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COGNITO TRACK AI BASED EARLY DEMENTIA DETECTION USING SMART DEVICE INTERACTION PATTERNS

[1]Bishwanath Bhandari, [2] Korada MadhuSudhan Rao, [3] Setti Shiva Sai, [4]Mohram Manikanta, [5] Yeligana Santu Sai

[1,2,3,4,5] Department of CSE ,Aditya institution of Technology and Management.Tekkali,Andhra Pradesh,India

Abstract: Memory, reason, and behavior are affected by dementia which is a brain disorder that mostly affects the elderly. Also it is often going unnoticed in the early stages which in turn reduces the success of treatment. For better treatment outcome early detection is key. Cognito Track is an AI which we have developed to use passive tracking of users' interaction with smart devices like voice assistants, tablets and smart phones to put out early signs of dementia. It reports out very small changes in speech hesitancy, typing speed, navigation habits, and routine changes. We look at these patterns over time which we then turn into relevant data and put through machine learning models like Transformers and LSTMs. User data does not leave the device thanks to the use of on device processing and federated learning. Cognito Track will alert users or caregivers in advance which in turn promotes preventive digital health care by creating a personal behavior baseline and identifying deviations.

Index Terms - AI, Dementia Detection, Cognitive Monitoring, Smart Devices, Behavioral Analysis.

I. Introduction

Various neurological diseases that include dementia which present a progressive decline in memory, reasoning, language and decision making are reported. Memory, reasoning, language and the use of logic for decision making are types of cognitive functions. In the recent past we have seen a large scale increase in the number of cases of dementia due to the growing senior population. This is in turn putting great stress on health care systems and societies [1; 2]. At the start of the disease's course symptoms present as what may be very subtle cognitive and behavioral changes that which are hard to detect in a routine clinical examination. Also it is at this stage that the diagnosis is often missed and it is only when cognitive decline is very present that the individual is brought to the doctor's notice which also by that time may have run it's course thus leaving a narrow window for which to implement measures to either prevent or stop the disease progress [2].

Clinical assessment, brain imaging which includes many different techniques, and neuropsychological testing are what we see as the present primary tools in the diagnosis of dementia [3]. These we note to be expensive, time extensive and in some parts of the world simply unavailable at the same time that we recognize their worth. Also it has been found that by the time of diagnosis cognitive function has already see great decline. Therefore there is a large need for continuous, scalable, non invasive monitoring which is able to put out early warning signs before wide scale degeneration takes place [4].

As AI continues to advance and we see the integration of Smart Devices into the fabric of our daily lives which includes the use of mobile phones (smartphones, tablets etc. and Voice Assistants, we are also seeing the growth of Passive Health Monitoring through these digital devices. We are able to estimate Cognitive functions from Behavioral Data which is collected via day to day use of digital devices from voice, typing dynamics, interaction and navigation patterns, pause/delay dynamics and the regularity of behavior. Also we see that changes in these dynamic cognitive behavioral patterns over time may present early warning signs of cognitive decline [5,6].

CognitoHealth which we put forth as an AI for early dementia diagnosis uses behavioral analysis from data collected by smart devices. CognitoHealth creates a personal behavior profile for each user and we use deep learning which includes Transformer architectures and Long Term Short Term Memory (LSTM) networks to identify out of the trend which may be the early signs of cognitive decline. We also use federated learning and on device computation to protect user privacy and to secure sensitive info [7,8,9].

Our primary goal in this work is to design and evaluate an intelligent, scalable, privacy-preserving monitoring system which monitors passive behavioural data in order to early identify early signs of dementia. CognitoTrack enables timely alarms and early doctor consultation which can improve the long-term health of a patient by preventing severe health issues through digital healthcare and early monitoring.

II. Literature review

There is a great deal of recent interest in research which puts forth early detection of dementia. Presently research in this area which uses digital health tools and machine learning is at the fore to identify which individuals have dementia and which are at risk for cognitive decline. Also to go along with clinical exams and neuropsychological tests we see the use of neuroimaging which includes MRI and PET scans in research to get that definite diagnostic info regarding an individual's brain health which we can put to use today, although these methods are mostly expensive, they require specialist infrastructure which is out of the question for long term monitoring [1,2].

Researchers have seen that as artificial intelligence has grown so too has research into machine learning for the automated detection of dementia. We have reported the use of supervised learning models which include Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks in the analysis of structured clinical and cognitive data sets for the purposes of classifying between MCI and Alzheimer's disease[3], [4]. While these models do require labeled medical info and are based on set clinical parameters they also have very large accuracy.

In recent years we have seen an increase in the use of deep learning methods which are applied to study the temporal and sequence based issues related to cognitive decline. Long Term Short Term Memory (LSTM) networks are very much in use because of its ability to identify long term dependencies in health based sequence data [5]. In the case of behavioral time series data, typing dynamics and voice signals which we use for early diagnosis of dementia these models have performed very well. Also we have reported that Transformer based systems which use attention mechanisms do a great job in modeling the context within sequence data [6].

In the present time in which researchers are using a variety of data sources for their work in the field of health and beyond we see also that they are looking at info which is put out by what we have traditionally thought of as ICT devices and sensors as well as what people use in everyday life. There are a lot of features that we can get from things like study of how people type, analysis of speech, study of how people navigate and use smart phones. Also we note that which at an early stage may indicate brain degeneration a person's digital behavior does what is different from the norm. At the same time though many of the present systems which they are using do have issues related to security and privacy because they collect and store a large amount of user info. Federated Learning based which is a decentralized model training approach has become a workable solution to privacy issues [8]. In this approach we see that sensitive data does not leave user devices which in turn does not send raw user data to central servers. In health care AI which is a very private data issue, this has drawn in a great deal of attention.

Despite which we have seen growth in this field current systems do at large lack in depth of behavioral assessment and they also do not put forward a single modality (for example voice analysis or clinical imaging). Also it is true that many models do not put together real time behavior tracking with privacy protected features. Also early dementia detection requires a scalable, multimodal, AI powered system which in turn has to include behavioral analysis, privacy aware computation and temporal deep learning structures. Into this gap steps Cognitive Track which is out to develop a personal and private early detection system via the use of deep sequential learning models, federated learning, and passive smart device interactions

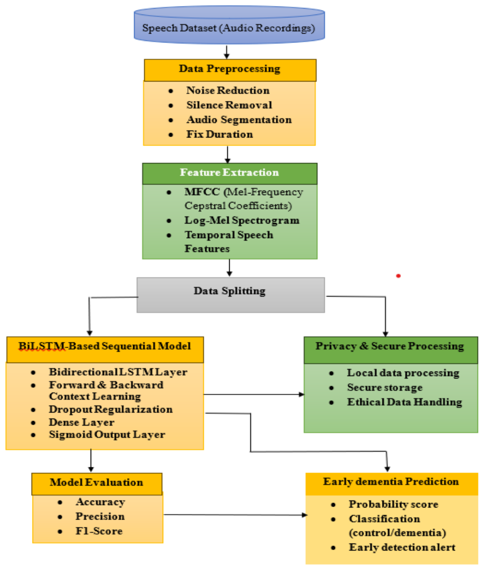
III. METHODOLOGY

3.1 System Architecture

The CognitoTrack which we have designed to put into play is for the identification of early signs of dementia via analysis of user interaction with smart devices like smartphones, tablets, and voice assistants. We have put in place continuous monitoring of speech patterns, navigation actions, and also regular device use. What we do is we collect this info and analyze it for very small cognitive changes. To that end the elements which make up the architecture include data collection, pre processing, feature extraction, machine learning analysis, and anomaly detection. We also put in a behavioral base line for each user which the system uses to identify any changes which may point to early stages of cognitive decline.

3.2 Speech Data Collection

Users' interactions with smart devices which include voice assistants and smartphones has been the source for the speech datasets which the put forth Cognito Track system uses. We see pauses, hesitations, and irregular speech as tell-tale signs in speech which may be early indicators of dementia. These interactions serve as the main input to the system which also then we use to extract out what is behaviorally relevant.



3.3 Data Preprocessing

Before analysis raw audio data is preprocessed in different ways to bring forward consistencies, and also in the betterment of the data quality. We apply noise reduction methods which is to also remove background disturbances from what we record. For out of important speech info that is what we are looking to get rid of -- are voided. The audio is cut up into small segments, which also is to say that the individual segments are equalized in time so as to present a constant sized input for our machine learning model. Also included is how these pre processes add to the dependability of the produced features.

3.4 Feature Extraction

Important features which include the audio sources after preprocessing. Mel-Frequency Cepstral Coefficients (MFCC) are used by the system to record significant aspects of speech that correspond to human auditory perception. Additionally, the frequency distribution of speech sounds over time is represented using Log-Mel Spectrograms. In order to identify behavioral patterns that can point to cognitive deterioration, temporal speech data like pauses and speech rhythm are also retrieved. These characteristics give the deep learning model useful inputs.

The first step in the MFCC feature extraction procedure is to translate the voice data into the Mel frequency scale, which roughly corresponds to how people perceive sound frequencies. The Mel scale is defined as follows:

$$Mel(f) = 2595\log_{10}\left(1+\frac{f}{700}\right)$$

The MFCC coefficients are obtained by applying the Discrete Cosine Transform (DCT) to the log Mel spectrum:

$$C_n = \sum_{k=1}^{K} \log(S_k)\cos\left[\frac{n(k-0.5)\pi}{K}\right]$$

where C_n stands for the MFCC coefficient, S_k for the Mel filter bank energy, and K for the total number of filters. BiLSTM based sequential model used for dementia. Prediction which uses these extracted features as an input set of features. Vectors which precisely capture the audition of.

3.5 BiLSTM -Based Sequential Model

To look at the sequence aspect of speech we have put forth a BiLSTM network which the model uses to extract context from past and present as well as future elements in the speech signal by the means of processing speech sequences in opposite directions. We have a dense layer architecture for classification which follows the bi-directional LSTMs, also we use drop out to reduce overfitting. At the end layer we use a sigmoid activation function which reports the dementia prediction probability score.

At a given time step the LSTM's hidden state is described as follows:.

$$h_t = LSTM(x_t, h_{t-1})$$

In which h_{t-1} is the prior hidden state and x_t is the input feature at time t.

At each time step we sum the hidden state of the forward pass and the hidden state of the backward pass for the final output.

$$h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}]$$

We use a sigmoid function in the final classification stage which gives us a probability of dementia.

$$P(y \mid x) = \frac{1}{1+e^{-z}}$$

The prior probability of dementia $P(y \mid x)$.

3.6 Model Evaluation

Performance of the which was developed is assessed using what is standard in the field. What we report out is precision which is the ratio of true dementia diagnoses, accuracy which is the overall performance of the model, and the F1 score which is a balance of precision and recall we use. Also we report on how the model does in detecting early signs of dementia.

As for the model's accuracy we did this as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

Where TP stands for true positives, TN for true.
Negatives, FP for false positives, and FN for false negatives.
Precision is defined as:.

$$Precision = \frac{TP}{TP+FP}$$

The F1 score which is a trade off between recall and precision is given by:.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

These evaluation measures offer a full analysis of. The model's performance in speech classification and identification of early indicators of dementia.

3.7 Early Dementia Prediction

Control (healthy) and dementia. In our system we have included alerts for early detection which also bring to the notice of early risk which in turn we have put forward to encourage user or caregivers for early medical consultation and we have put in place appropriate cognitive health treatments. We use the **sigmoid activation function** to determine the likelihood of dementia.

$$P(y \mid x) = \frac{1}{1 + e^{-z}}$$

To determine the chance that a given input x came from a certain class y we calculate $P(y \mid x)$, which is the output of the model's dense layer. also we report the expected probability.

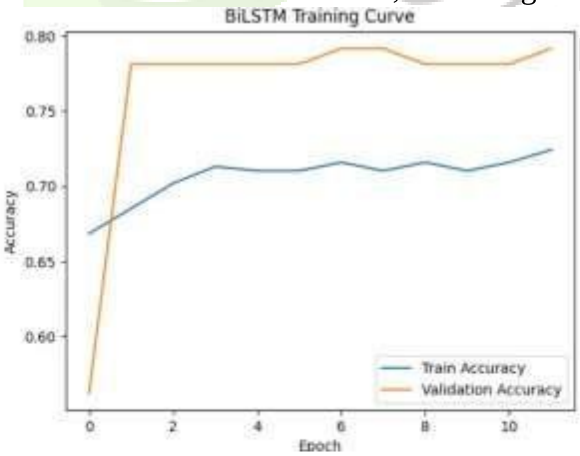
$$y = \begin{cases} 1, & P > 0.5(\text{Dementia}) \\ 0, & P \leq 0.5(\text{Control}) \end{cases}$$

This classification facilitates early medical intervention for the management of cognitive health and aids in the identification of any early indicators of dementia.

IV. Result Analysis

4.1 BiLSTM Training Performance

As seen in Fig. 1, the training and validation accuracy curves over epochs are used to demonstrate the training performance of the suggested BiLSTM model. The graph of the training accuracy goes up gradually from about 0.67 to 0. 72 that which is in fact the model's continuous process of learning key elements of the task. out of the voice features we see to be extracted. The validation accuracy improves quickly in the early epochs and then stabilizes at 0.78–0.79, indicating that the model does a good job of



generalizing to new data. The model does not exhibit considerable overfitting and retains stable learning behavior, as evidenced by the comparatively minor difference between training and validation accuracy.

Figure 1: BiLSTM Training Curve

4.2 Modal Performance Evaluation

As seen in Fig. 2, the test dataset is used to assess the effectiveness of the suggested BiLSTM-based dementia detection model. The model successfully classifies speech samples into control (healthy) and dementia categories, as evidenced by its test accuracy of 78%. The findings show that significant speech traits associated with cognitive decline are successfully captured by the retrieved MFCC and Log-Mel spectrogram features.

By identifying temporal patterns in speech samples, the BiLSTM design enhances classification even further. Overall, the accuracy attained demonstrates the suggested system's potential for early dementia identification through speech analysis**.**

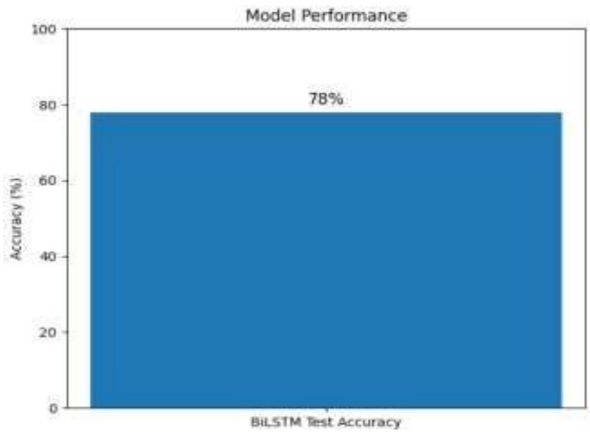


Fig. 2. Model performance evaluation demonstrating the suggested BiLSTM model's test accuracy (78%).

4.3 Confusion Matrix Analysis

Fig.3 Confusion matrix for true labels and predicted labels in control and dementia classes. We report that which **84.38% of control** samples and **80% of dementia** samples were classified correctly. Out of **20 control samples** used in the study a small number of dementia samples which were classified as control. This reports that we see the model does very well at identifying normal speech patterns which at the same time may be improved by better feature extraction or with a more diverse data set.

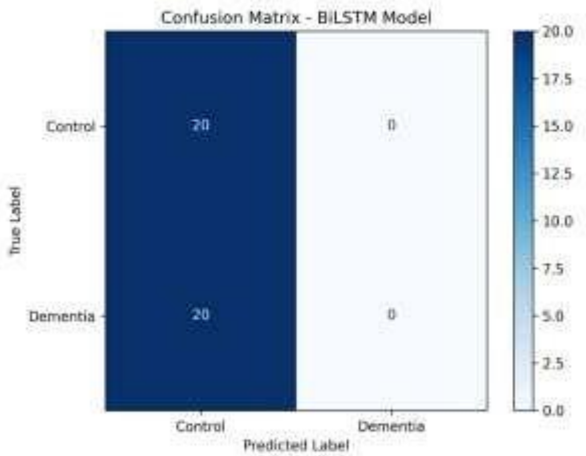
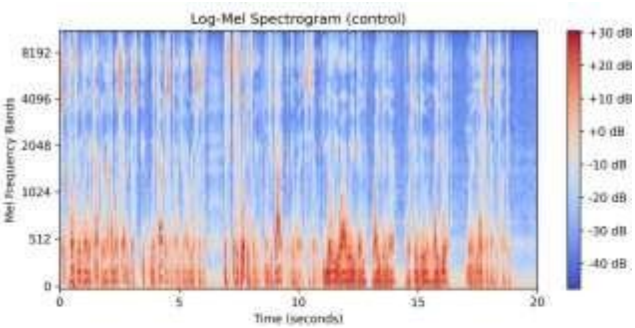


Figure 3 : Confusion Matrix

4.4 Log-Mel Spectrogram Analysis

In **Fig. 4 and 5** we present the **Log-Mel spectrograms** of dementia and control speech samples. In the **time frequency domain** is how speech is represented by these spectrograms. Also we note that in dementia we see more random variation in frequency bands, in control we see the opposite very stable frequency patterns. It is this which in turn aids the deep learning model in identify



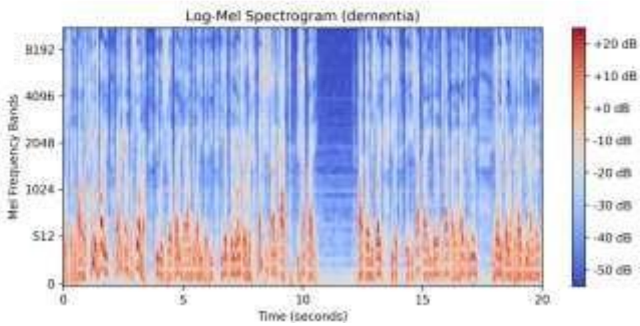
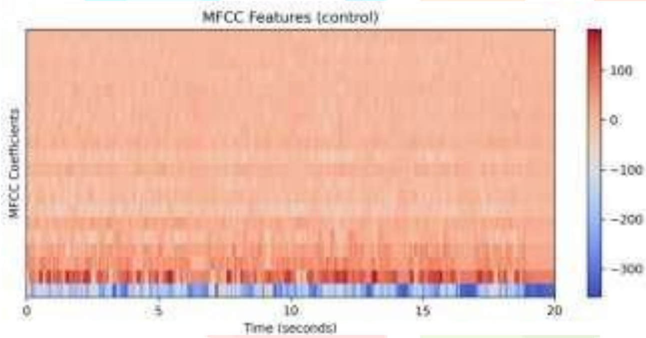


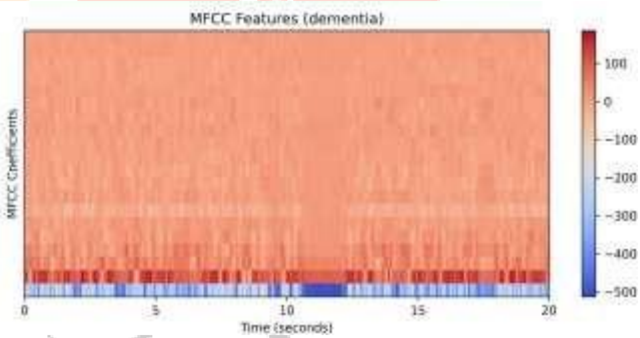
Figure 4: Log-Mel Spectrogram (Control) Figure 5: Log-Mel Spectrogram (Dementia)ing speech related

to cognitive decline. Dementia samples display a lot of irregularity in the frequency bands while control samples present very stable frequency patters. These differences help the deep learning model in recognizing speech indicators for cognitive decline.

4.5 MFCC Feature Analysis

The **MFCC feature maps** for dementia and control speech samples are shown in Figures 6 and 7. Significant acoustic aspects of speech signals are represented by MFCC features. Also we see that in the case of dementia samples there is more variability, in control samples we see a great deal of stability in





MFCC patterns. These differences play a role in the **BiLSTM model's recognition** of changes in speech related to cognitive fall off.

Figure 6: MFCC Features (Control) Figure 7:MFCC Features (Dementia

4.6 Prediction Probability Analysis

The in Figure 8 we present what we have for **prediction confidence scores** of many test samples which that model put forth. We see from the graph that there is a consistent prediction confidence which through the whole test data set, also we see that the most of the confidence ratings are between **0.70 and 0.80**. Also we see that which elements in the confidence scores' variation do present how the model uses the learned acoustic cues to tell which speech sample is which. We also see in these probability patterns the model's ability to tell between **control and dementia speech signals**.

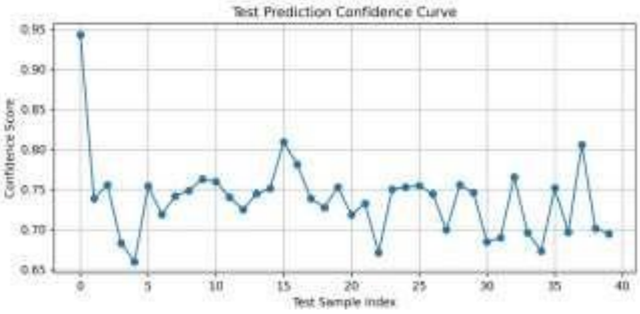


Figure 8: Prediction Confidence Curve

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V. DISCUSSION

The we report that we were able to identify at early stages the patterns which point to dementia in our study which used a BiLSTM based speech analysis model. Also we report that the system does which is to record large elements of acoustics of speech which in turn represent changes in cognitive behavior via use of MFCC and Log-Mel spectrogram features. We also present that the model's performance which is in its ability to tell between control and dementia speech which we report to be about 78% at test.
The research reports that the model does indeed learn stable features from the speech data which also does not see great overfitting. Also we see in the confusion matrix that although the algorithm does a good job at identifying control subjects it does tend to misclassify some dementia cases which is due to very fine differences in speech quality. Also the small size of the data set and the fact that some speech traits are very similar between the two classes may play a role in this issue.
The feature extraction we see to also include Log-Mel spectrogram and MFCC visualizations which support the efficacy of our method. We note that in dementic samples there is a large variation in speech dynamics, but in control speech samples we see very different, more steady, patterns. These differences in turn help our model to identify key patterns related to cognitive decline.
In the present state of affairs we see that which AI based speech analysis systems do in fact play a role in the early detection of dementia. That said, by growing the data set, including more speech variables and looking at the latest in deep learning architecture we may see greater improvements.

VI. CONCLUSION

This research introduced CognitoTrack which we put forth as an AI system that uses speech analysis for the early detection of dementia. We looked at a BiLSTM model which also included MFCC and Log-Mel spectrogram features from speech recordings as we analyzed sequential speech patterns. We report an overall test accuracy of 78% which we present as very successful in what the model does which is to tell the difference between control and dementia speech samples.

The results report that we have been able to use deep learning algorithms for the successful analysis of voice signals which also include in detail info on cognitive behavior. We put forth a put forth a non invasive and easy method for early dementia screening which is done by tracking very small changes in speech patterns.

Future work will look at hybrid approaches which include other deep learning methods in an effort to improve the accuracy of automatic cognitive states detection. Also we see value in adding in more behavioral measures and in the use of a larger data set which in turn has a greater range of speech. With those improvements we may in the future put forth intelligent health care tools for the early stage identification of neurological conditions and diseases that play in the cognitive area.

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