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AN ENSEMBLING PLMRI:ALZHEIMER DETECTION WITH THE MAGNETIC RESONANCE IMAGING WITH PROMPT LEARNING MODEL.

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Abstract

Alzheimer's disease is an example of the illnesses that primarily affects elderly individuals but is not related to aging. Disorientation and communication issues, as well as difficulties with abstract thought, are the most typical symptoms. Premature Alzheimer's Disease(AD) detection is crucial in order to treat the condition with therapy and medicine & restore memory and cognition. In order to aid early detection efforts at the preclinical stage, this work presents two attention model networks in this research for detecting Alzheimer's Disease using Magnetic Resonance Imaging (MRI) scans. According to studies, addressing AD symptoms and halting deterioration at an early stage can significantly affect outcomes. Early AD diagnosis made possible by conventional MRI scanning and the Prompt Learning Model would boost patients' life expectancies and quality of life by enabling Prompt Learning Model(PLM), incorporating the LSTM (Long Short Term Evaluation) technique and effective interventions and therapies.

Keywords : Alzheimer's Disease(AD), Prompt Learning Model (PLM), LSTM (Long Short Term Evaluation), Magnetic Resonance Imaging (MRI).

1. Introduction

In the current digital era, a rapid improvement in communication as well as technology has led to the incorporation of cognitive automated systems that analyze resident welfare and provide many services. This is accomplished by monitoring the actions of people using various technologies, and with the use of activity-based learning, it helps to uncover individuals suffering from early-stage Alzheimer's that can be predicted without changing their way of life. Alzheimer's patients have serious impairments in their regular tasks[1]. Elderly individuals with minor cognitive impairment also experience this problem, but to a lesser extent. Alzheimer's disease is a form of dementia that causes a long-term condition associated with increasing memory loss, abstract thought, and a decline in intellectual capacity and cognitive loss. However, early Alzheimer's diagnosis can halt the disease's progression, and developing automated detection and classification models is a difficult undertaking. In order to treat this there is no effective way of Alzheimer's disease, however there is the option to take drugs to help alleviate dementia symptoms. Dementia research over the last three decades has generated an in-depth knowledge of the way the disease known as Alzheimer's influences the brain. Research is being done to find medicines that can successfully treat or prevent Alzheimer's disease and improve brain health [2].

The three stages of Alzheimer's disease (AD) are preclinical, "Mild Cognitive Impairment (MCI)", and Alzheimer's dementia, which occurs once the symptoms of dementia were severe enough to cause problems in everyday tasks. According to the National Institute on Ageing, preclinical Alzheimer's disease occurs when patients have no symptoms yet their structure of brain neurons is starting to degenerate.Because of the advancement of MRI technology and the more recent development of deep learning-based computer vision technologies, the diagnosis of AD in MCI and dementia stages (stages 2 and 3) using MRI brain scans has been the focus of numerous studies. Although the research has improved the knowledge of Alzheimer's disease, it cannot be useful for early stage therapeutics because stages 2 as well as 3 may be reliably detected through clinical diagnosis. [3,4].

1.1 Magnetic Resonance Imaging and Alzheimer

Three-dimensional (3D) captures of the inner workings of the brain are produced through MRI brain scans. To identify disease-based structures in the 3-dimensional brain, a number of sequential classifiers have been constructed, including the 3D recurrent visual attention (RVN) model and the 3D convolutional neural network (CNN) model [5]. Recently, it was shown that the Transformer model outperformed all of the sequential classifiers currently in use.

1.2 Prompt Learning and Alzheimer

Early Alzheimer's disease (AD) identification is essential for enabling preventative therapy and halting future progression. An alternative to traditional clinical screening methods that is less intrusive and more scalable is provided by speech-based automatic AD screening systems. These systems frequently employ textual embedding characteristics generated by pre-trained language models (PLMs), like BERT. The back-end AD detection task is inconsistent with the PLM domain fine-tuning, which is frequently based on masked word or sentence prediction costs.

2. Related Works

Studies have shown that treating AD symptoms and preventing deterioration at an early stage can have a considerable impact. Conventional MRI scanning/ Prompt Learning Model can diagnose AD early, allowing for timely and efficient interventions and treatments that will increase patients' life expectancies and quality of life.

Table-1: Previous Studies of Alzheimer Disease Detection via MRI and PLM		
S.No	**MRI-Magnetic Resonance Imaging Based Studies**	**PLM- Prompt Learning Model Based Studies**
1	Due to the high performance of deep learning algorithms which determine complicated patterns in data with a high dimension, there is a wealth of literature on the detection of diseases using positron emission tomography and magnetic resonance imaging. used two different 3D CNN approaches—***VoxCNN and residual neural networks (RNN)*** —on MRI data to investigate the existence of Alzheimer's disease [6].	Typical acoustic feature formats of AD detection via PLM include ***linguistic features (handcrafted ones), lexical or syntactic cues, or text neural embeddings*** that have been previously taught[11].
2	Several researchers have identified the diagnosis of Alzheimer's disease in MCI and dementia stages (stages 2 and 3) from MRI brain scans which helps with recent developments in ***Deep learning-based computer vision algorithms*** and the progress of MRI technology [7].	For tasks involving AD identification, measures of speech ***Disfluency*** were also found to be helpful [12].
3	According to contemporary Alzheimer's disease (AD) research, alterations in the brain can be seen 20 years before demented (before reach the stage-3), and by the stage of mild cognitive impairment (MCI) (which is known as stage 2), there has already been significant neuronal death[8].	***ASR- Automatic Speech Recognition systems*** [13] have been utilized more frequently than ground truth hand transcripts [14] to produce speech transcripts in order to fully automate the AD detection procedure.
4	It has been demonstrated that early stage AD patients' general cognitive abilities improved following 12 weeks of ***Paper-based Cognitive Training***, demonstrating the importance of early detection of AD in	Some of the research demonstrates that when employing ***speech-based AD detection algorithms***, the use of linguistic features taken from the speech recorded transcripts of senior people is

	the development of the best treatment for each patient. Along these lines, much research has been done in an effort to distinguish between Alzheimer's disease (AD) and mild cognitive impairment (MCI)[9].	very helpful in differentiating between labels for AD and no-AD, as opposed to utilizing only acoustic features [15].
5	To explore the conversion of MCI to AD, authors suggested a ***Four-class SVM classifier*** with AD, MCI stable, MCI converted, and healthy individuals[10].	***Pre-trained language models (PLM)***, can be used as extractors of features [16] or actively fine-tuned on the AD/no-AD classification task. [17], might obtain the highest detection accuracy possible with manual transcripts.

All of the discussed methods aim to identify AD (stage 3), or to identify MCI instances (stage 2) that will progress to AD. To the best of our knowledge, no prior research has been done on identifying preclinical stage Alzheimer's disease (stage 1) occurs when all of the signs, particularly tests performed by medical specialists, are positive. confirm that the patient is healthy and free of any signs of the disease. The primary objective of our research is to use Prompt Learning Model in the stage-1 of MRI scan patterns to detect future AD even in the preclinical stages of the disease, before MCI manifests.

3. Methodology

Numerous research has focused on the detection of AD that includes recent developments in deep learning-based computer vision methods and MRI technologies. Even though concentrating stage-1 of MRI which is the input of a PLM trained module.

3.1 Data Creation**:** The data for each participant consists of one speech recording of a Cookie Theft scenario, manual transcripts annotated with the "CHAT coding scheme, and a binary AD label." Both the interviewer and participant roles are offered, but only the participant role is employed in our investigations. The input text is created by combining all of the speech fragments from each participant.

3.2 Model Description: One of the significant differences between this research and the latest research is that it concentrates on the particularly challenging problem of detecting preclinical Alzheimer's disease (stage 1). This study only employed 3D MRI brain pictures as input to assure the extraction of latent brain patterns for the preliminary identification of AD challenge. This complicates classification since researchers can't change the models to account for other variables that may be helpful for forecasting AD, including the patient's age or gender. To address this complex challenge, the proposed method adapts and employs two distinct focus processes, the attention transformer and the 3D recurrent visual attention model.

Algorithm-1 : Stepwise Procedure of Ensembling PLMRI
Step-1 : The foundational model is built on a 3D CNN model that was first used for video classification tasks. This model convolves video input, which is seen as 3D data, using 3D kernels and channels. Here, we create a stack of all the images from a brain scan, convert them into 3D input data, and then feed it to the network as our baseline model. **Step-2 :** On the training data, MLM is used to fine-tune the PLM text encoders. The detection accuracy ratings at subsequent epochs vary because MLM classification rather than AD classification is the fine-tuning target. **Step-3 :** The 30-epoch fine-tuning produced independent text embedding features for back-end classifiers using models during the final three update epochs. **Step-4 :** The majority voting method is used to combine the outputs of AD detection in order to lessen the possibility of overfitting and stabilize the performance. **Step- 5 :** The back-end classifier is LSTM, which outperformed the competition. Different PLMs used by the systems as the feature extractor demonstrate complementarity.

3.3 Technology Discussion :Some of the Deep Learning algorithms that have been compared, and LSTM has been chosen for its improved IoT attack identification using PLMRI based Model via Artificial Intelligence based Interpolation Technique. In 1997, Hochreiter and Schmidhuber proposed the LSTM , which quickly gained acceptance, especially for problems involving time series forecasting. LSTM seems to be more effective than other Deep Learning-based algorithms. because of our ability to learn about the future. Our trained model will benefit more from this and be better able to forecast the assault structure. the LSTM model, which has three possible states: input, output, and forget. Long-term memory is referred to as the cell state. The looping arrows demonstrate the cell's recursive nature. This makes it possible to store historical data in LSTM cells. The input modulator gate alters it, and the forget gate, which is below the cell state, positions it.

3.4 Ensembling LSTMs:

This research's main goal is to employ the Prompt Learning Model in stage-1 MRI scan patterns to identify AD even in its preclinical phases, before MCI develops. This work integrates a PLM component into the suggested strategy in order to reach an overall judgment regarding the output of LSTMs. The PLM chooses on output after accepting a collection of confidence rates for each class in the dataset.The MRI module receives the following input from LSTMs:

"Input of MRI = $\{LSTM_{i,c}$ where $i \in \{Number\ o\ f\ LST\ M\ s\}$ AND $c \in Number\ o\ f\ Classes\}$"

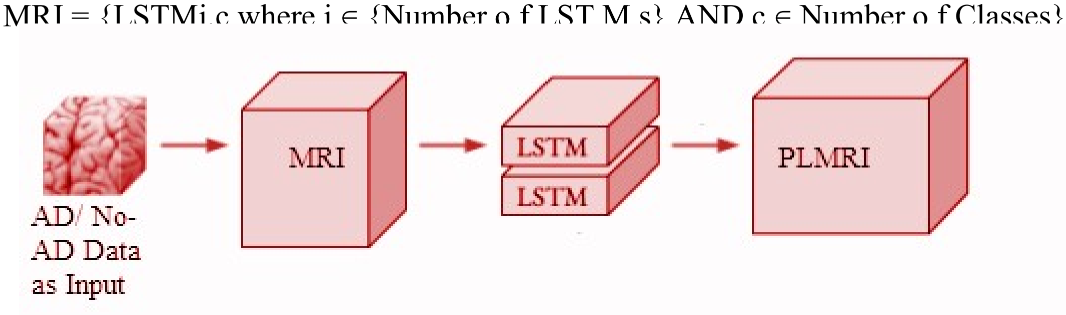


Figure-1 : Process of PLMRI Model

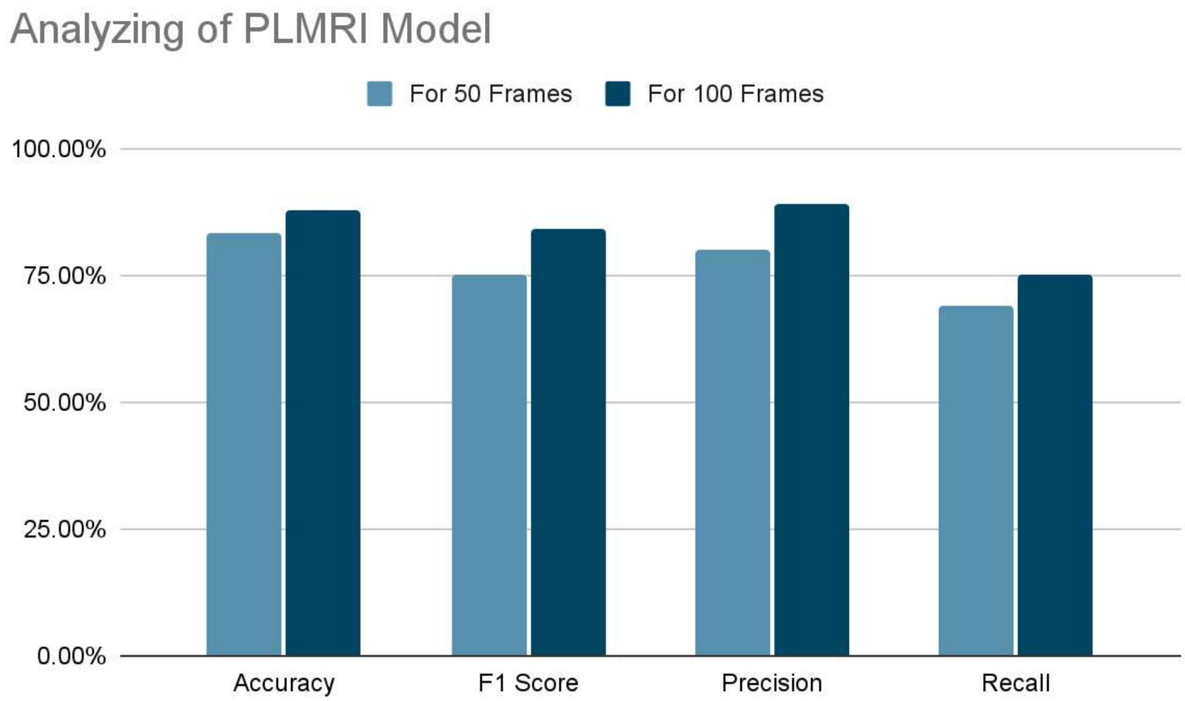
LSTMi,c stands for the confidence level of the class c LSTM trained model. These confidence ratings are accepted as inputs by the PLM, which then learns hierarchically how to correlate them with the real label of network traffic. The proposed method's use of the PLM component is schematically shown in Figure 1. In other words, PLM identifies the manifold of the LSTMs' output space and gives us a model that may be understood to help us choose the final label.

4. Analyzing Results

In contrast to previous models, the PLMRI model is trained in a distinct manner. First, MRI images are fed to the mode in this case rather than stacked 3D images. Model as the base to extract characteristics, as indicated in the Proposed Approach section. To examine the impact of trained weights, they used a PLMRI model that has already been trained. Table 2 demonstrates that the PLMRI model had a 4.6% higher F1 score after being trained from scratch.

Table-2: Analyzing of PLMRI model			
S.No	**Parameters**	**For 50 Frames**	**For 100 Frames**

1	Accuracy	83.13%	87.82%
2	F1 Score	0.75	0.84
3	Precision	0.80	0.89
4	Recall	0.69	0.75



Unable to use all brain MRI scan frames due to memory restrictions. The maximum number of frames we can choose with our present GPU configuration is 100, so this work has started by choosing 50 frames from the middle and worked way up to that number. The best results were obtained with 100 frames in the proposed work, which also trained the model using the same number of images from each scan.

5. Conclusion

This study investigates quick learning-based prompt learning model (PLM) fine tuning strategies for automatic AD detection using minimizing AD classification errors as the training objective function. To do this, this study changed PLMRI models and tested their effectiveness with some of the new parameters. Unlike prior models, the PLMRI model is trained in a unique way. First, rather than stacked 3D images, MRI scans are given to the model in this scenario. The model is used as the foundation for extracting characteristics.

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