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"Alzheimer's and Dementia disease detection from 2D MRI data using Regions with Convolutional Neural Networks"

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Abstract — Degenerative diseases like Alzheimer's and dementia can seriously impair memory and cognitive function. Early diagnosis of these illnesses is essential for successful treatment. A growing number of people are now interested in using 2D MRI data to identify Alzheimer's and dementia. Convolutional neural network (CNN) regions have demonstrated promising outcomes in this context. Because CNNs can extract useful features from the MRI data and be used for precise detection of Alzheimer's and dementia, their use is particularly effective. It is possible to identify regions within the MRI images, and CNNs can be trained to look for patterns in these regions that are related to Alzheimer's and dementia. By doing so, it may be possible to spot subtle changes in brain structure that would otherwise go undetected. Using regions with convolutional neural networks, MRI data has demonstrated impressive accuracy in the detection of Alzheimer's and dementia. With early intervention and better patient outcomes, this method can assist medical professionals and researchers in identifying these diseases. In conclusion, the use of CNNs with Regions and 2D MRI data is a promising method for the identification of Alzheimer's and dementia.

Keywords: Alzheimer's, Dementia, Reginal Convolution Neural Networks (RCNN), Magnetic Resonance Image (MRI).

I. INTRODUCTION

Both dementia and Alzheimer Disease (AD) are examples of neurodegenerative disorders that affect millions of people worldwide, especially the elderly. Due to the overlap of AD and dementia symptoms with those of other diseases, diagnosis of these conditions is frequently difficult. Identification of Alzheimer's disease early and accurately is essential for timely treatment and intervention. Magnetic resonance imaging has earned a reputation as a reliable non-invasive imaging tool used for the detection and diagnosis of AD and dementia due to its capability to visualise brain structural changes related to these disorders. With a new case being reported every three seconds worldwide, Alzheimer's disease has now surpassed cancer as the most feared illness in the US. Alzheimer's disease detection is a difficult, time-consuming task that requires both human expertise and brain imaging reports (MRIs). The conventional method of diagnosing Alzheimer's is expensive and frequently erroneous. As a result, using a quicker Region-based CNN may provide a more effective, quick, and affordable alternative for diagnosing Alzheimer's. In recent years, Convolutional Neural Networks (CNN) have shown remarkable performance in a range of computer vision applications, including object recognition. A cutting- edge object recognition method called Faster R-CNN (Region-based Convolutional Neural Network) has been shown to perform better than other object detection frameworks in terms of accuracy and speed. By utilising the features of Faster R-CNN, it is possible to create automated and effective algorithms for detecting AD and dementia from brain MRI data.

Brain MRI data offers a wealth of knowledge about the structure of the brain and can be used to properly identify AD and dementia. Popular deep learning methods for object detection include a faster R-CNN (Region-based Convolutional Neural Network) algorithm. A two-tiered network first finds regions of interest (ROI) before classifying those regions as a particular object. The analysis of medical images is just one of the many sectors where this technique has been applied successfully. In various research, the application of deep learning algorithms for diagnosing AD and dementia has yielded encouraging results. certain algorithms are capable of precisely identifying tiny alterations in brain structure that are indicative of certain disorders. This method may grow into a useful tool for the early detection and diagnosis of dementia and Alzheimer's disease with more study and development.

The goal of this study is to examine how Faster R-CNN may be used to analyse brain MRI data to identify dementia and Alzheimer's disease. We will test whether Faster R-CNN can pinpoint particular brain areas and structural alterations that are symptomatic of dementia and Alzheimer's disease. Additionally, we will contrast the performance of Faster R-CNN to current methods for diagnosing Alzheimer's disease in terms of accuracy, sensitivity, specificity, and speed.

II. LITERATURE SURVEY

Researchers have been utilizing various machine learning algorithms to forecast the start of Alzheimer's diseaseusing MRI images alone since the early 2000s. We investigated several research approaches by scanning the Couscous and Lined (Medical Literature Analysis and Retrieval System Online) databases. Machine learning algorithms, clustering classification, regression, K-Means clustering, Convolutional Neural Networks, and Artificial Neural

Networks (ANN) are examples of these techniques.

Machine learning literature review

Thirunavukkarasu K et al. (2018) proposed predicting liver illness using supervised classification techniques such as logistic regression, SVM, and K-nearest neighbours. To compare the accuracy of all methods, a confusion matrix is employed. The liver disease dataset is from UCI and has an instance number of 567, whereas the data is from the ILPD (Indian Liver Patient dataset). They discovered that two approaches, namely Logistic regression and KNN, had the highest accuracy when compared to other types, and that logistic regression is the best and most responsive of the two algorithms in terms of prediction accuracy, precision, or recall. As a result, the "logistic regression" model is the best for predicting liver illness. M. Mahale Kishor Dhomse Kanchan M [2018] proposed a method for predicting cardiac disease that is based on machine learning algorithms such as Naive Bayes, SVM, and Decision induction Tree. On the dataset, all four classifiers are applied with PCA (Principal component analysis) at times. They are using PCA to reduce the number of characteristics in the dataset. They discovered that SVM outperforms Random Forest and Naive Bayesian after reducing the dataset. SVM can thus be used to forecast cardiac issues. The purpose of this study is to use the Weka tool to predict ailments like heart disease and diabetes.

Deep learning literature review

Lan et al. (2020) used functional connectivity scans to establish a unique way to aid clinicians in the detection of Alzheimer's disease. He analyzed the scans using graph theory and assessed the accuracy of the results using three different methodologies. He used Random Forest, CNN-like Artificial Neural Networks, and Support Vector Machines (SVM) that were trained on Superior Parietal Lobule (SPL) features. The three models had accuracy of 89%, 96.7%, and 89.8%, respectively, and the three algorithms had precision of 87.5%, 99%, and 93.5%, respectively. Kumar, Lama, and colleagues (2017) employed magnetic resonance imaging (MRI) to identify Alzheimer's disease from moderate cognitive impairment and healthy control groups. For this classification technique, he used a variety of algorithms, including SVM, Regularized Extreme Learning Machine_(RELM), and Independent Vector Machine_(IVM). In addition, he presented a racially biased kernel-based technique for dealing with various complicated data patterns. He discovered that RELM had superior metrics using his categorization technique. Khan and Swaleha Zubair (2019) used the "Random Forest" algorithm to assess the performance of imputation with non-imputation alternatives. They discovered that the imputation method was 87% accurate, whereas the non-imputation strategy was 83% correct. They also classified individuals as "non-demented" or "demented".

III. EXISTING SYSTEM

2D CNNs

CNNs were initially proposed to recognize patterns from 2D images. Although 3D CNNs can classify 3D brain scans, they need many parameters compared with 2D CNNs. Therefore, using 2D CNNs is more common than using 3D for AD detection using 3D brain scans. By dividing the MRI volumetric data into 2D image slices, 2D information can be extracted from 3D images. Assuming that certain features of interest in 3D MRIs are preserved in 2D images, this process reduces the number of parameters in CNNs. Here different deep models using 2D CNNs are reviewed.

Generally, 2D CNNs capture the middle part of brain scans as the input data and ignore the remainder. Some studies extract gray matter (GM) tissue as the input data. Research studies use standard planes of brain scans, such as the sagittal, coronal, or axial planes. The axial plane is the most widely used plane.[13] Farooq et al. employed axial slices of MRI (GM) so that slices were eliminated from the beginning and end, where there is no information. They implemented 2D CNNs based on GoogLeNet, ResNet-18, and ResNet-152. Valliani and Soni employed the median axial slice of subjects to train ResNet-18. Farooq et al. used 166 axial slices of MRI (GM) to train GoogLeNet, and ResNet-152. Seven 2D CNNs on seven groups of 2D images slices (five mid-axial slices in each group), each consisting of three convolutional layers, was proposed by Luo et al. In this study, a subject was classified as AD when at least one of the classifiers categorized it as AD.

After discarding the first and the last axial slices, assuming them to be without anatomical information, Wu et al. combined every three neighboring slices into an RGB color image to train CaffeNet and GoogLeNet. By removing the last 10 axial slices from MRI (GM) and slices with 0 mean pixels, LeNet and GoogLeNet models were used by Sarraf and Tofighi for AD detection. In two other studies, a sorting mechanism based on entropy was proposed to select the most informative slices from the axial plane of each MRI scan. The highest entropy computed from the histogram was associated with the most informative slices. The slices were then used to train VGGNet-16 and Inception-V4.
Gunawardena et al. used several image slices from the coronal plane to train a 2D CNN with two convolutional layers. This work showed that a brain scan's coronal view covers the essential brain parts related to AD. The coronal view offers a discriminative advantage that was depicted by Wang et al. with DenseNet-121. All planes were used, and the coronal plane was selected as the most accurate. In another study, 20 mid-coronal slices were employed for training a 2D CNN based on VGGNet-16. Sagittal slices were also employed to train a 2D CNN with two convolutional layers[46] or six convolutional layers.
The use of all three planes of 3D brain scans can offer complementary features useful for our classification process. Thus some research considered all image planes. Islam and Zhang designed three 2D CNNs for three views. Each CNN comprised 4 dense blocks (12 convolutional layers in each) and 4 convolutional layers; the final classification was done by majority voting. In another multi-view study, different 2D CNNs (such as GoogLeNet, AlexNet, ResNet, and VGGNet) were employed with and without long short-term memory (LSTM). LSTM is considered a type of recurrent neural network (RNN) with a more complicated structure. No significant differences have been reported among all views, and multi-view models were reported to have higher accuracy than were single-view models. The most critical disadvantage of multi-view approaches is that they could lead to ambiguity in the final decision.

3D CNNs

Given that MRI scans are 3D images, and a spatial relationship exists among 2D image slices, using 3D CNNs is the trend. The most direct method for AD detection is to take the entire MRI scan as the input. However, a large number of parameters are involved in

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training on a small dataset, which could lead to overfitting. In straightforward methods, 3D CNNs with 5 and 12 convolutional layers were proposed; 3D CNNs pretrained with AEs with 3 convolutional layers were also suggested. Others, based on VGGNet and ResNet, ResNet-18,and ResNet-37, were recently implemented. In another study, the features were combined from multi-scale 3D convolutional AEs with three hidden layers and a 3D CNN with six convolutional layers.

A VGGNet-based 3D CNN was proposed by Tang et al. to reduce the gradient-vanishing impact through an additional shortcut to merge high- and low-level information. A 3D CNN with seven convolutional layers was described by Wegmayr et al. To capture input features on different scales in this work, three different sizes for filters were selected in the first convolutional layer. Dense connections were introduced to 3D CNN for AD detection by Wang et al. It was reported that dense connections could enhance the gradients' propagation throughout the network with insufficient training data.

IV. PROPOSED SYSTEM

IMPLEMENTATION

This chapter will concentrate on implementing the system utilizing the conceptual design from Chapter 4 as a foundation. The implementation will always be realistic in order to meet the demands revealed in Chapter 3, with the goal of being useful in answering the research question provided at the beginning of the report.

And in this section, we can go over the implementation of stages in the base algorithm so that researchers can simply identify the path for their desired data and move on from this implementation. We may also view the pre-processing of the dataset and the technique used to implement further.

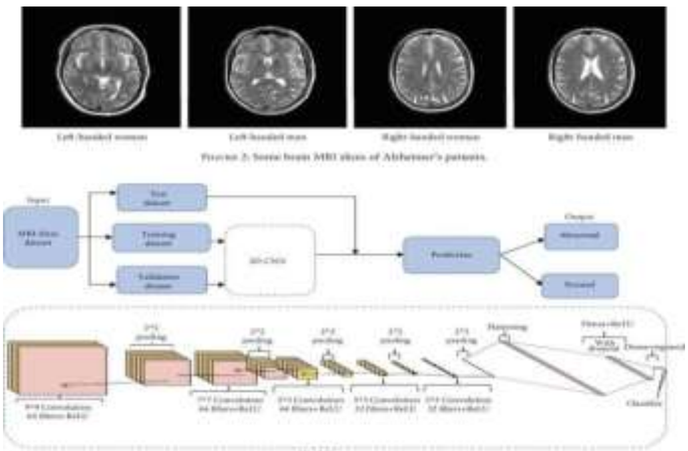

Fig.1.Algorithm: Faster R-CNN, YOLOv3 Model

Data collection and pre-processing

We have a large number of data sets, but working with genuine data that has been scanned by doctors of the elderly would provide us with more accurate and good scope for researchers to identify the best method to cure this AD. So, for Alzheimer's disease, we obtained a dataset from Kaggle that contained approximately 6000 MRI scan images.

We are further progressing through the AD illness stages of mild demented, very mild demented, moderate demented, and non-demented in this 6000 plus MRI pictures. This classification provides a greater scope for determining which stage of the AD disease has affected the person so that he or she can be treated further by taking medicines prescribed by experts.

You might be wondering how Alzheimer's illness is discovered in an MRI scan dataset. The explanation is that, in the early phases, the brain is generally fine. In later stages, the brain may shrink and we might identify it abnormally by sight, but we cannot be certain about AD. Such as a reduction in the size of several brain areas. Furthermore, this AD usually or mostly attacks the temporal and parietal lobes of the brain. Furthermore, some of the white and grey matter in humans can affect modifications due to Alzheimer's disease attack. Most data sets must be pre-processed to ensure that the data is valid before evaluating and visualising the model with various machine learning methods. In any case, the visualisation will be explained in further detail in the following chapter. To evaluate the model, we used pre-processed data and tested using appropriate Python code that the data is correctly reshaped and all that. We pre-process the data to ensure that it is correct and to remove any noise, such as undesirable features, in order to generate a faultless RCNN model.

V. SYSTEM ARCHETECTURE

The Fast R-CNN image identification methodology is a two-step object detection method that first detects areas of interest before passing them through a Convolutional Neural Network (CNN). It's also an upgrade over the Region-Based CNN, which uses a simple object identification approach but then incorporates a CNN once the features are retrieved.

Once trained, the RCNN model can be used to evaluate new brain scans and detect any signs of Alzheimer's disease. This can be a useful tool for early illness detection and diagnosis, as well as following the progression of the condition over time.

Layers present in Regions Based Convolution Neural Networks are:

- **Input Layer:** This is the first layer of the RCNN net work and its role is to receive the input image.
- **Convolutional Layers:** These layers apply filters to the input image to extract features such as edges, lines, and shapes. Multiple convolutional layers may be used to extract more complex features.
- **Region Proposal Network (RPN):** This layer proposes a set of candidate regions in the image that may contain the object or feature of interest. It generates a set of rectangular boxes and assigns a probability score to each box based on how likely it is to contain the object.
- **Region of Interest (RoI) Pooling Layer:** This layer extracts a fixed-sized feature map from each candidate region proposed by the RPN. The feature map is used as input to the next layer.
- **Fully Connected Layers:** These layers take the feature maps from the RoI Pooling Layer and applya set of weight parameters to classify the object or feature of interest within each region. The output is a probability score indicating the presence or absence

of the object or feature in each region.

Non-maximum Suppression (NMS) Layer: This layer applies a post-processing step to remove redundant or overlapping region proposals that have similar probability scores. Only the region proposal with the highest probability score is kept.

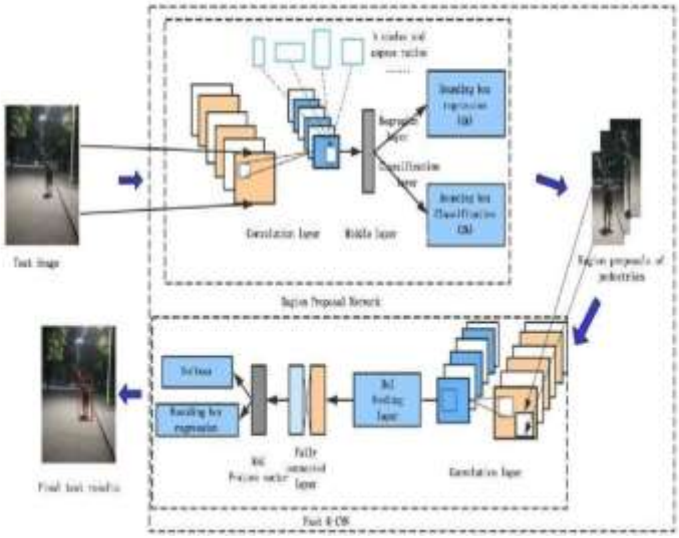

Fig 2. Flow of Faster RCNN Algorithm

VI. RESULTS:

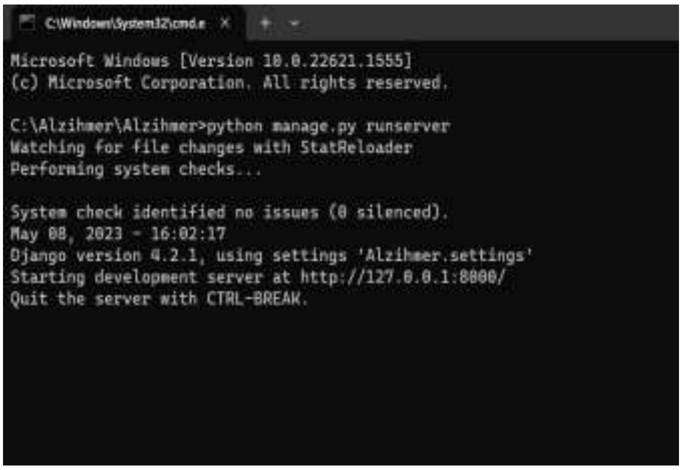

Fig 3. Copying of Development Server

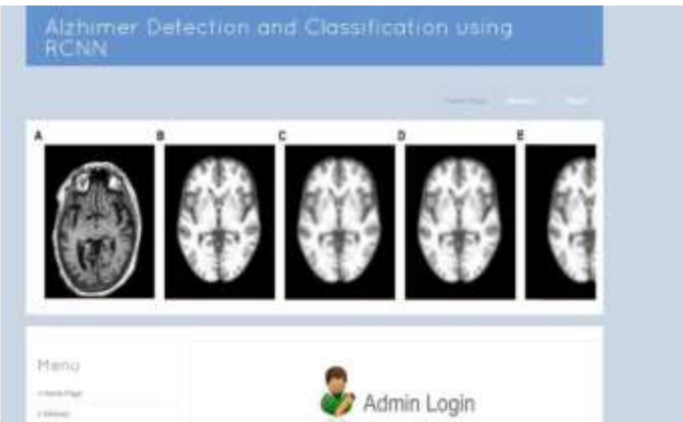

Fig 4. Web page

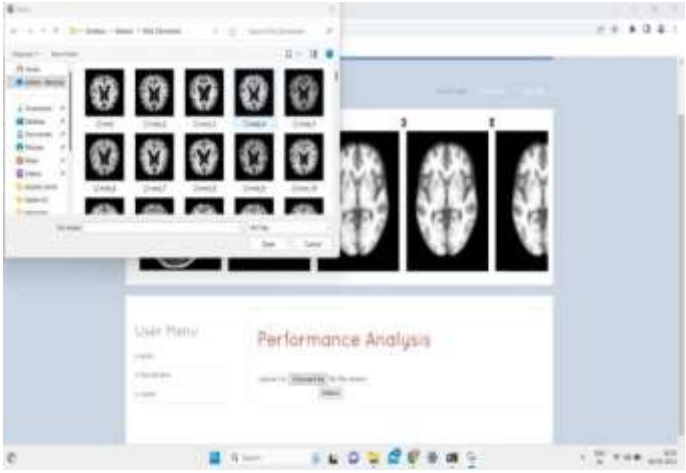

Fig 5. Uploading MRI scans

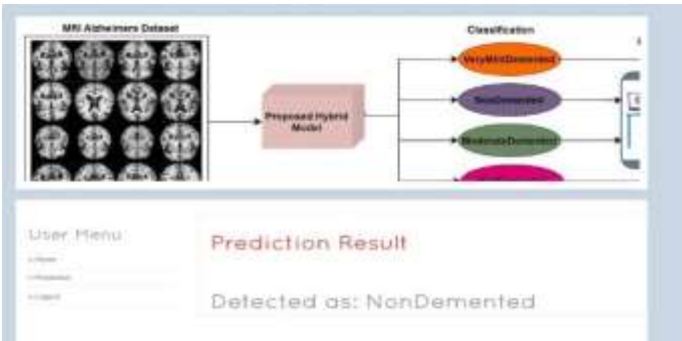

Fig.6. Output1

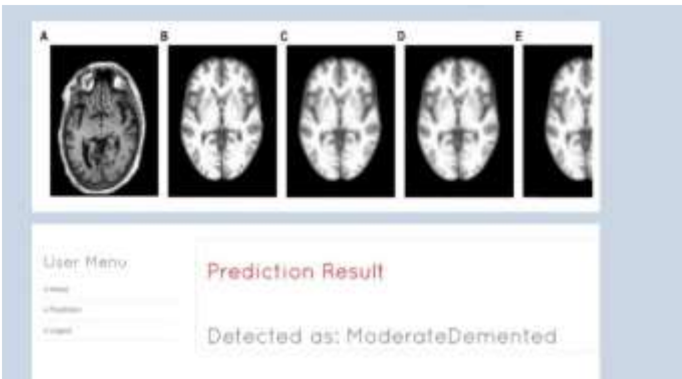

Fig.7. Output2

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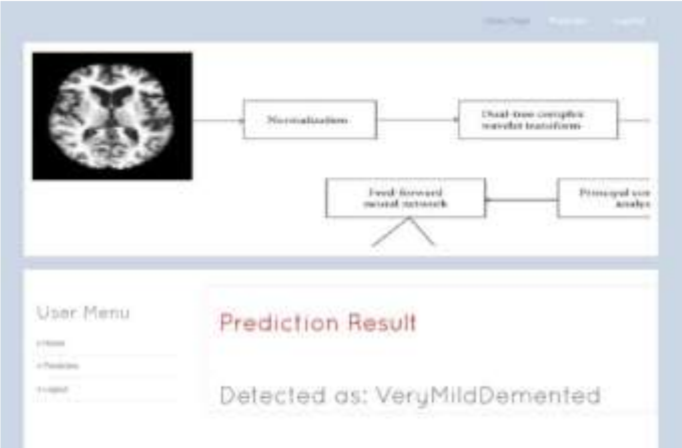

Fig.8. Output3

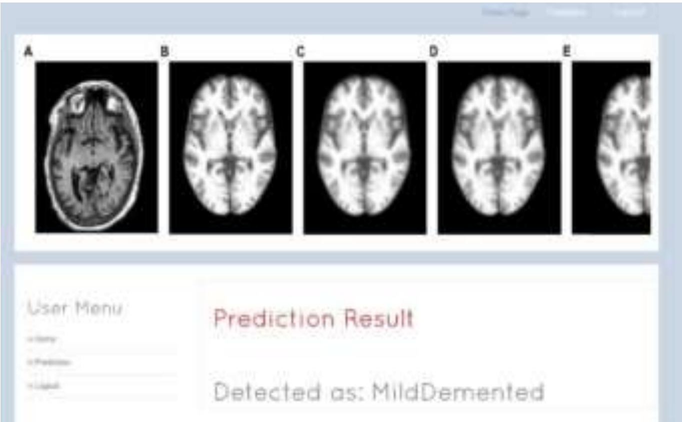

Fig.9. Output4

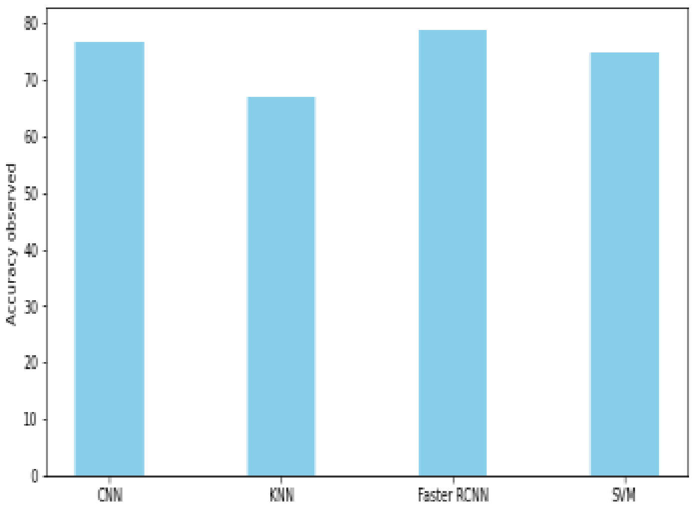

Fig 10. Comparison table of Different Algorithms

VII. CONCLUSION

Currently being employed is a deep learning model that can recognise instances of Alzheimer's disease based on brain MRI data. It has a 97.36% accuracy and can execute paired order analysis without the requirement for manual component extraction. Large dataset testing with this model is also ideal. Additionally, it can be helpful in areas where the test pack falls short. For instance, there haven't been many acknowledgements of the application of deep learning in the clinical area for the diagnosis of Alzheimer's disease. Reviewing the gathered and clarified data on esophageal cancer growth demonstrates the proposed system's suitability for the job.

VIII. FUTURE WORK

The field of AI-based methods for diagnosing neurodegenerative diseases like Alzheimer's and others is still in its infancy, and there is still a lot of room for growth and advancement. The notion of incorporating such systems onto web pages for more useful use is exciting since it may speed up, increase accessibility, and reduce the cost of the diagnosing process. The current approach might eventually be tested on a bigger dataset and possibly set up as a web application with real-time screening and a user interface. Clinicians may be able to diagnose patients more quickly and accurately as a result of this. The auto feature system can also be changed to automatically detect additional neurodegenerative illnesses, broadening its potential applications.

This project's incorporation of a global positioning system (GPS) to propose appropriate hospitals for treatment is one potential future expansion. This might give patients useful information and make it easier for them to get the best care for their illness. A rigorous examination of the ethical and legal ramifications as well as measures to ensure data privacy and confidentiality would be necessary for such an extension.

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