequency, and identity matrices, respectively. X(f) and E(f), respectively, are the frequency domain representations of X(n) and E(n). A transfer function is denoted by E(f). The information flow between channel j and channel i at frequency f is thus described as follows by DTF:

$$E(x)=f(x)\, H(x) \quad (4)$$

The element of matrix H(f) with index (i, j), and so on, is called Kij(f). A value of zero indicates that there is no information flow from channel j to channel i, while a value of 1 indicates that the activity at channel i is solely driven by the activity at channel j. DTF is expressed in the frequency domain and ranges from 0 to 1.

$$Htfij = |Kij\,(x)|/\sqrt{}\ \sum_{i=1}^{N} |Kij\ (x)|\text{^}2 \quad (5)$$

where ‖ gauges the size of a set and Pk,H reflects the percentage of samples in dataset H that are classified as the k-th class. The dimensionality is decreased when a decision tree is built by excluding the features with poor classification abilities.

$$S=\mathrm{fix}(\sqrt{h}\,) \quad (6)$$

The greatest integer that is less than the input value is returned by the integral function fix(), where.After carrying out the process N times using the collected samples and features, N basic classifiers are then produced, allowing for the creation of a standard RF model. Work introduce D = D1...DN to designate the set of all classifiers, and Di to represent the i-th decision tree. The classification accuracy of each base classifier is then determined using validation set Bvalidate, and the accuracy is used to determine the weight of the corresponding base classifier. The weight calculation equation is displayed as

$$Xi= Si' /S \quad (7)$$

where T′i represents the number of samples in Bvalidate that the i-th base classifier correctly classified, and T represents the size of Bvalidate.

$$Hi=|T| - \sum_{k=1}^{i} Ok \quad (8)$$

where Nk represents the number of features removed in the i-th iteration. This formula is used to assess the impact of each stage of evolution. The final WERF model is the output of Algorithm 1, which depicts the creation and evolution of the WERF model. Its inputs are the initial sample set B and feature set H.

$$Ta=\sum_{K=1}^{N} Ia\,\big(hk\,(x)\big)yk \quad (9)$$

where x stands for each sample from the test set and fk(x)1,+1 is the classification outcome produced for x by the k-th base classifier. The final categorization label for the samples in Btest will be chosen based on which label received the most votes.

4. PERFORMANCE ANALYSIS

First, the dataset was divided into two groups at random, one for training and the other for testing, with a 70:30 ratio. To create and improve the diagnosis models, the training data was subjected to 5-fold cross-validation, feature selection, and model optimization. Ultimately, the models were evaluated using the test data in order to determine the best diagnosis model with a help of sensor.

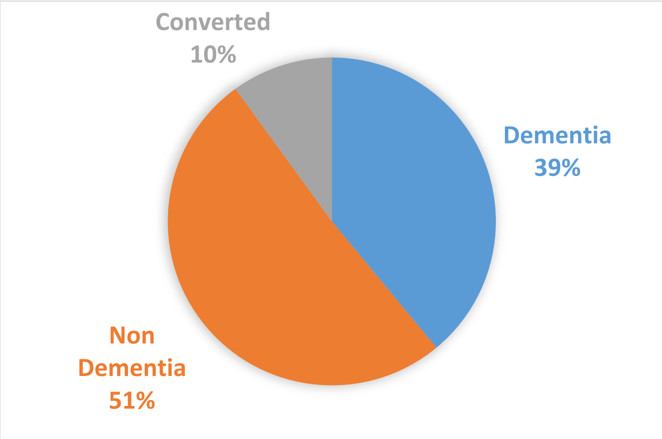

Figure 2. Percentage of cases of Dementia.converted and Non Dementia

With an emphasis on the use of sensor networks for foretelling the dementia scale score in a real-world living environment, Work investigate a number of sensors from various perspectives in this study.

Fig. 2 explains the percentage of dementia patients that have been transformed to non-dementia cases. Indoor positioning can be used to determine roughly where each person is at any given time. The use of RSSIs in enhanced indoor locating algorithms is reviewed. Frequently, a large-scale set of

Reference points must be established in order to estimate precise positions. Work used a straightforward feature extraction technique, but Work also tried to be as independent of the collection environment as feasible. Location data from indoor positioning was the most crucial categorization component in this study, however participants had to wear beacons at all times while sensing. Due to the intended usage of the sensor system in numerous situations, there are some challenges in extracting parts. These are combined in this situation different floorplans for residential constructions.

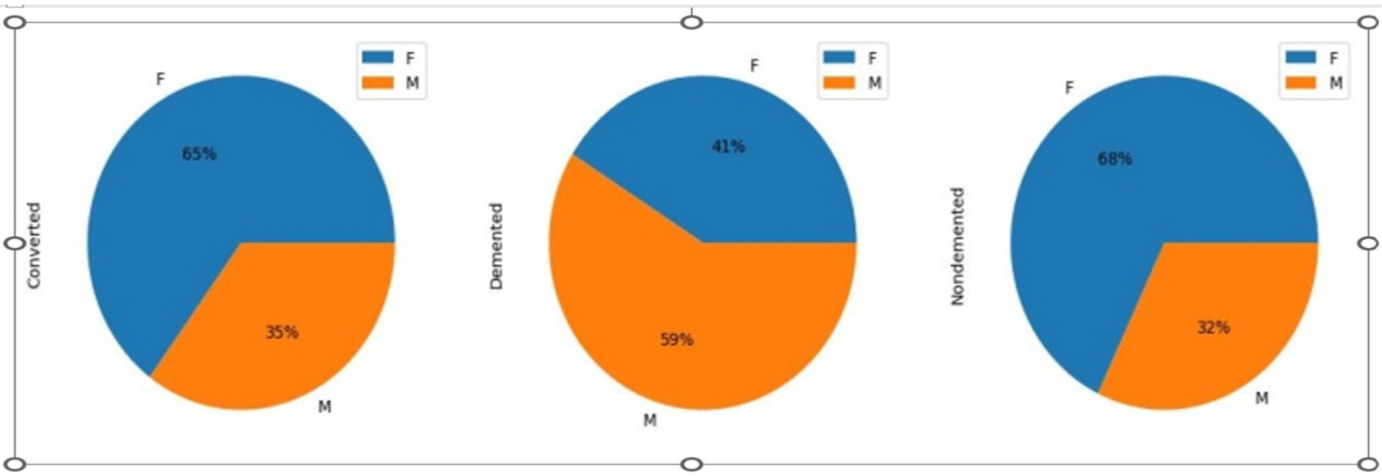

Figure 3. Females have less case of Dementia

The approximate location of any individual at any one time can be determined using indoor positioning. In this study, RSSI-based improved indoor locating algorithms are reviewed. Often, in order to estimate precise positions, a large-scale set of reference points must be developed. Work nevertheless used a straightforward feature extraction technique to be as unreliant on the collection environment as possible. Participants in this study had to wear beacons at all times while sensing, however location data from indoor placement was the most important categorizing component. Since the sensor system is meant to be used in residences with a variety of floor plans, there are certain difficulties in removing components that are joined in various circumstances.

The incidence of dementia is lower in women, as seen in Figure 3. This experiment correctly identified the dementia scale scores using sleep data, including biological information gleaned from bed sensors. Since the noncontact sensor's sleep data are least affected by the monitoring environment among the sensors used in this experiment, it is reasonably simple to maintain data collection over an extended period of time under a stable sensing environment. For a variety of nursing care support systems, such as the analysis of sleep stages and sleep quality, information on older people's sleeping habits can be acquired. In the future, research will concentrate on creating more intricate models using sleep sensor data by removing elements that illustrate the variations in specific sleep patterns to identify trends to dementia screening tests. The sensing approach might be effective.

This experiment correctly identified the dementia scale scores using sleep data, including biological information gleaned from bed sensors. Since the noncontact sensor's sleep data are least affected by the monitoring environment among the sensors used in this experiment, it is reasonably simple to maintain data collection over an extended period of time under a stable sensing environment. For a variety of nursing care support systems, such as the analysis of sleep stages and sleep quality, information on older people's sleeping habits can be acquired. In order to create more complex models and identify patterns that correspond to dementia scale scores, future studies will concentrate on extracting characteristics that reflect variations in specific sleep patterns from data gathered by sleep sensors. It's possible that the sensing approach will work.

Non-demented patients visit the hospital more frequently than those with dementia, who only visit twice and once, respectively According to their MMSE scores, study participants were divided into two groups. Work did not evaluate the outcomes of medical diagnoses, and the experimental participants with the lowest MMSE scores included bedridden patients. According to Brodaty et al., dementia is not always the outcome when MCI symptoms are treated and recovery is feasible. In elderly person support systems, estimating MMSE scores is much less crucial than making an early MCI diagnosis. Due to the small number of participants in this sample who had MCI, Work decided not to attempt to address its classification. Future research should concentrate on long-term data collection and monitoring of changes in the MMSE for participants with MCI utilizing an actual sensing system, according to the study's conclusions.

Participants in this study were divided into two groups based on their MMSE scores, however Work did not evaluate the outcomes of medical diagnoses, and the experimental participants with the lowest MMSE scores included patients who were bedridden. According to Brodaty et al., recovery from MCI symptoms is possible and dementia is not invariably the result. Estimating MMSE scores is significantly less important in elderly person support systems than early MCI diagnoses. Work chose not to try to address the classification of MCI because there were so few MCI participants in this group. Future research should concentrate on acquiring long-term data and tracking modifications in the MMSE for participants with MCI using an actual sensing method, the study's findings suggest with a help of sensor.

The correlations between certain behavioural traits and feature values deduced from activity patterns might also be challenging to interpret. It is best to incorporate interpretable feature values, such as how much exercise and sleep a person gets, when designing a system to aid medical practitioners in interpreting dementia scale results. The traits that were extracted using dimensionality reduction methods like PCA and AEs are carefully assessed. Future research should concentrate on precisely quantifying dementia by visualizing aspects based on activity patterns.

Fig 4 Describe about EEG electrode recordings for an MCI patient.The EEG signal is nonstationary, which causes its spectrum to change over time. As a result, it can be conceptualized as a collection of distinct stationary signal components. The data collected and processed by extracting the FourierCoefficients(N) must be converted into a comma-separated matrix file in order to move on to the following stage.

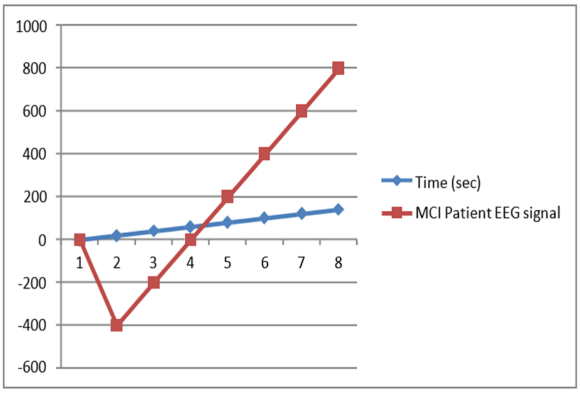

Figure 4. 180-secondEEGelectroderecordings foran MCIpatient

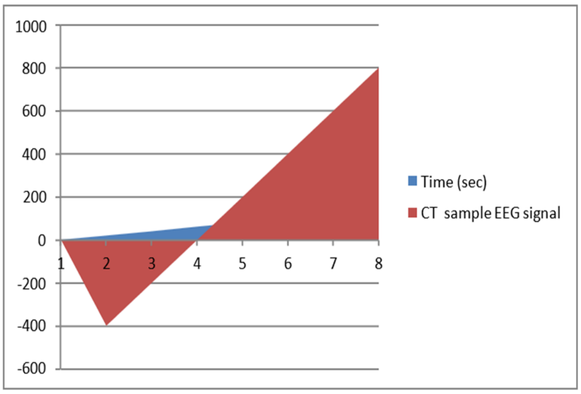

Figure 5.- 180 seconds of EEG electrode recordings for a CT sample

Fig 6 Describe a CT sample's EEG electrode recordings for roughly 180 seconds.MATLAB was used to conduct the spectrum analysis. With an interactive environment for algorithm development, data visualization and analysis, signal processing, numerical integration, and a wide range of other application disciplines, MATLAB is a high-level technical computer language. Fast Fourier Transform Functions (FFT) are specifically used by us to process EEG data.

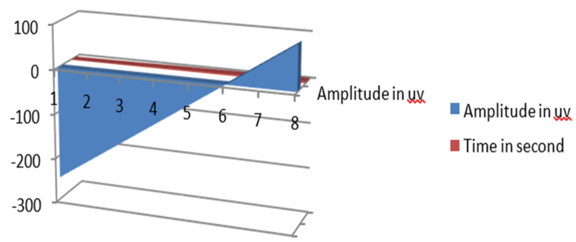

Figure 6. Ictal EEG Record

Figures 6,7,8 explain regarding Sampling Record of Although the results were ineffective, non-linear dynamics like the correlation dimension and lyapunov exponent were retrieved. Sample entropy, symbolic entropy, and lempel-ziv complexity features are retrieved in this study because they both reflect unpredictability and can give precise information about seizure activity in EEG signals. Comparisons are made between the effectiveness of a multi-class least squares support vector machine and a kernel-based least squares support vector machine for the aforementioned feature set.

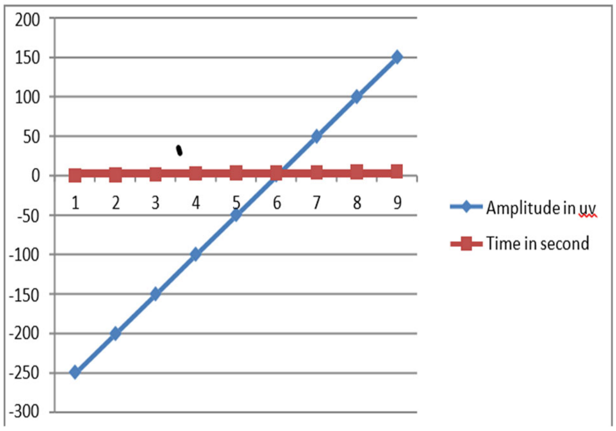

Figure 7. Inter-octal EEG Signal

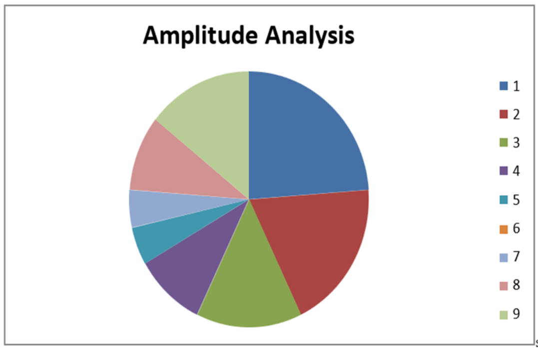

Figure 8. Healthy EEG Record

Table 1. Prediction Analysis

SL. No	PREDICTION					Accuracy
	Data (n)	TP	FP	FN	TN	
Random Forest	60	30	0	2	28	96.66
Decision Tree	60	30	0	3	27	95
Logistic Regression	60	25	5	2	28	88.33
Naïve Bayes	60	30	0	29	1	51.66

In the above Table 1 , Random forest method produced better results compared to other machine learning algorithms in terms of accuracy.

5. CONCLUSION

To better understand the many sensor and activity characteristic types that could be used to categorize dementia patients, our goal was to throw some light on them. Our research, however, suggests that it would be able to estimate the dementia scale score using covertly implanted and straightforward to collect behavioral data from the patient's home. As Workgather more location and sleep data, the model ought to continue to improve. Using our results, Workinvestigated the activity patterns specific to dementia and found that It is possible to create a dementia detection system using practical settings and efficient data collection methods. Additionally, this study emphasized the shortcomings of the previously suggested methodologies and critically assessed them. In order to get over these restrictions, our work offered potential avenues for future machine learning research in the field of automated dementia prediction with a help of sensor. Future goals include the creation of sensing techniques that might be applied in various living environments, the creation of models for assessing dementia severity, and the examination of activity pattern elements that could increase classification precision.

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