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BRAIN TUMOR DIAGNOSIS USING ADVANCED MACHINE LEARNING TECHNIQUES

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ABSTRACT

Brain is the controlling center of our body. With the advent of time, newer and newer brain diseasesare being discovered. Thus, because of the variability of brain diseases, existing diagnosis or detection systems are becoming challenging and are still an open problem for research. Detection of brain diseases at an early stagecan make a huge difference in attempting to cure them. In recent years, the use of artificial intelligence (AI) is surging through all spheres of science, and no doubt, it is revolutionizing the field of neurology. Application of AI in medical science has made brain disease prediction and detection more accurate and precise. In this study, we present a review on recent machine learning and deep learning approaches in detecting four brain diseases such as Alzheimer's disease (AD), brain tumor, epilepsy, and Parkinson's disease. Recent articles on four brain diseases are reviewed considering diverse machine learning and deep learning approaches, modalities, datasets etc. Twenty-two datasets are discussed which are used most frequently in the reviewed articles as a primary sourceof brain disease data. Moreover, a brief overview of different feature extraction techniques that are used in diagnosing brain diseases is provided. Finally, key findings from the reviewed articles are summarized and a number of major issues related to machine learning/deep learning-based brain disease diagnostic approaches are discussed. Through this study, we aim at finding the most accurate technique for detecting different brain diseaseswhich can be employed for future betterment.

KEYWORDS : Alzheimer's disease, brain tumor, deep learning, epilepsy, Parkinson's disease, machine learning.

I. INTRODUCTION

Memory, vision, hearing, knowledge, and temperament are all normal brain functioning.Images of the brain include bone-lined brains, fluids, and lipids. Growth defines the abnormal progression of problems. Brain tumours are classified as benign (noncancerous) or malignant (cancerous) (abnormal). Tumors can be detected by magnetic resonance imaging, computed tomography, and ultrasound.Magnetic resonance imaging (MRI) is critical in tumour analysis, diagnosis, and therapy planning.Brain tumours are classified as benign (noncancerous) or malignant (cancerous) (abnormal). Tumors can be detected by magnetic resonance imaging, computed tomography, and ultrasound. It aids doctors in detecting tumours in their early stages.Before using a segmentationapproach to detect the growth, pre-processing procedures such as bone removal are required to improve the picture quality, as the image quality is dependent on the segmentation results. Our primary goal in this project will be toimprove the accuracy of the tumor detection because physicians cannot detect the precise position of the growth set within the brain due to manual detection.Various algorithms that have been devised do not match the accuracyof the brain's growing set. There were various health issues occurring over the world that went unaddressed. Ourgoal is to find a reliable mechanism for identifying health outcomes such as tumors.

II. EXISTING SYSTEM

Image processing techniques are used to detect brain tumours. To achieve the best outcomes, various methods areutilised to partially fulfil the requirements. Probabilistic neural networks have been employed for increased productivity using CNN and KNN techniques, among other algorithms. Brain tumour detection relies heavily onsegmentation.

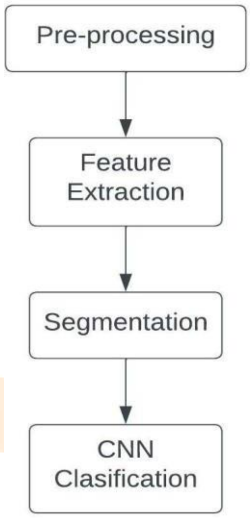

Fig 1. Existing block diagram

Pre-processing is performed in this procedure to improve the image without changing the information content. Image artefacts, inadequate resolution, low contrast, and Geometric Distortion are the most common causes of image flaws. The picture feature was then extracted from the datasets using the feature Extractions. This systemproduces a moderate outcome (i.e., the tumour identification is accurate, but the tumour categorization is not done in the circuit).

A. PRE- PROCESSING

The pre-processing is an essential and initial step in improving the quality of the brain MRI Image. The critical steps in pre-processing are the reduction of impulsive noises and image resizing. In the initial phase, we convertthe brain MRI image into its corresponding gray-scale image. The removal of unwanted noise is done using the adaptive bilateral filtering technique to remove the distorted noises that are present in the brain picture. This improves the diagnosis and also increase the classification accuracy rate.

B. SEGMENTATION

Image segmentation is a method of dividing an image into many pieces. This separation's major purpose is to make photographs easier to examine and comprehend while keeping image quality. This method is also used totrace the edges of object within photographs. Pixels are classified using this method based on their intensity andcharacteristics. This approach classifies pixels based on their brightness, and those pieces reflect the entire original image, taking on properties such as brightness and similarity. The photo segmentation technique is used to create body contours for healthcare purposes. Machine perception, malignant disease analysis, tissue volumes, anatomical and functional analyses, virtual reality visualisation, anomaly analysis, and object definition and identification are all examples of when segmentation is applied. Segmentation algorithms can findor identify anomalous areas of an image, which is important for assessing the size, volume, position, texture, and shape of the extracted image.MR image segmentation with the help of threshold information, which allows for more precise identification of broken regions. Previously, it was fashionable to suppose that objects placed close together would have similar habitats and features.

C. CONVOLUTION NEURAL NETWORK

Convolutional Neural Network (CNN) are easier to coach and fewer liable to over fitting. Classification is one ofthe most effective methods for identifying images, such as medical imaging. All classification algorithms work on the assumption that an image has one or more characteristics, each of which belongs to one of several classes.

III. MODULES

SUPPORT VECTOR MACHINE (SVM)

We used a support vector machine approach with the radial basis function (RBF) kernel to build prediction models. The tree-based models are distinct from the related ensemble approach, random forest. The SVM is a supervisedmachine learning technology that may be applied to classification and regression problems. Support vectors are just the coordinates of each individual observation. The SVM classifier is a frontier that effectively separates thetwo classes.

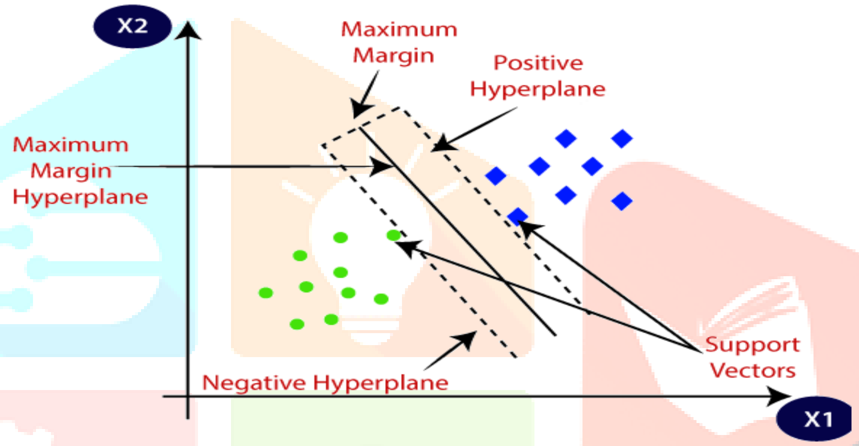

Fig 2.Support Vector Machine

DECISION TREE CLASSIFIER

DT were trained sequentially, and each base model was updated to correct the error produced by its previous treemodels, called a learning rate. To optimize parameters in this method, we examined combinations of the followingfive hyper-parameters: maxdepth, ntree, minsplit, minsample, and learning rate. The first four parameters were the same as in the random forest algorithm.

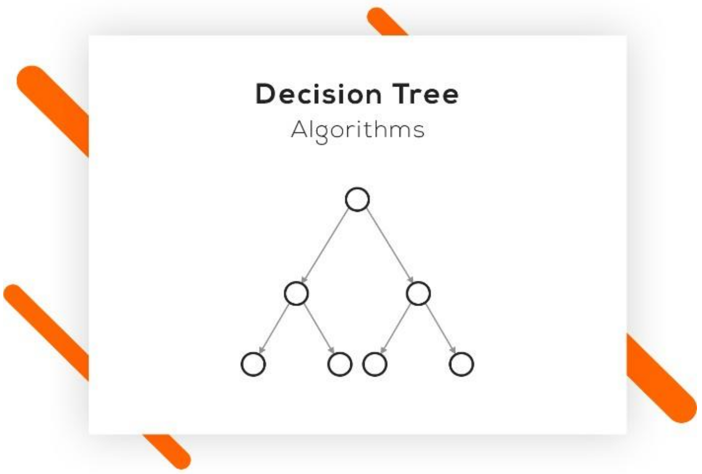

Fig 3. Decision Tree Classifier

RANDOM FOREST (RF)

Using the best prediction model based on random forest method, we investigated the optimal combination of parameters to give the better output and the accuracy.The overall identification of the brain disease diagnosis willbe better than the **CNN** algorithm.

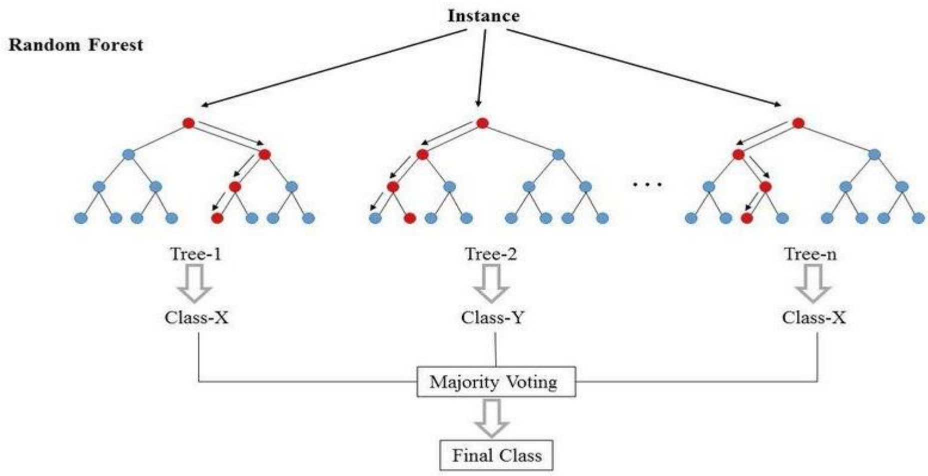

Fig 4.Random Forest

IV. SYSTEM ARCHITECTURE

Architecture diagram shows the relationship between different components of system. This diagram is very important to understand overall concept of the system. Architecture diagram is a diagram of a system, in whichthe principal part or function are represented by blocks connected by lines that shows the relationship of the blocks.

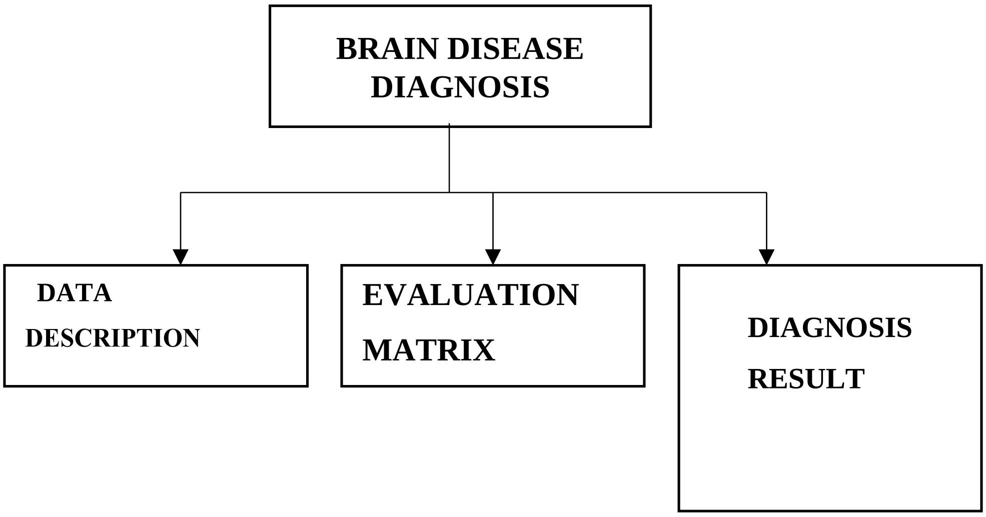

Fig 5. Overall Architecture Diagram

DATA DESCRIPTION

Clinical Dementia Rating (**CDR**) is used as the input dataset Clinical Dementia Rating Scale–Sum of Boxes (CDR–SB) scores. These were derived from the Alzheimer's disease Neuroimaging Initiative study, of Alzheimer's disease and mild cognitive impairment patients. The CDR Dementia Staging Instrument in one aspectis a 5-point scale used to characterize six domains of cognitive and functional performance applicable to Alzheimer disease and related dementias like brain disorder.

EVALUATION MATRIX

The suggested machine learning methods, such as the random forest classifier, SVM, and decision tree classifier,outperform the existing CNN algorithm. The most efficient features exhibit a smaller association than predicted between the final method's ranking of feature relevance and the top-ranked miRNAs. This suggests that our prediction model still has potential for improvement. One possibility is to include functional units like metabolicpathways in our final risk prediction model, as miRNAs with high feature relevance in the GBDT were linked tomultiple biological processes..

TUMOR SEGMENTATION

Tumor segmentation is the process of correctly identifying the geographic position of a tumour using techniquessuch as decision trees, random forests, and support vector machines.The process of separating the tumour from normal brain tissues is known as brain tumour segmentation, It's also used in clinical practise to help with diagnostic and treatment planning.

V. PROPOSED SYSTEM

The proposed technique is based on Support Vector Machine (SVM) classifier for brain tumour classification however it can be also used for regression challenges.SVM is a supervised learning method that looks data and sorts it into two categories. In SVM algorithm, we plot each data item as a point in n-dimensional space. then , we perform classification by finding the hyper-plane that differentiate two classes.

Decision tree(DT) were trained sequentially, and each base model was updated to correct the error produced by its previous tree models, called a learning rate.The goal of DT is to create a model that predictsthe value of a target variable based on several input variables.

Random forest is a Supervised Machine Learning Algorithm that is used widely in Classification and Regression problems. It builds decision trees on different samples and takes their majority vote for classification and average in case of regression.

ADVANTAGES

- In SVM the data can be either linear or non-linear.
- The important advantage of SVM algorithm is that it is able to handle high dimensional too.
- Better accuracy as compare to other classifiers.
- It also works well with unstructured data.
- It solves both classification and regression problems.
- After doing little modification in the feature extracted data does not affect the results which wereexpected before.

➢ It can perform in n-Dimensional space. it has a better accuracy in results. ➢ The Execution time comesout to be very little in comparison to algorithm such as Artificial Neural Network

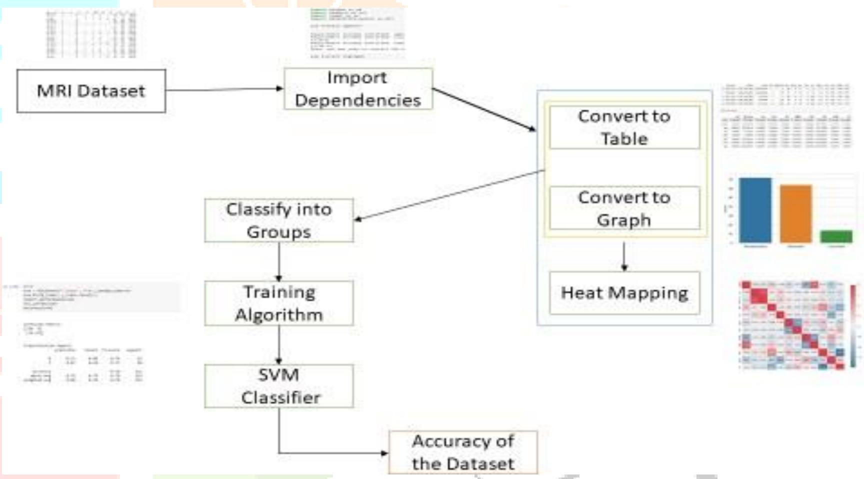

Fig 6.Control Flow Diagram

VI. RESULT AND ANALYSIS

Hardware restrictions are common in machine learning and deep learning applications. Because of the limitationof lossless data retention, the problem becomes more serious when the computing processing is applied to medicaldata. Increased processing capacity eventually necessitates greater memory and computing resources. In ML andDL, image pre-processing is a crucial challenge. The proposed classifiers and methods achieve a high level of accuracy and detection for the machine learning algorithm. The SVM and RF algorithms produce better results than the CNN method.

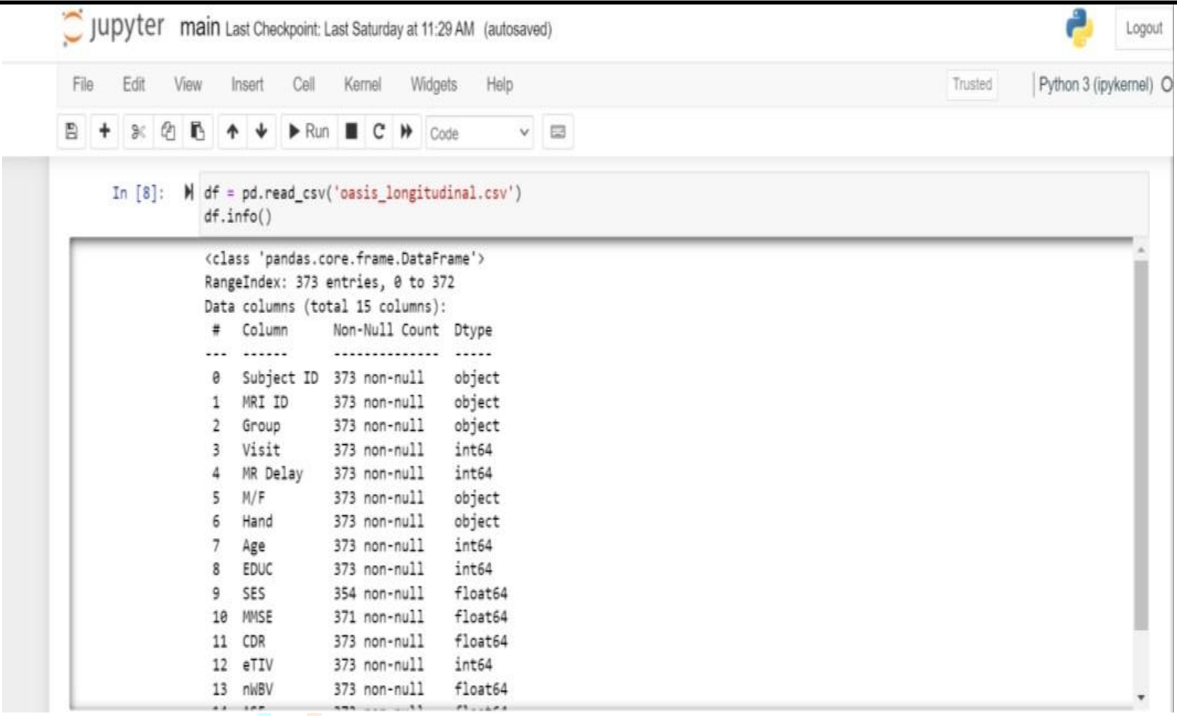

Fig 7. Data Input Modules

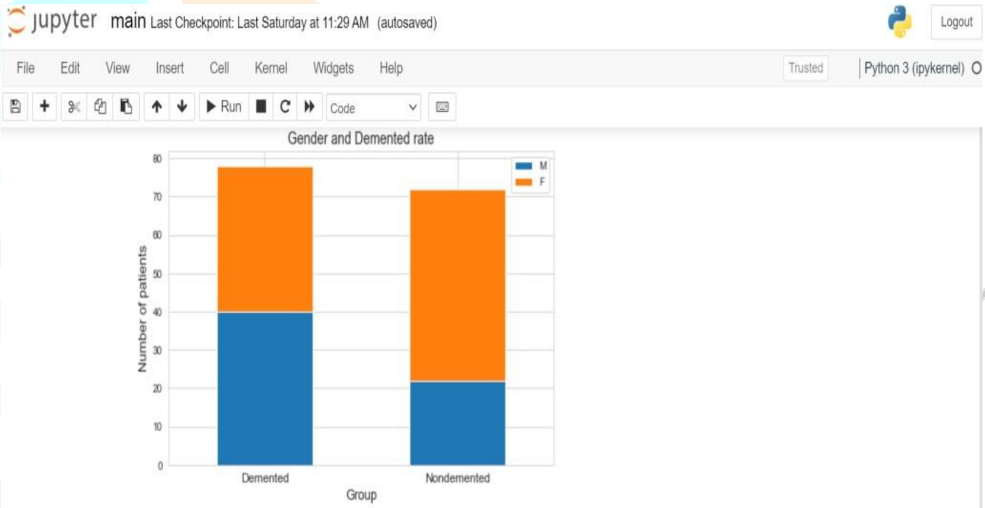

Fig 8. Graph Modules

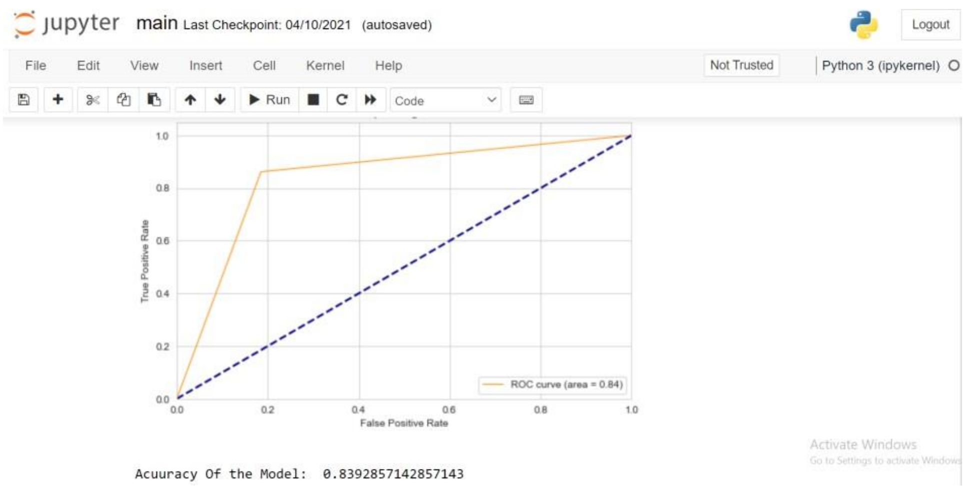

Fig 9. Support Vector Machine Accuracy

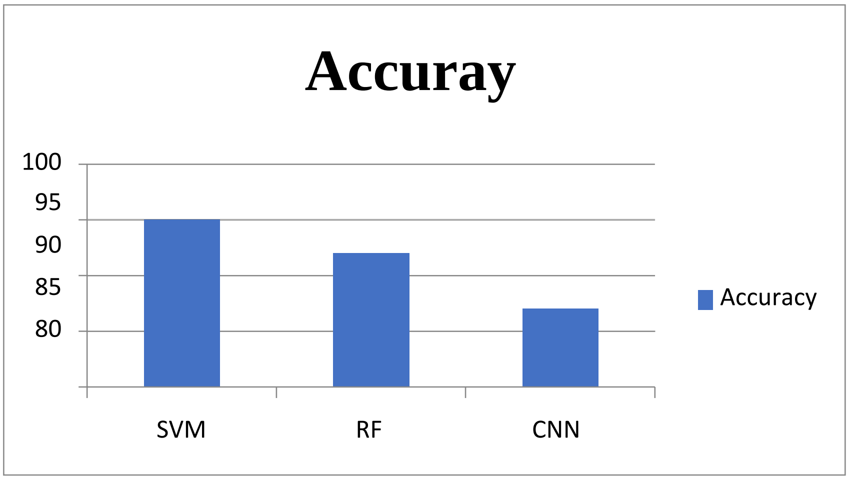

Fig 10. Overall Accuracy of all the Modules

VII. CONCLUSION

In this paper, we have presented a survey on the four most dangerous brain disease detection processes using machine and deep learning. The survey reveals some important insights into contemporary ML/DL techniques inthe medical field used in today's brain disorder research. With the passage of time, identification, feature extraction, and classification methods are becoming more challenging in the field of ML and DL. Researchers across the globe are working hard to improve these processes by exploring different possible ways. One of the most important factors is to improve classification accuracy. The number of training data needs to be increased because the more the data is involved, the more accurate the results will be. The use of hybrid algorithms and a combination of supervised with unsupervised and ML with DL methods are promising to provide better results. Even, various fine tunings can sometimes offer promising improvements. The SVM and the random forest algorithm provide the better result than the previous algorithms.

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