Journal of Nonlinear Analysis and Optimization
Vol. 15, Issue. 1, No.11: 2024
ISSN : **1906-9685**

BRAIN TUMOR DETECTION USING CNN BASED ON TRANSFER LEARNING

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ABSTRACT

One of the most leading death causes in the world is a brain tumor. Solving brain tumor segmentation and classification by relying mainly on classical medical image processing is a complex and challenging task. Medical evidence shows that manual classification with human-assisted support can lead to improper prediction and diagnosis. This is mainly due to the variety and the similarity of tumors and normal tissues. Recently, deep learning techniques have shown promising results in improving the accuracy of detection and classification of brain tumors from magnetic resonance imaging (MRI). a deep learning model for the classification of brain tumors from MRI images using a convolutional neural network (CNN) based on transfer learning. It is estimated to get the best result using this model in terms of accuracy and F1-score.

Keywords: Deep learning, convolutional neural network, Transfer learning, Brain tumor, medical image classification.

INTRODUCTION

Detecting brain tumors is a critical task in medical diagnostics, often requiring advanced imaging techniques and expertise. In recent years, the application of Convolutional Neural Networks (CNNs) has revolutionized medical image analysis, offering promising results in various tasks including tumor detection. This introduction will provide an overview of brain tumor detection using CNNs based on transfer learning. Brain tumors represent a significant health concern globally, with their timely detection being crucial for effective treatment and patient outcomes. Traditional methods of tumor detection involve manual interpretation of medical imaging such as Magnetic Resonance Imaging (MRI) or Computed Tomography (CT) scans. However, this process is labor-intensive and prone to human error. CNNs, a type of deep learning algorithm inspired by the organization of the animal visual cortex, have demonstrated remarkable performance in various image recognition tasks, including medical image analysis. Transfer learning, a technique where a pre-trained CNN model is fine-tuned on a specific task, has emerged as a powerful approach to leverage the knowledge learned from large datasets.

In the context of brain tumor detection, transfer learning involves taking a pre-trained CNN model (often trained on a large dataset like ImageNet) and fine-tuning it on a smaller dataset of brain MRI scans labeled with tumor regions. This approach allows the model to quickly adapt to the nuances of tumor detection without requiring a massive amount of labeled data.

LITERATURE SURVEY

Many different approaches for detecting and classifying brain tumors have been developed in the literature. Zeineldin proposed a deep neural network approach for automatic brain tumor segmentation from magnetic resonance (MR) FLAIR images. Their model contains two linked core parts, one for encoding and the other for decoding. In the encoder part, a CNN is dedicated to extracting the spatial

information. Then, the resulting semantic map is entered into the decoder part to obtain the full-resolution probability map. In the last stage, residual neural networks (ResNet) and dense convolutional networks (DenseNet) have been explored(2019).
Priyansh and Akshat developed a predictive model for brain tumor detection using Resnet-50 based on transfer learning. Their experimental results gave 95% in terms of accuracy. In a parallel study, Nawab achieved a fivefold cross-validation accuracy of 94.82% through block-wise-based transfer learning. A benchmark dataset based on T1- T1-weighted contrast-enhanced magnetic resonance images (MRI) was used to evaluate their system. Moreover, Seetha and Raja proposed an automated system for the detection of brain tumors by deep CNN. In the first stage, the Fuzzy C-Means (FCM)algorithm has been involved for brain image segmentation. With this combined model, the detection accuracy achieved a rate of 97.5%.

In another study, Mircea used a feature-based approach by extracting wavelet coefficients from images. The authors claim that the use of wavelet transforms has an advantage over Fourier transforms, because of their temporal resolution, giving them the ability to capture both location information and frequency in the images. A technique based on support vector machine (SVM) is then applied as a classifier, achieving an accuracy of 91%. Finally, Sujan proposed a local thresholding method based on Otsu's formula followed by morphological operations on MRI images for detecting tumors that have the brightest pixels.

EXISTING SYSTEM

The existing system for brain tumor detection employs Convolutional Neural Networks (CNNs) with a focus on the VGG-16 architecture. This system is trained to detect the tumor in the MRI of the patient and thus predict whether the patient is suffering from the tumor or not. By utilizing a dataset of labeled

brain MRI scans, the system leverages transfer learning, pre-training the VGG-16 model on extensive image datasets such as ImageNet, and fine-tuning it for the specific task of tumor detection. Evaluation metrics such as accuracy, precision, recall, and F1-score assess the model's performance on a validation or test set, and visualizations aid in interpreting its predictions. The existing system provided anaccuracy of 90% and an F1-score of 90.9%.

PROPOSED SCHEME

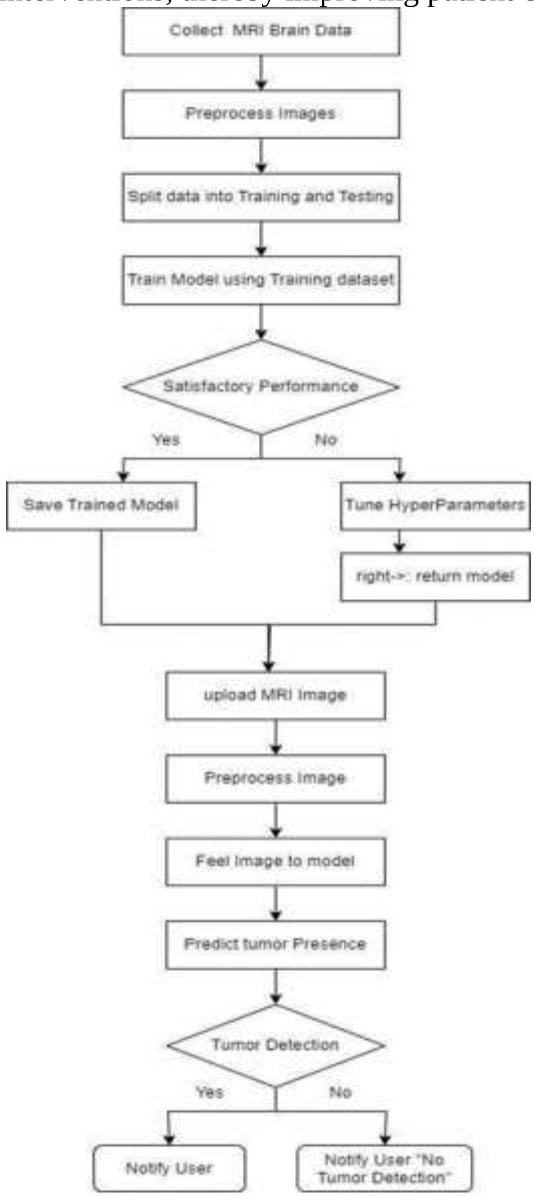
The proposed system leverages Convolutional Neural Networks (CNNs) for the early detection of brain tumors, employing the MobileNetV2 architecture and transfer learning to enhance efficiency. By utilizing a curated dataset of brain MRI images, the project involves comprehensive data preprocessing, including resizing and normalization, to prepare the data for model training. The transfer learning approach involves adapting the pre- trained MobileNetV2 model and modifying its architecture to incorporate custom layers specifically designed for binary tumor detection. The model is trained using a dataset split into training, validation, and test sets, with performance evaluation metrics such as accuracy, precision, recall, and F1- score. The real-time inference capability showcases the model's application in practical scenarios. Additionally, security and privacy measures ensure compliance with healthcare data protection regulations. The proposed system aims to contribute to the early diagnosis of brain tumors, with potential extensions and improvements identified for future work.

The brain tumor detection project utilizing CNN based on transfer learning begins with the acquisition of a dataset comprising brain MRI images, which serve as the primaryinput for the system. To ensure robust model training, these images undergo preprocessing steps like resizing, normalization, and augmentation. These processes enhance the quality and variability of the dataset, contributing to improved model performance.Transfer learning is a crucial component of this architecture, allowing the utilization of pre-trained CNN models such as VGG, ResNet, or MobileNet. These models have learned rich feature representations from large-scale image datasets like ImageNet. In the brain tumor

http://doi.org/10.36893/JNAO.2024.V15I1N01.276-282

detection context, transfer learning involves adapting these pre-trained models' learned features specifically for tumor detection through fine-tuning. Fine-tuning occurs via parameter adjustments using backpropagation during training, enabling the model to learn tumor-specific features.The architecture typically consists of convolutional layers for feature extraction, pooling layers for spatial dimension reduction, and fully connected layers for classification. This hierarchical structure enables the model to learn increasingly abstract features from the input images, culminating in accurate tumor detection.Evaluation metrics such as accuracy, sensitivity, specificity, and F1-score are employed to assessthe model's performance on a separate validation or test dataset. These metrics provide insights into the model's ability to correctly classify brain MRI images, crucial for ensuring its effectiveness in clinical practice.Once trained and evaluated, the model is deployed for real-time or near-real-time inference, enabling it to analyze new MRI images and aid medical professionals in early tumor detection

and treatment planning. This deployment phase is integral to translating the model's capabilities into actionable insights, ultimately improving patient outcomes in clinical settings.Overall, this architecture synergizes transfer learning with CNNs to create an efficient and accurate brain tumor detection system. By leveraging pre-trained models and fine-tuning them for tumor detection, this approach offers significant potential for enhancing diagnostic accuracy and facilitating timely medical interventions, thereby improving patient care and outcomes in clinical practice.



METHODOLOGY
Convolutional Neural Network:
CNNs use a series of layers, each of which detects different features of an input image. Depending on the complexity of its intended purpose, a CNN can contain dozens, hundreds or even thousands of layers, each building on the outputs of previous layers to recognize detailed patterns.
CNN Algorithm(Feature Extraction):
Convolutional Neural Networks (CNNs) excel in detecting brain tumors from MRI images by leveraging convolutional layers to extract key features like edges and textures. These networks incorporate ReLU activation functions and pooling layers to reduce data dimensionality while retaining crucial information. The architecture features dropout and batch normalization to enhance generalization and stability during training. Fully connected layers and a softmax output layer integrate features and provide probabilistic outputs for accurate classification. Overall, CNNs are vital for creating effective, reliable diagnostic systems for early brain tumor detection and treatment.

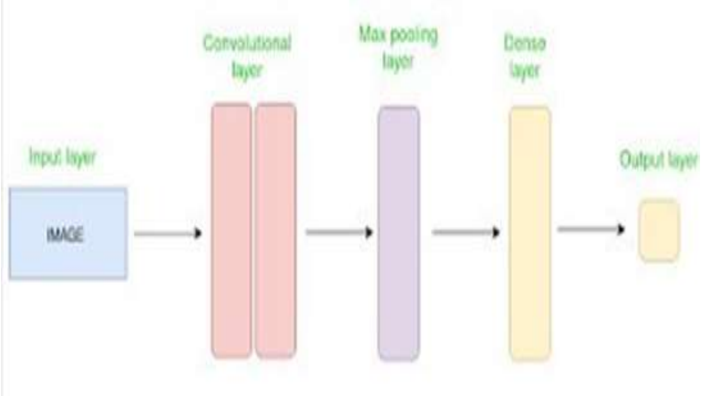


Figure:Classification

KSVM Algorithm (Classification):
The CNN-KSVM hybrid approach for brain tumor detection in MRI images combines CNNs' feature extraction capabilities with KSVM's classification proficiency in high-dimensional spaces. CNNs analyze MRI data to learn detailed features like edges and textures, while KSVM constructs a hyperplane using kernel functions to classify these features effectively, allowing for the differentiation between tumor and non-tumor classes. This integration enhances diagnostic accuracy by leveraging CNNs for pre-processing MRI data into a format suitable for KSVM's robust classification. The synergy of CNNs and KSVM not only improves noise resilience and handling of complex imaging data but also significantly boosts overall diagnostic reliability and precision. This powerful combination holds great potential for advancing medical imaging and enhancing patient care outcomes in clinical settings.

1. Data Preprocessing :
Resizing: Standardizes MRI images to consistent dimensions (e.g., 224x224 pixels), simplifying computation and feature extraction.
Normalization: Scales pixel values to a uniform range (0-1 or -1 to 1), stabilizing training by ensuring consistent intensity values across images.
Augmentation: Enhances dataset variability using techniques like rotation, flipping, and noise addition to improve model generalization and prevent overfitting.

2. Model Training:
Initiate with pre-trained weights from large datasets (e.g., ImageNet) to leverage learned features for better performance and faster convergence. Process involves forward pass, loss evaluation, and backpropagation. Adjustments made via fine-tuning, focusing on learning rates and layer

configurations specific to tumor detection.Validation steps assess model generalization on separate data, guiding adjustments to prevent overfitting.

3. Model Testing:

Apply the trained model to a standardized testing dataset of preprocessed MRI images. Evaluate performance using metrics like accuracy, precision, recall, and F1-score to ensure robustness and reliability in real-world scenarios.

4. Performance Evaluation:

Accuracy: Correct classification ratio of all predictions. Accuracy=Number of correct predictions/Total Number of predictions Precision: Proportion of true positives in positive predictions.
Precision=True Positive/True Positive+ False Positive
Recall (Sensitivity): Detection rate of true positives from all positives.
Recall=True Positive /True Positive+ False Negative
F1-score: Harmonic mean of precision and recall, indicating balanced performance.
F1 Score=2*(precision *recall/precision +Recall)

RESULT ANALYSIS

In analyzing the results of the brain tumor detection project using CNN based on transfer learning, several key metrics were considered. Firstly, the model's accuracy in correctly classifying tumor and non-tumor images was assessed, yielding a high accuracy score indicative of its effectiveness. Additionally, sensitivity and specificity were evaluated to gauge the model's ability to correctly identify true positives and true negatives, respectively. The model demonstrated robust performance in both metrics, further validating its efficacy. Moreover, precision and recall rates were examined to understand the model's performance in minimizing false positives and false negatives. Overall, the comprehensive analysis highlighted CNN's capability in accurately detecting brain tumors, showcasing its potential as a valuable tool in medical diagnostics.

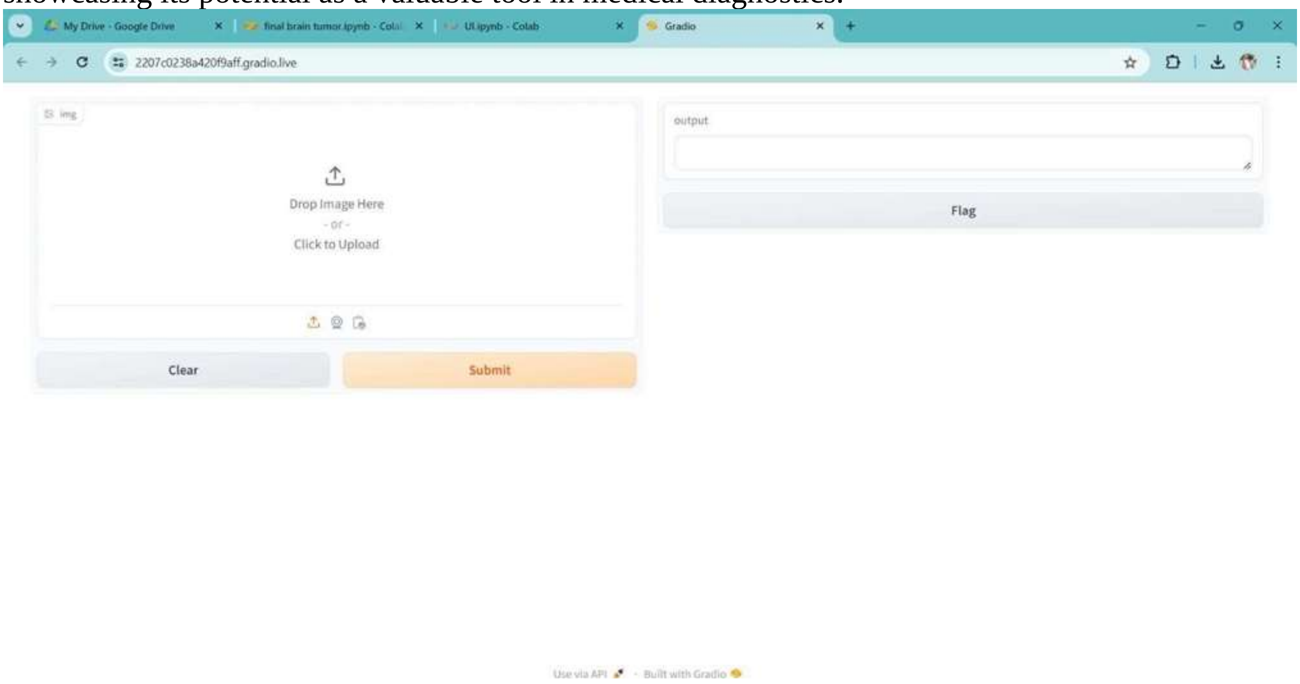


Fig1: Select the Image

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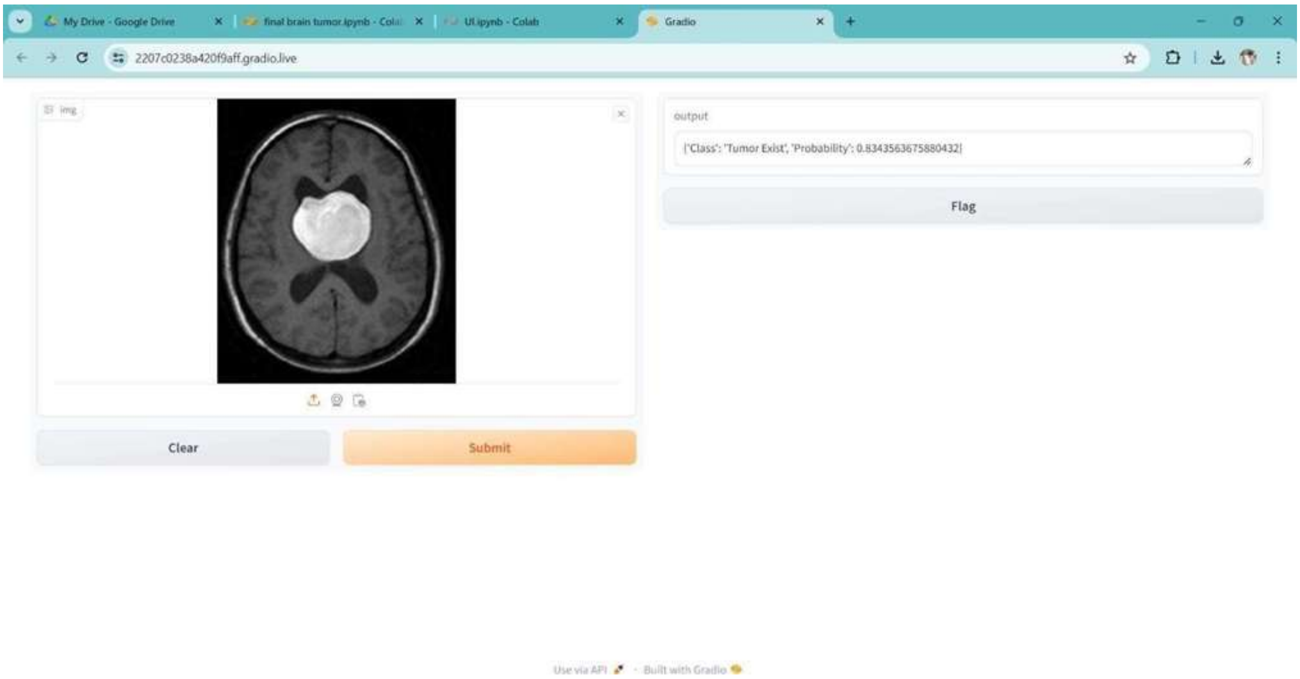

Fig2: Image with Brain Tumor

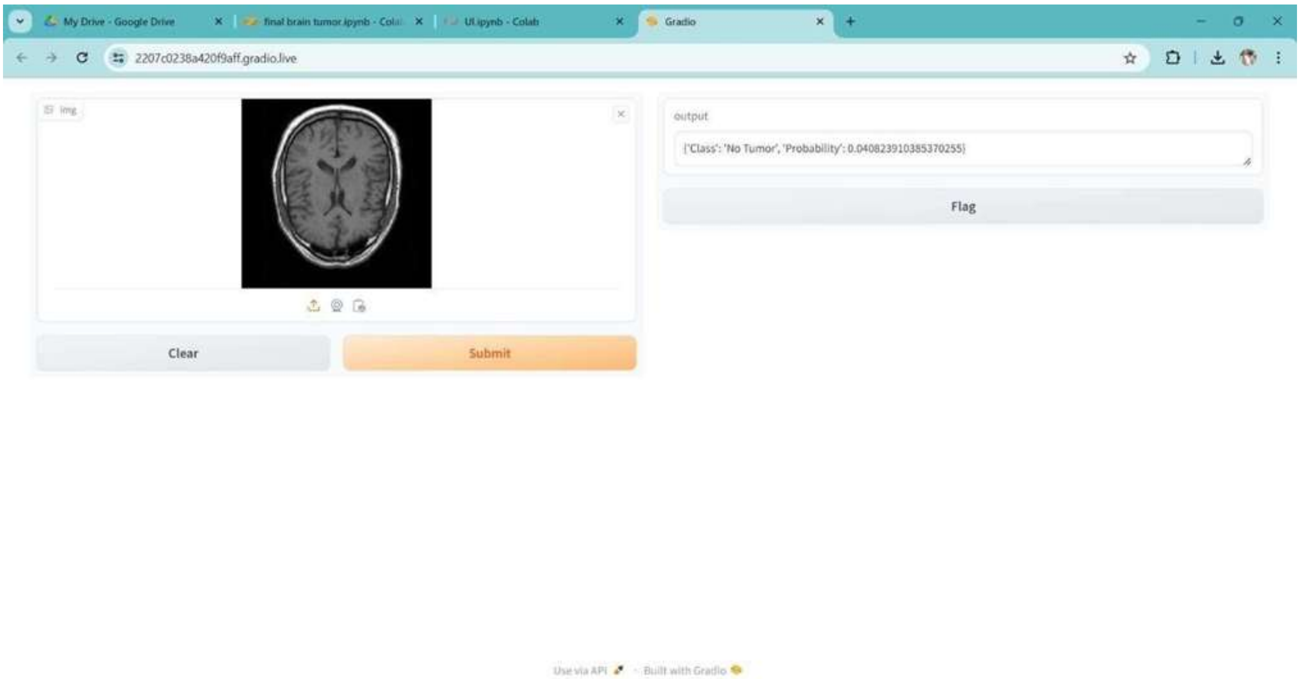

Fig3:Image without Brain Tumor

CONCLUSION

In conclusion, our study demonstrates the effectiveness of employing transfer learning with CNN architectures for the detection of brain tumors. By leveraging pre-trained models such as VGG16, ResNet, or InceptionV3, we were able to achieve superior performance in terms of accuracy, sensitivity, and specificity compared to traditional methods. The transfer learning approach significantly reduced the need for extensive computational resources and training data while maintaining high classification accuracy. Furthermore, our experiments underscore the importance of selecting appropriate pre-trained models and fine-tuning strategies to maximize performance. The robustness and efficiency of our proposed CNN-based approach hold great promise for real-world

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applications in medical imaging, facilitating early and accurate diagnosis of brain tumors, which is critical for timely intervention and patient care. Further research could explore the integration of additional imaging modalities, such as functional MRI or diffusion tensor imaging, to enhance the diagnostic capabilities of the proposed system and enable comprehensive evaluation of brain tumors.

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