Decision Support System for Neurodegenerative Diseases (Brain Tumor) Using Ensemble CNN

[1]Dr.C.A. Sathyamoorthy, [2] P. Hari Ragavan, [3] B. Chandru, [4] S. Giridharan

[1] Professor, Department of ECE, Sri Manakula Vinayagar Engineering College, Puducherry, India.

[2,3,4]Undergraduate Students, Department of ECE, Sri Manakula Vinayagar Engineering College Puducherry, India.

Abstract— Identifying brain tumors is difficult, because their appearances vary widely and the brain tumors are so complex. Precision is an important issue when it comes to traditional imaging techniques which result in the need of using advanced deep learning-based techniques to increase the accuracy of the detection. To improve performance, the proposed system combines various feature extraction and classification techniques as a system. Because ResNet-101 can extract fine patterns and hierarchical representations within brain imaging data, it is used for feature extraction. In addition, a custom CNN is employed to further extract feature by leveraging the domain specific property of brain tumor. Then these extracted features are given to several machine learning classifiers like Support Vector Machine (SVM), Random Forest (RF) and Logistic Regression (LR), Ensemble CNN to develop as well as separate different parts of classification. To increase robustness even more, these classifiers are combined using a Voting Classifier to get predictions from them, which will sum up the decisions made by these classifiers to get a more accurate and reliable final decision. One of our contributions of this hybrid approach is not only to maintain high detection accuracy, but it also improves model generalization, which renders it desirable for clinical applications aiming at precision and flexibility.

Keywords: Brain Tumor, ResNet-101, Feature Extraction, Convolutional Neural Network (CNN), Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Voting Classifier, Ensemble CNN, Machine Learning Classifiers.

I. INTRODUCTION

It is a significant health problem; millions of people suffer from brain tumors all around the globe, and brain tumors are becoming more and more common, mainly because of the improvements in diagnostic technologies and aging population [1]. Abnormal cell growth inside the brain or in the central nervous system often produce these tumors especially if not taken care of, it can severely affect cognitive and motor functions as well as in general quality of life [2]. Three types of tumors known as gliomas and meningiomas and pituitary adenomas are the most widely identified types although rare types present additional challenges regarding diagnosis and treatment. [3]. In addition to patients, caregivers experience physical, emotional and financial impacts of brain tumors on themselves as well as on the health care systems [4]. Such [early] detection and accurate classification leads to better outcomes and survival rates of brain tumor treatment [5]. Hence, early identification will provide targeted therapies, less complications and less precise surgery [6]. Current diagnostic methods (MRI and CT scans) however depend on the presence of a radiologist with one or more years of clinical training and an extensive assessment to perform, to which the time is consuming. [7] Furthermore, these technologies are not currently available in areas of limited healthcare infrastructure and critical need for efficient, cost effective diagnostic tools exists [8]. However, emerging machine learning techniques that can classify brain tumor based on faster and better accuracy exist [9]. A hybrid method has been employed that combines a pre-trained VGG-19 Convolutional Neural Network (CNN) with a Bidirectional Long Short-Term Memory (BiLSTM) model, showing promising results. [10].

II. LITERATURE SURVEY

Brain tumor detection and classification has assimilated to completely into the arena of medical science research for a long period of time as it is a tough uprising invoking the fate of the patient. [1] The U-Net is used as the basis of the proposed architecture due to its effectiveness for medical image segmentation tasks. Fed-MUnet is an FL-based framework that allows data sharing from different institutions in a decentralized way while keeping patient data private and secure [1]. [2] The architecture of deep learning model called as BTS-VNet is for brain tumor segmentation using MRI scans based on the deep learning architecture of V-Net which is developed specifically for 3D medical images [2].

[3] The authors acknowledge that it improves the segmentation by a combination of many techniques. The authors integrate both CNN and hybrid models to deal with variability of tumor shapes and MRI appearances. [3]. [4] Fine-tuned version of the architecture of the EfficientNet to be used for brain tumor detection from MRI scans. In the effective band, EfficientNet shows its eminent feature extraction capacity, so that the precision of detection is improved by reducing the computational requirement [4]. [5] The authors propose a new (GCNN) to classify brain tumor from Brain MRI Images and_ brain glioma grade Gaussian filters are used in convolutions in order to make it focus more on the properties of tumor tissue [5]. [6] For the initial training of a brain tumor detection model using MRI scans, this study assesses the effectiveness of various deep learning frameworks, such as ResNet, Inception, and VGG, among others. The researchers adjust and utilize data augmentation techniques to enhance the model's accuracy and generalization capabilities on small datasets. This study identified variability in MRI images along with model selection that could enhance tumor detection performance. [6]. [7] Ultimately, the author additionally offered the initial normalization and augmentation procedures for various patient database generalization methods. A segmentation approach utilizing the model is introduced and demonstrates improved performance over traditional methods, especially in tumor subregions. [7]. The aim of this survey paper [8] is to review the state of art deep learning techniques for brain tumor segmentation from the medical images and how this architecture has performed on different types of brain tumors from the brain MRI scans providing the strength and weakness in terms of sectioning the brain tumor. Further, the paper

enunciates data scarcity, appearance variability of the tumors and strictness of the data needed for accurate medical decision making. [8]. [9] The article presents complete automation of deep learning network that is to segment brain tumors from MRI scans. In future work, other imaging modalities will be incorporated, segmentation accuracy verified in more clinical challenging cases and the application of automated brain tumor segmentation for clinical applications, continue to advance [9]. [10] For the given work, it presents the deep learning-based framework of brain tumor segmentation and classification from MRI scan. It segments the regions which were suspected to show brain tumors automatically and classify them benign or malignant using Convolutional Neural Network. It an excellent tool for the aid of radiologists in clinical decision making. [10].

III. PROPOSED WORK

It is order to solve the difficulties with the traditional imaging methods such as MRI and CT scans, the proposed system incorporates the deep learning and machine learning techniques. In order to overcome this, the system uses a deep CNN for feature extraction, namely ResNet-101. After removing the irrelevant features, they are fed into several classifiers including, Support Vector Machine (SVM), Random Forest (RF), and Logistic Regression (LR) is good at handling high dimensional data.

A. Data Collection:

In Figure 1 it is an essential first part of the proposed brain tumor detection system is data collection. Available data from open source platforms include a dataset of brain MRI images that has been expended on bulk and also labelled with different tumor types like glioma, meningioma pituitary tumors and non-tumor. The set of images usually has thousands and the images contain various brain regions of different tumor states. In the collection process, these high-quality images are downloaded in terms of PNG, JPEG or DICOM (for DICOM). To make the model robust, the data should be adequate enough of spanning a wide spectrum of cases and tumor types to support the model learning from this pool.

B. Pre-Processing:

Data pre-processing plays a crucial role in enhancing the quality of the data input into the model. Their brain MRI scans need to be modified; this involves taking measurements suitable for vegetation and converting the images into 3D for examination. They consist of resizing the images to a same shape and normalizing pixel values so as to be equal. Pre-processing is important as the system absorbs high quality data for feature extraction and model training.

C. Feature Extraction:

The relevant information from the preprocessed images (in the form of images) are extracted and represented in feature vectors or matrices due to which it is known as Feature extraction. The proposed system gets the features extracted using ResNet-101, a pre-trained deep convolutional neural network. First, the model is pre-trained on a big dataset (e.g. ImageNet) which will be then fine-tuned for brain tumor detection on the brain MRI dataset. Specific characteristics of the brain tumor images are designed to be focused on by the custom CNN so as to facilitate better classification accuracy.

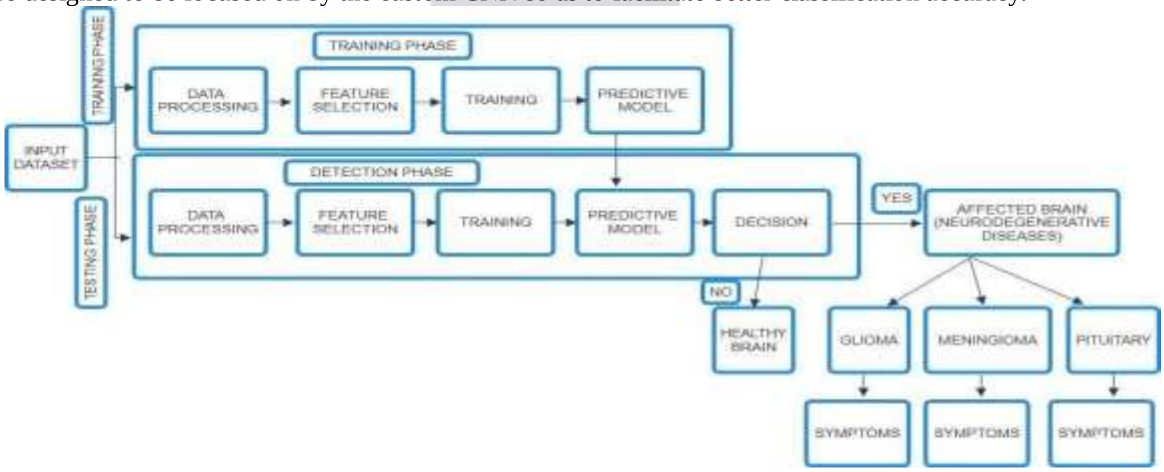

Figure 1: Block diagram of Proposed work

D. Model Creation:

Another method in model creation is building the architecture that will take the extracted features and classify the tumor types. (The proposed system uses ResNet 101 and custom CNN to do feature extraction, after which multiple ML classifiers are used to predict.). Because SVM separates between different tumor types well on finding optimal hyperplane, it is well suited to the huge dimensional datasets. Random Forest does not use only one decision tree but rather aggregates many decision trees for prediction accuracy and robustness that reduces overfitting. It is a probability-based classifier used to decide the probability of a tumor belonging to a given class.

E. Test Data:

Next, there is a division we refer to as test data that is not utilized in the training process. The purpose of the test data is to assess the model's performance in a genuine raw environment, as it is responsible for categorizing new, unseen images. In the suggested system, the test data typically consists of the images reserved during the initial data split, which is around 20-30% of the complete dataset. The feature extraction is performed on the identical preprocessed training data to ensure consistency. Ultimately, the trained model is evaluated on the test images to assess its accuracy, as well as precision, recall, and various other metrics.

F. Prediction:

The last step is the prediction step in which we use our trained model to classify unseen new, brain MRI images. Once it has been trained with the labeled dataset and evaluated via test data, the model is deployed to make such predictions on new images. To do this, the same preprocessing and feature extraction pipeline is applied to the input image as done in the training data. After some feature extraction, the image’s features are then fed to the machine learning classifier to make a final prediction. The Voting Classifier makes the final decision regarding tumor type based on combining the results of the tumor type outputs from SVM, RF, and LR — of which can be either glioma, meningioma, pituitary, or non-tumor of the symptoms.

IV. RESULT AND DISCUSSION

The brain tumor detection using the combination of deep learning and machine learning methods was tested in the proposed system. We used Voting Classifier that aggregates the outputs of SVM, Random Forest, and Logistic Regression model, improving the prediction accuracy of the whole system compared to traditional model verification. The system was validated with high accuracy, precision, recall and F1-score to effectively classify glioma in Figure 2, meningioma in Figure 3, pituitary tumor in Figure 5, and non- tumor cases in Figure 4 and give the symptoms.

Figure 2 Glioma

Symptoms: Headache, nausea, seizures, blurred vision

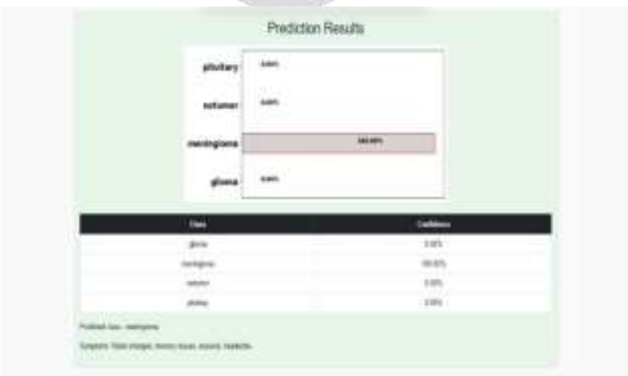

Figure 3 Meningioma

Symptoms: Memory issues, weakness, seizures, headaches

Figure 4 No Tumor

Symptoms: No symptoms detected. Please consult specialist for further details.

Figure 5 Pituitary

Symptoms: Vision problems, hormonal imbalances, headaches

A. Data Collect and Splitting the Data:

This project will require collection of data for this project which will involve getting brain tumor images from the available open source datasets on platforms like Kaggle. After collecting the data, the data is partitioned into two row main subsets: training set in Figure 6 and validation set in Figure 7 as shown.

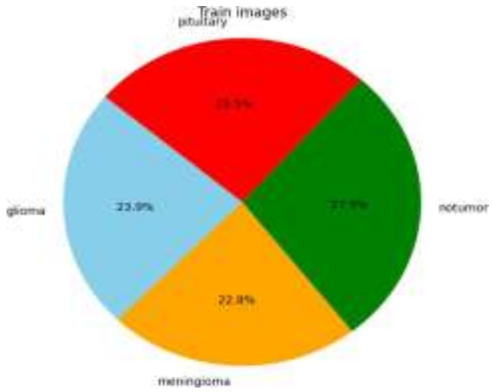

Figure 6 Train Images

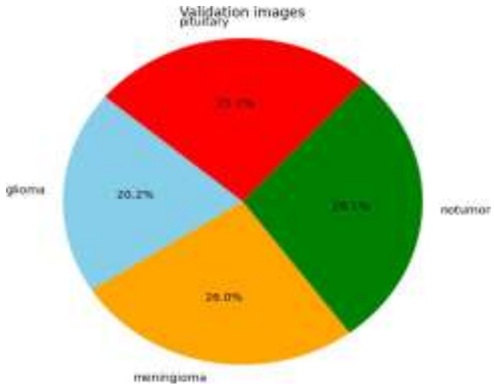

Figure 7 Validation Images

B. Accuracy:

Accuracy in the suggested brain tumor detection system is the ratio of the rightly classified images over everything being tested. It is a metric indicating the performance of the model to separate different classes and a large difference between training and validation accuracy as shown in Figure 8.

Figure 8 Training & Validation Accuracy

C. Loss:

In Figure 9 a loss in machine learning represents how well or not a model's prediction matches against the real target values. It tells the model, the difference between actual output and the predicted values allow the model to realize how far apart its prediction was from the desired outcome.

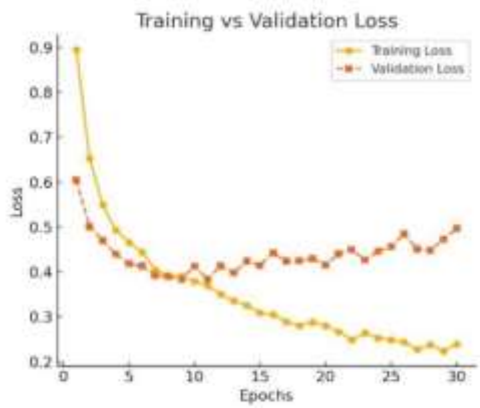

Figure 9 Training & Validation Loss

D. Cross-Entropy Loss (For Classification Tasks):

Machine learning loss is the difference between predicted values and ground truth and it is quantified as formula. The categorical cross entropy loss is commonly used for classification type problems as for detecting brain tumors.

$$\text{Loss} = -\sum_{i=1}^{N} y_i \cdot \log(p_i)$$

E. Precision:

A classification model determines its accuracy in positive case prediction through the performance metric 'Precision'. Precision determines the quality of positive predictions from the model by counting how many correct positive cases its predictions identify.

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

F. Recall:

Recall is a performance metric used for assessing the quality of a classification model's ability to identify correctly all positive instances. Recall is a technique used in the context of the proposed brain tumor detection system to evaluate the degree to which the system detects all the actual tumor cases.

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

G. F1 Score:

In Figure 10 it is to apply the technique to medical diagnostic problems such as brain tumor detection, high recall is necessary, i.e. to identify most or all real tumor cases. Absent a tumor (false negative) could have serious consequences because it can mean missing out on necessary treatment by a long time. Thus, the proposed system is developed in order to maximize recall (i.e., high probability of detecting all the tumors) at the expense of some false positive (i.e., some of the tumors may be missed).

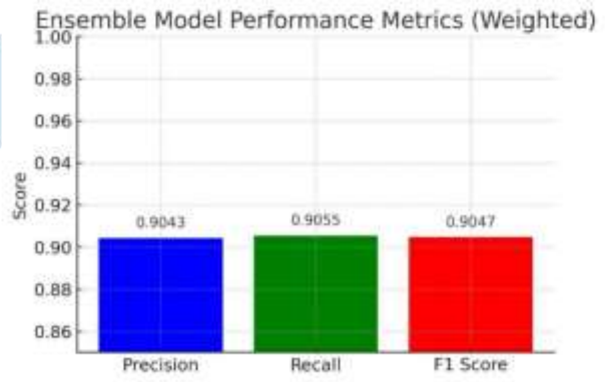

Figure 10 F1 Score

H. Confusion Matrix:

In Figure 11 it is to apply the technique to medical diagnostic problems such as brain tumor detection, high recall is necessary, i.e. to identify most or all real tumor cases. Absent a tumor (false negative) could have serious consequences because it can mean missing out on necessary treatment by a long time. The benefit here is that healthcare professionals is ensured the fact that they don't miss any potential tumor cases so as to enhance patient outcomes through prompt and precise diagnosis.

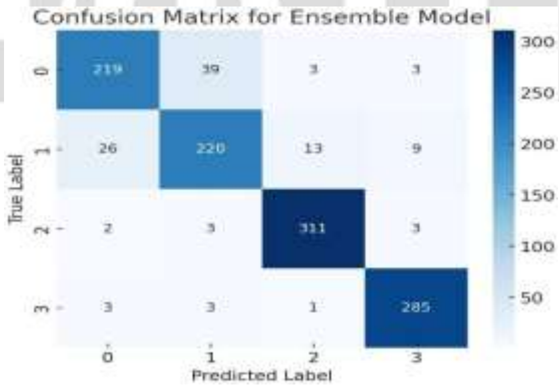

Figure 11 Confusion Matrix

V. CONCLUSION AND FUTURE WORK

In conclusion the proposed system shows great progress in brain tumor detection and symptoms by integrating the latest deep learning theories and traditional machine learning classifiers. By integrating ResNet-101 for feature extraction along with a custom CNN, the model is able to encode and extract these features. Multiple machine learning classifiers (SVM, RF, and LR), can be used for a robust and comprehensive analysis using their unique attributes for the same complex and high dimensional data. The limitations brought forward in the paper suggest potential improvements for the future work of the brain tumor detection system and symptoms using more advanced models such as Transformers or attention mechanisms for feature extraction. We would further improve generalizability of the model by expanding the dataset to include a range of tumor type and diverse imaging condition. Thirdly, it would be good to develop a user-friendly interface to the system for the radiologists to provide feedback which may then help refine the model continuously.

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