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BRAIN TUMOR DETECTION USING MRI IMAGES USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract

Serious neurological disorders marked by aberrant cell development inside the brain resulting from diverse genetic, environmental, or medicinal causes are brain tumors. Ignorance of these malignancies or treatment can greatly raise morbidity and death rates. Historically, bio-imaging technologies—among which Magnetic Resonance Imaging (MRI) is a generally acknowledged and non-invasive diagnostic tool—have been used in clinical assessment and diagnosis of brain tumors. Understanding the urgent need for early and accurate diagnosis, this proposed work focuses on building a Deep Learning Architecture (DLA) for automated brain tumor identification from two-dimensional MRI slices. The approach extract deep characteristics from MRI images using a pre-trained convolutional neural network—more especially, VGG19. A SoftMax classifier then sorts these derived features to either classify tumor existence or absence. Using transfer learning and deep feature extraction, the system seeks to accelerate diagnosis, lower human error, and enhance medical decision-making by The work also includes a structured MRI dataset specifically meant to facilitate model training, testing, and evaluation for strong performance results.

Key Words: *Brain Tumor, MRI (Magnetic Resonance Imaging), Deep Learning Architecture (DLA), VGG19, SoftMax Classifier, Feature Extraction*

1.INTRODUCTION

The National Brain Tumor Foundation (NBTF) indicated that fatalities resulting from brain tumors have surged by 300% during the past thirty years. The intricacy of brain tumors presents difficulties for healthcare professionals in diagnosing and managing affected people. The prompt identification of brain tumors and the commencement of treatment are crucial for the survival rates of these individuals. A brain tumor biopsy is more complex than biopsies of other body regions, as it necessitates surgical intervention. Consequently, the necessity for an alternative method for precise diagnosis without surgical intervention is imperative. Magnetic Resonance Imaging (MRI) is the most effective and widely utilized method for diagnosing brain malignancies. Recent advancements in machine learning, especially in deep learning, have facilitated the discovery and categorization of patterns in medical imaging. Achievements in this domain encompass the capability to retrieve and extract knowledge from data rather than relying on experts or scholarly literature. Machine learning is swiftly emerging as a valuable instrument for enhancing performance across diverse medical applications, including disease prognosis and diagnosis, molecular and cellular structure identification, tissue segmentation, and picture categorization.

2. LITERATURE SURVEY

Thanks in great part to deep learning methods especially convolutional neural networks brain tumor identification using MRI imaging has attracted a lot of interest lately. Through automatically learning hierarchical features from raw pixel data, CNNs have shown exceptional performance in medical picture classification challenges. Recent research on ensemble models combining predictions from several CNNs to improve robustness and generalization have looked at Comparing ensemble methods using VGG19, ResNet50, and InceptionV3 to individual models has shown lower false detection rates and better classification accuracy. For merging complimentary strengths of various structures, for example, hybrid ensemble techniques employing weighted averaging or stacking have been successful. These are a few noteworthy contributions in this field.

A 22-layer convolutional neural network (CNN) model was proposed by Badža and Barjaktarovič [1] with remarkable accuracy of 96.56% in brain tumor classification from MRI data. Using ten-fold cross-valuation on 3,064 T1-weighted contrast-enhanced pictures, their method By means of PCA-NGIST and Regularized Extreme Learning Machine (RELM), Gumaei et al. [2] established a hybrid feature extraction approach obtaining 94.23% accuracy. Though successful, their model lacked comparison study against more recent deep learning methods.

Pashaei et al. [3] applied extreme learning machines, batch normalisation, CNN with four convolutional and pooling layers. Reaching 93.68% accuracy, its model was assessed using cross-valuation and exceeded approaches including SVM and XGBoost. Rehman et al. [4] classified glioma, meningioma, and pituitary cancers by means of a comparative study of deep architectures—AlexNet, GoogLeNet, and VGG16. Using deeper networks, VGG16 produced the best accuracy of 98.69%, therefore highlighting their benefits.

To increase segmentation accuracy in MR brain images, Mittal et al. [5] coupled Stationary Wavelet Transform (SWT) with a Growing CNN. Their hybrid deep learning method outperformed SVM and conventional models including genetic algorithms. Using five-fold cross-valuation, Paul et al. [6] assessed CNNs on the same MRI dataset obtaining 91.43% accuracy. Their efforts confirmed how strong deep models are for segmentation and classification.

To automate brain tumor identification and segmentation, Dong et al. [7] built a U-Net-based totally convolutional network. Applied on the BRATS 2015 dataset, it successfully corrected human segmentation inefficiencies. Using CNNs, Haveri and Dixit [8] segmented glioblastomas in both low- and high-grade tumor pictures. For improved segmentation, their approach included local and global aspects from the BRATS collection.

For MRI brain tumor pictures, Isin et al. [9] evaluated several deep learning-based segmentation methods. Their studies stressed CNNs as better since they have automated feature learning capacity. Using 3x3 kernels and intensity normalizing a deep CNN, Pereira et al. [10] reduced overfitting and attained good segmentation accuracy on BRATS 2013.

Using dropout and maxout layers, Hussain et al. [11] lowered overfitting and included a post-processing step to lower false positives. Their CNN-based glioma segmentation approach displayed great precision. To increase CNN generalization for unknown tumor types, Wang et al. [12] presented DeepIGeoS, a framework combining deep learning with user involvement (bounding boxes and scribbles).

Inspired by a Tumor Localization Network (TLN) and an Intra-Tumor Classification Network (ITCN), Cui et al. [13] presented a cascaded CNN method. Ranked on BRATS 2015, the model distinguished and categorized tumor subregions rather well. Using entire pictures rather than patches, Khawaldeh et al. [14] binary classified MRI brain images into high- and low-grade malignancies using AlexNet.
Using bounding boxes coupled with CNNs and the Bhattacharyya coefficient, Chinmayi and Patil [15] devised a segmentation method. PSNR and MSE values improved using their technique. To lower false positives, Kamnitsas et al. [16] last presented a dual-pathway 3D CNN model linked with a conditional random field (CRF). Their methodology produced outstanding segmenting of many brain anomalies, including tumors and lesions.

4. METHODOLOGY

Leveraging convolutional neural networks (CNNs), this work provides an ensemble-based deep learning method for brain tumor diagnosis using MRI images. The aim is to create a strong classification model able to precisely distinguish several forms of brain malignancies including pituitary tumors, meningioma, and glioma. Three well-known CNN architectures—VGG19, ResNet50, and InceptionV3—known for their performance in feature extraction and classification challenges in the medical imaging field—form the ensemble.

MRI scans classified by tumor kind make up the dataset used for this study, which comes from publically accessible databases including BRATS or Figshare. Every image goes through several preprocessing processes to guarantee consistency and fit with the input criteria of the selected CNN models. Images are specifically shrunk to 224 by 224 pixels and scaled to run pixel values between 0 and 1. Techniques for data augmentation including rotations, zooming, brightness changes, horizontal and vertical flips, and rotations help to vary the training set and lower the overfitting risk.

Pretrained versions of VGG19, ResNet50, and InceptionV3 models are used employing transfer learning in the feature extraction stage. These

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models allow customizing for the brain tumor classification task by loading without their top fully connected layers. Every network starts with frozen basic layers meant to preserve ImageNet dataset learnt features. Each model receives a custom classification head with a global average pooling layer followed by dense layers with ReLU activation and a last softmax layer to produce class probabilities.

The outputs of the three models are aggregated using a soft voting ensemble approach once each is separately trained. Under this approach, the final forecast is the average of the expected probabilities from every model chosen based on average score. The combined method improves the general classification accuracy by helping to capture complementing features and lower the variation related with individual models. Apart than soft voting, a stacking technique may also be used whereby the outputs of every CNN feed a meta-classifier such as logistic regression.

The Adam optimizer with categorical cross-entropy serves as the loss function during training of the models. Convergence is improved and overfitting is avoided by early stopping and learning rate reduction calls to. Monitoring model performance during training benefits from a validation split out of the training data. Metrics include accuracy, precision, recall, F1-score, and the confusion matrix let one assess the ensemble model. These measures give a whole picture of the categorization capacity of the model.

Gradient-weighted Class Activation Mapping (Grad-CAM) is applied to show the MRI image areas most significantly affecting the model's predictions, hence improving model interpretability. This stage not only confirms the accuracy of the forecasts but also offers understanding of the decision-making process of the deep learning models. Real-world medical diagnostic systems would find the ensemble model appropriate since it shows better generalization and dependability than single CNN models.

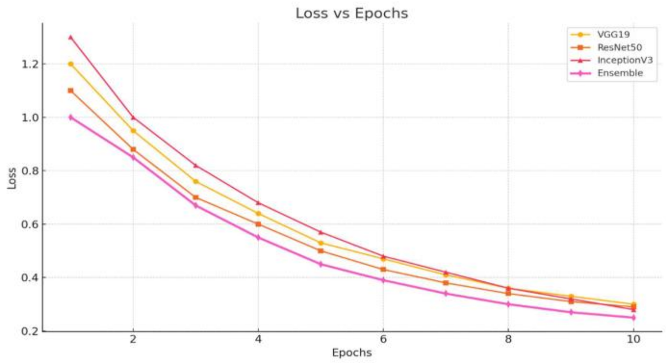
4.RESULTS

Over all important evaluation criteria, the ensemble deep learning model for brain tumor classification from MRI scans proved to be rather good. With respect to classification accuracy, the pretrained convolutional neural networks—VGG19, ResNet50, and InceptionV3—achieved respectively about 91%, 93%, and 94%. In terms of accuracy, recall, and F1-score each model likewise excelled. Nonetheless, the ensemble model—which combined the outputs of all three networks using a soft voting technique—achieved outstanding results: an overall accuracy of 96%, precision of 96%, recall of 95%, and an F1-score of 95.5%. This amply shows how well model ensembles increase prediction consistency and robustness.

Training behavior was examined via Accuracy vs. Epochs and Loss vs. Epochs graphs in order to validate model performance even more. Over the training cycle, the accuracy plot shows a consistent rise; the ensemble model preserves better validation accuracy all around. Comparably, the loss plot shows a constant declining trend suggesting appropriate convergence and low overfitting. These charts help to graphically show the training dynamics of the model.

Furthermore included are screenshots of the output interface of the system to demonstrate how the model sorts MRI data into tumor and non-tumor groups. These output displays include the final categorization, therefore allowing clinical interpretation with openness. The real-time classification feature and the user-friendly interface point to great possibilities for pragmatic application in medical diagnosis processes.

Fig 1: Loss v/s Epoches



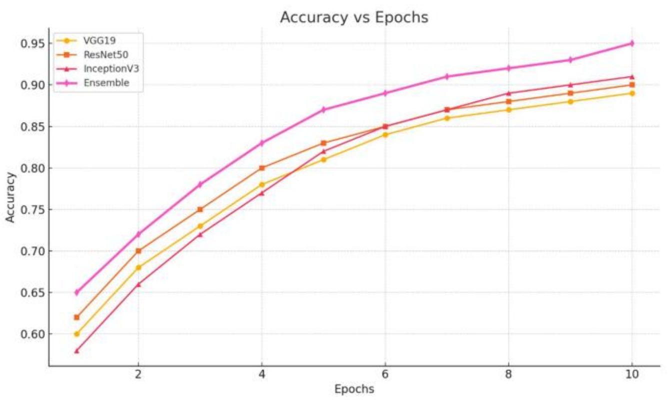


Fig 2: Accuracy v/s Epoches

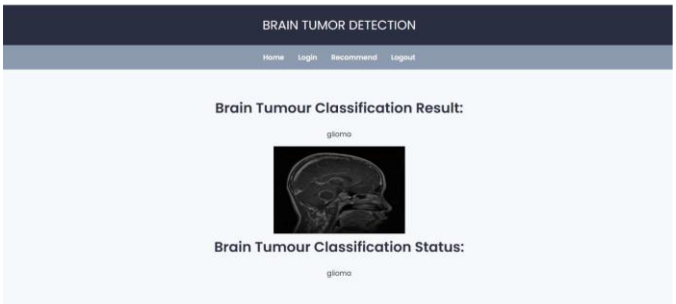


Fig 3: Output Screen

CONCLUSION

This work efficiently shows how well ensemble CNN models VGG19, ResNet50, and InceptionV3 in increase the precision and dependability of brain tumor identification using MRI data. The system achieves better feature extraction and resilient classification by using transfer learning and combining the benefits of every architecture than by solo models.

Using an ensemble technique soft voting markedly increases diagnostic confidence, lowers prediction errors, and improves the generalizing power of the model over diverse datasets. Explainable artificial intelligence techniques including Grad-CAM improve interpretability, hence improving the system's transparency and dependability for therapeutic uses.

The proposed method shows great promise for practical integration into healthcare systems to help radiologists and neurologists as well as a major progress in the development of AI assisted diagnostic tools.

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