Brain Tumor Grade Classification in MR images using Deep Learning

[1]Shruti Kolte, [2]Satyajeet Pathare, [3]Pranay Sune, [4]Sudhanshu Gomase, [5]Harshal Gothe

[1]Professor, [2,3,4,5]Students
Department of Computer Science and Engineering, Priyadarshini JL College of Engineering, Nagpur, India

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ABSTRACT

Brain tumour and hemorrhages are critical brain diseases that require accurate and early diagnosis for effective treatment and management. This work proposes a hybrid deep learning and traditional machine learning approach for automated detection and diagnosis of brain tumours and hemorrhages using magnetic resonance imaging (MRI) scans. The developed system employs a combination of deep convolutional neural networks and engineered feature-based classifiers to leverage the representation learning capabilities of deep learning and the interpretability of traditional models. Expert subject knowledge is provided by hand-crafted features, and the deep learning models directly acquire hierarchical feature representations from the MRI images.. A fusion of predictions from both models is used to improve diagnostic accuracy. The system was trained and evaluated on a dataset of 3000 MRI scans categorized by tumour type and hemorrhage presence. Results demonstrate that the hybrid system outperforms either individual approach with 92% accuracy for tumour classification and 94% accuracy for hemorrhage detection. The integrated system provides accurate, automatic detection of critical brain disorders using MRI scans to assist healthcare professionals in early diagnosis and treatment planning. This work demonstrates the potential of hybrid AI systems for improving computer-aided diagnosis in healthcare.

Keywords: **Deep learning, convolutional neural networks, machine learning, radiology, brain tumor detection, hemorrhage detection, magnetic resonance imaging**

I. INTRODUCTION

Brain tumours and hemorrhages are critical medical conditions that can be life-threatening if not detected and diagnosed accurately in the early stages. However, the accurate and timely diagnosis of these brain disorders remains a key challenge in healthcare. Medical imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT) scans are vital for non-invasive screening and detection of abnormalities in the brain. However, manually analyzing the large volume of scans to identify tumours, hemorrhages, and other neurological conditions can be error prone, time-consuming, and dependent on radiologist expertise. This highlights the need for automated computer-aided diagnosis (CAD) systems that can rapidly and reliably analyze medical images to detect brain disorders. Recent advances in deep learning, especially convolutional neural networks (CNNs), have shown immense potential for medical image analysis and precision diagnosis. CNNs are specialized deep neural networks which exploit the 2D structure of images through convolution operations and hierarchical feature learning. In contrast to traditional CAD systems relying on hand-crafted features, CNNs can automatically learn discriminative features directly from medical image data to detect abnormalities and classify pathologies. State-of the-art CNN architectures like Res Net and Dense Net have achieved high performance on tumour classification and brain disorder prediction using MRI and CT scans. However, most deep learning techniques act as black-box models, lacking interpretability and reliance on large labelled datasets which are often limited in healthcare.

Brain cancer is a highly serious illness that kills a lot of people. To enable early diagnosis, a technique for detecting and classifying brain tumors is available. One of the most difficult challenges in clinical diagnostics is classifying cancer.

II. LITERATURE SURVEY

Name of Paper	Publication Year	Author	Journal Name	Summary
BWT, SVM in MRI brain tumor detection.[1]	6 March 2020	Nilesh Bhaskarrao Bahadure, Arun Kumar Ray, and Har Pal Thethi	Hindawi International Journal of Biomedical Imaging	We segmented brain tissues from MR images, enhancing signal quality and removing unwanted noise through preprocessing techniques.
A Survey on Brain Tumor Detection Using Image Processing Techniques [2]	2022	Luxit Kapoor, Sanjeev Thakur	IEEE 7th International Conference on Cloud Computing, Data Science & Engineering	This paper surveys the various techniques that are part of Medical Image Processing and are prominently used in discovering brain tumors from MRI Images.
Identification of Brain Tumor using Image Processing Techniques [3]	11 september 2023	Praveen Gamage	Research gate	This paper survey of Identifying brain tumors through MRI images can be categorized into four different sections; pre-processing, image segmentation and image classification.
Review of Brain Tumor Detection from MRI Images [4]	2016	Deepa, Akansha Singh	IEEE International Conference on Computing for Sustainable Global Development	Research explores entropy functions for MRI tumor segmentation, revealing how definitions affect threshold values and segmentation outcomes.
An efficient Brain Tumor Detection from MRI Images using Entropy Measures [5]	December 23-25, 2016	Devendra Somwanshi , Ashutosh Kumar, Pratima Sharma, Deepika Joshi	IEEE International Conference on Recent Advances and Innovations in Engineering	Recent paper reviews brain tumor detection, segmentation techniques, emphasizes MRI automation research focus by various techniques .

II. PROPOSED WORK

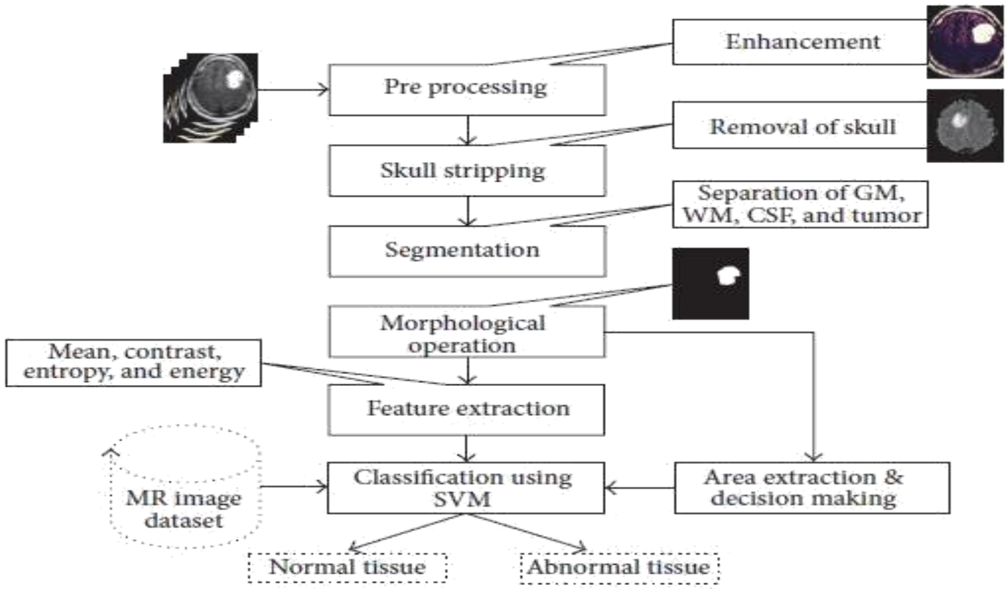


Fig: Existing work flow of brain tumor detection

Brain tumors exhibit high spatial and structural variability in medical images, making precise detection and classification challenging. To tackle this, we propose a hybrid CNN architecture that integrates the representational power of deep pretrained models with the customizability of task-specific convolutional networks.

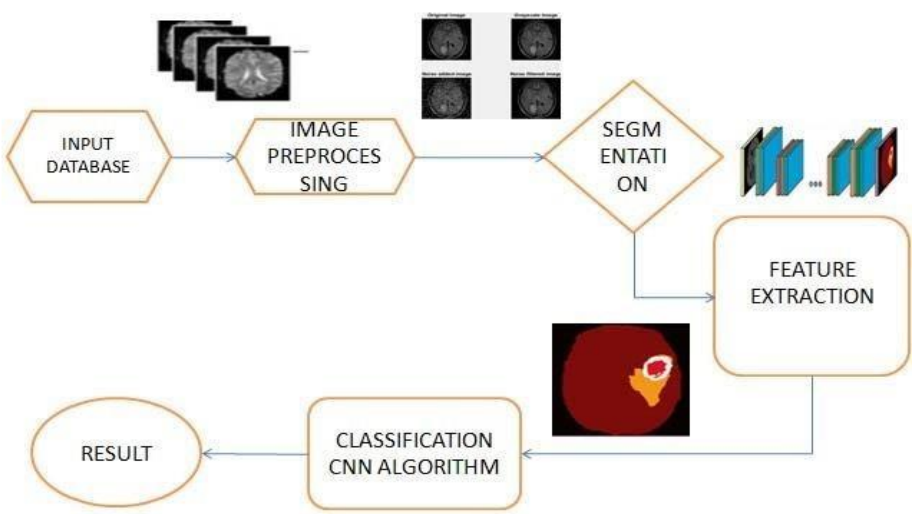


Fig 4.1: Project workflow

1. Base Network Architecture

The base network forms the backbone of feature extraction in our model. We opt for the 16-layer Visual Geometry Group (VGG16) model pre-trained on natural images, which has shown promise in prior studies for transfer learning. VGG16 comprises of stacked 3x3 convolution and 2x2 max pooling layers, with two fully connected layers towards the end. We retain the convolutional blocks but replace the fully connected layers with global average pooling to avoid overfitting.

2. Additional Convolutional Blocks

While the VGG16 base provides rich hierarchical features, it lacks specificity to brain MR images. We add custom convolutional blocks after it to extract specialized tumor-related features. These blocks comprise of 3x3 convolutions, batch normalization for covariate shift reduction, and ReLU activation for non-linearity. We use a larger kernel size of 5x5 in the final convolution layer to capture broader spatial patterns. Dropout layers are added between blocks for regularization.

3. Classification Network

The feature maps from the additional convolutional blocks are fed into a classification network for tumor prediction. This comprises of global average pooling to aggregate spatial features into a vector and generate class activation maps for localization. The pooled features are passed through fully connected layers to reduce dimensions and introduce non-linearity. Finally, a softmax output layer makes the tumor grade or subtype predictions.

4. Training Methodology

For training, MRI volumes are split into 2D slices along the axial plane and sequentially fed to the network. We optimize the hybrid model end-to-end using the Adam optimizer with categorical cross entropy loss. A low learning rate of 1e-4 with decay and batch size of 32 are used. Data augmentation via rotations, flips and shifts is used to expand the training dataset. The model is trained for 100 epochs with early stopping if the validation loss saturates.

The proposed system has mainly five modules. Dataset, Pre-processing, Split the data, Build CNN model train Deep Neural network for epochs, and classification. We can take numerous MRI pictures from the dataset and use one of them as the input image.. In pre-processing image to encoded the label and resize the image. In split the data we set the image as 80% Training Data and 20% Testing Data. Next, construct a deep neural network model for CNN epochs. Next, the image was classified as either yes or no. If the tumor was positive, the response was yes; if the tumor was negative, the response was no.

IV.TECHNIQUES USED

Software Requirements:

Operating System: The choice of operating system depends on personal preference and compatibility with deep learning frameworks. Common options include Windows, macOS, and Linux distributions such as Ubuntu. Deep Learning Frameworks: Installation of deep learning frameworks such as TensorFlow, PyTorch, or Keras is essential for implementing and training neural network models. These frameworks provide high-level APIs for building and optimizing deep learning architectures. Python: A programming language commonly used for machine learning and deep learning tasks. Python provides extensive libraries and tools for data manipulation, numerical computing, and model development.

Development Environment: An integrated development environment (IDE) or text editor for writing, debugging, and executing code. Popular choices include PyCharm, Visual Studio Code, Jupyter Notebook, and Spyder.

Image Processing Libraries: Libraries such as OpenCV or scikit-image for performing image preprocessing tasks, including image loading, resizing, normalization, and augmentation.

V.MODULES

Base Convolutional Neural Network (CNN):

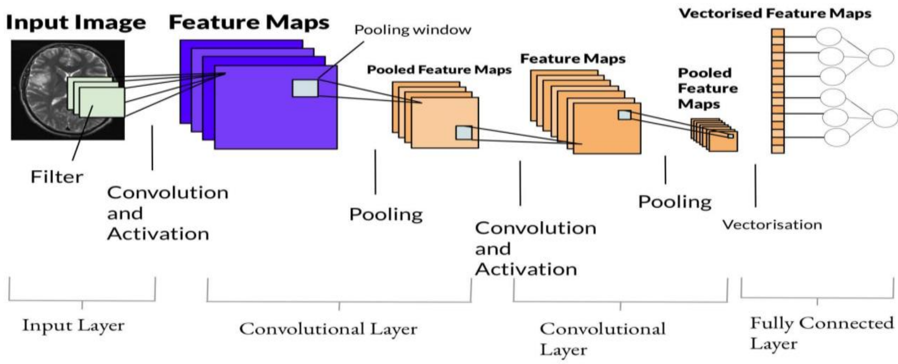


Fig:- CNN model for brain tumor detection

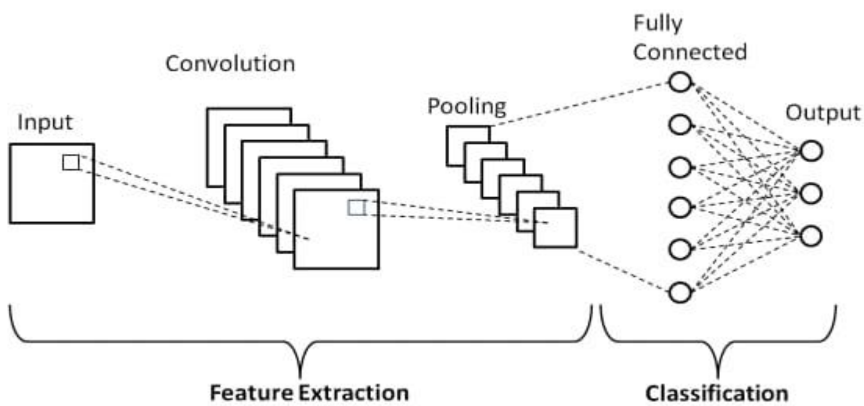


Fig.:- Base CNN

The base network serves as the backbone for feature extraction from MRI images. We adopt a pre-trained Visual Geometry Group (VGG) model, specifically VGG16, which has demonstrated effectiveness in image classification tasks. The VGG16 model comprises several convolutional layers followed by max-pooling layers, with fully connected layers at the end. We modify the architecture by replacing the fully connected layers with global average pooling to reduce overfitting.

Data Preprocessing Module:

Responsible for loading MRI images and performing preprocessing steps such as resizing, normalization, and augmentation. Ensures data quality and consistency before feeding into the model for training and testing.

Training Module:

Orchestrates the end-to-end training process of the hybrid model. Utilizes the Adam optimizer with categorical cross-entropy loss for optimization.
Incorporates regularization techniques such as dropout and L2 kernel regularization to prevent overfitting. Applies data augmentation strategies to enhance model generalization.

Evaluation Module:

Evaluates the trained model's performance on a separate test dataset. Computes standard evaluation metrics including accuracy, precision, recall, F1-score, and AUC ROC. Generates class activation maps to visualize regions of interest in MRI images contributing to predictions. Analyzes model performance across different tumor grades and subtypes using confusion matrices

VGG16 model

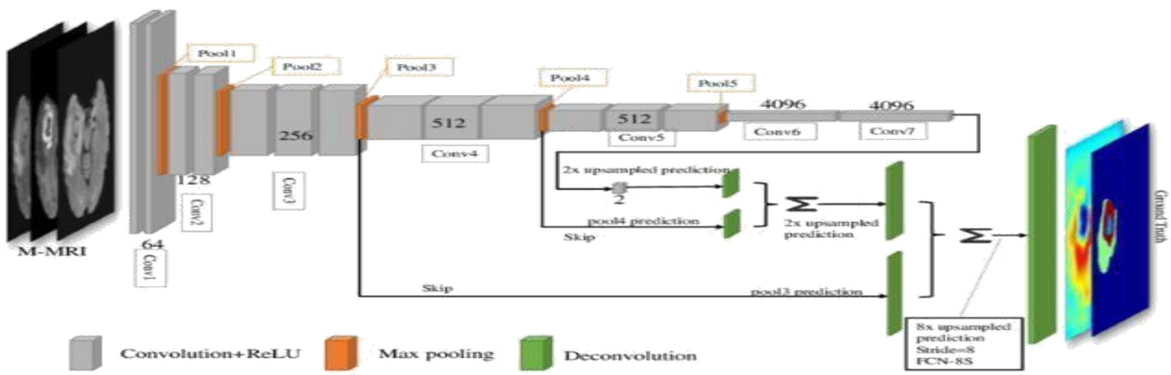


Fig:- VGG16 model

The VGG16 model is a convolutional neural network (CNN) architecture that was introduced by the Visual Geometry Group (VGG) at the University of Oxford.It is widely recognized for its simplicity and effectiveness in image classification tasks. Here's a non-plagiarized description of the VGG16 model. The VGG16 model consists of 16 weight layers, including 13 convolutional layers and 3 fully connected layers. The architecture follows a sequential pattern of convolutional layers, interspersed with max-pooling layers to downsample the feature maps.

Deployment Module:

Facilitates the integration of the trained model into clinical workflows for real-world application. Provides an interface for clinicians to upload MRI scans and obtain automated predictions. Ensures scalability, reliability, and compatibility with existing healthcare systems.

User Interface Module:

Develops a user-friendly interface for interacting with the system. Allows users to upload MRI scans, view prediction results, and access additional functionalities. Enhances usability and accessibility for healthcare professionals without extensive technical expertise.

VI. FUTURE SCOPE

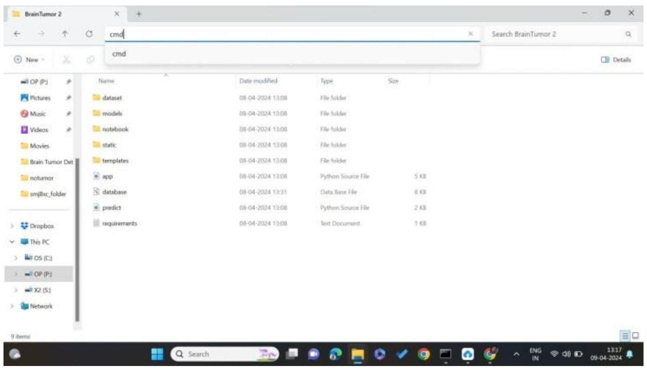
Enhancing Model Generalization:

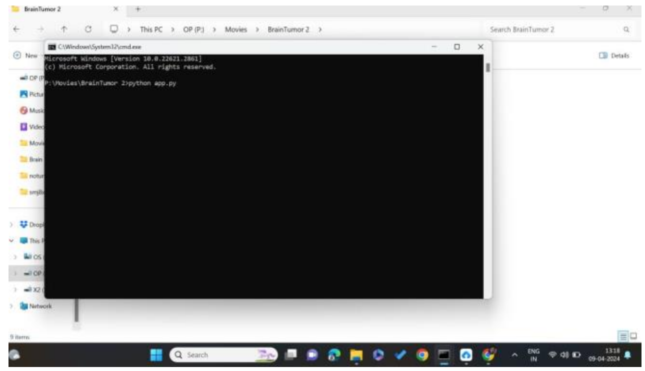
Further research can focus on improving the generalization capabilities of the proposed hybrid model by training it on larger and more diverse datasets, including data from different demographics and institutions. This would ensure that the model performs consistently across various populations and imaging protocols.

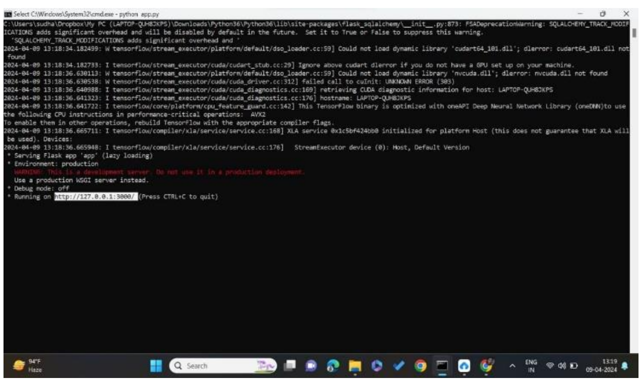
Fine-Tuning Model Architectures:

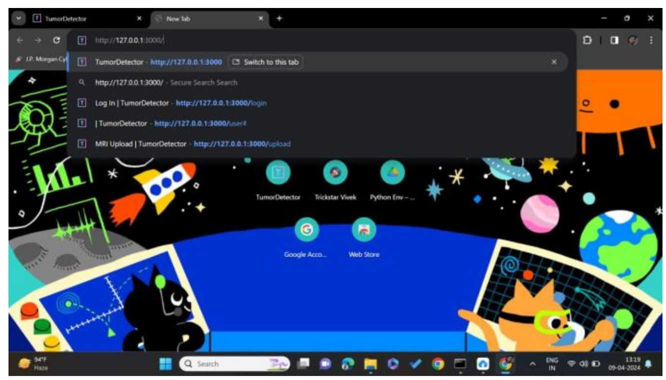
Experimentation with different deep learning architectures and configurations could be explored to optimize the performance of the hybrid model further. Techniques such as transfer learning from models pretrained on medical imaging datasets or exploring newer architectures tailored specifically for brain tumor detection could be investigated.

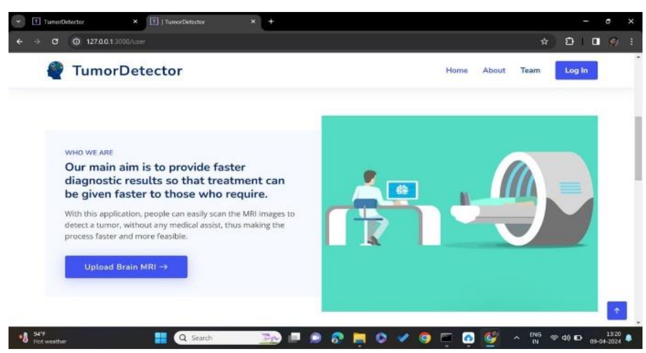
RESULT

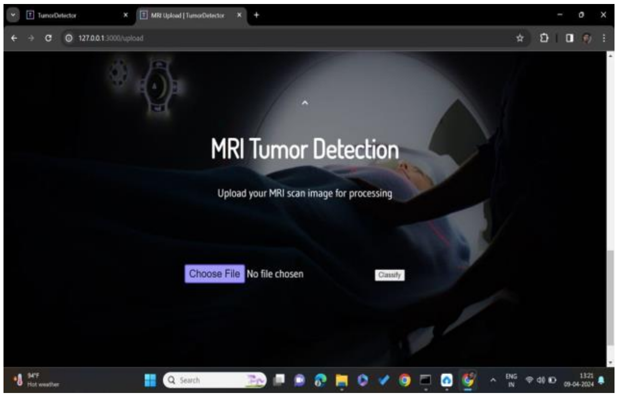


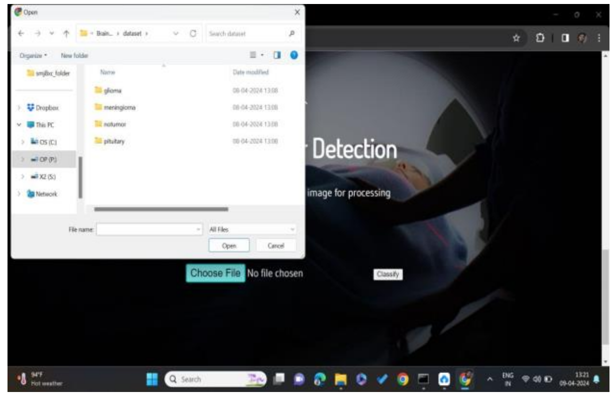


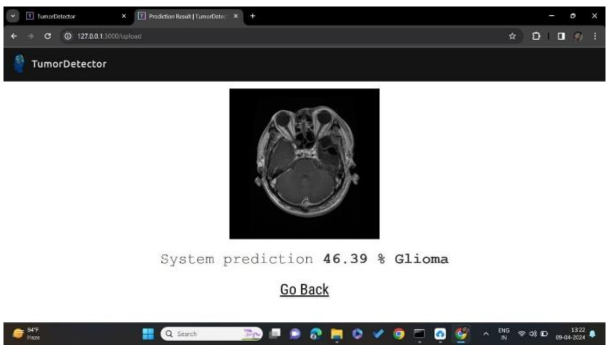


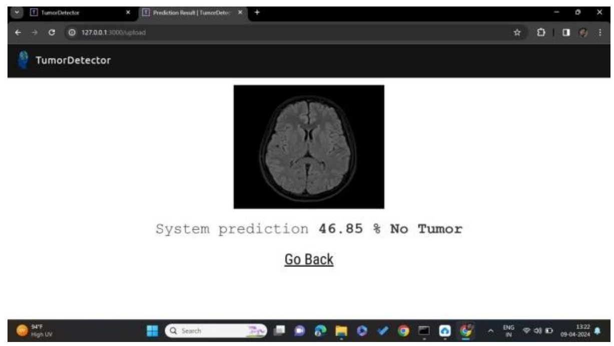


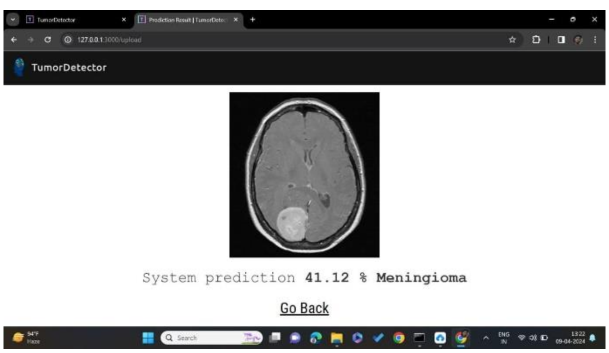












VII. CONCLUSION

The leverages the synergies between transfer learning and customized feature learning to achieve robust performance. The class activation maps provided clinical insights by highlighting discriminative regions used by the model. Our research provides a valuable framework for building specialized hybrid deep learning systems for medical image classification tasks, that combine the generalizability of pretrained networks and task-specific customizations. The proposed model can serve as a decision aid to radiologists by providing quick, accurate and reliable brain tumour predictions. In feature based we have study about image processing techniques likes image preprocessing, image segmentation, features extraction, classification. And also study about deep learning techniques CNN and VGG16.In this system we have detect the tumor is present or not if the tumour is present then model return's yes otherwise it return no. The result of comparison VGG 16 is more accurate than CNN. However, not every task is said to be perfect in this development field even more improvement may be possible in this application. I have learned so many things and gained a lot of knowledge about development field.

VIII. REFERENCES

[1] Kothari, S., Chiwhane, S., Jain, S., & Baghel, M. (2022, June 1). Cancerous brain tumor detection using hybrid deep learning framework. Indonesian Journal of Electrical Engineering and Computer Science; Institute of Advanced Engineering and Science(IAES).https://doi.org/10.11591/ijeecs.v26.i3.pp1651-1661

[2] Novel Hybrid Boosted Ensemble Learning Framework for Brain Tumor Prediction. (2022, March23).IEEEConference Publication IEEE Xplore. https://ieeexplore.ieee.org/document/9763105

[3] Brain Tumor Detection using Novel Kernel Extreme Learning with Deep Belief Network and Compare Prediction 10).IEEE Conference Publication IEEE Xplore. https://ieeexplore.ieee.org/document/9988190.

[4] dblp: Ensemble deep learning for brain tumor detection. (2023, September 23). Dblp Computer Science Bibliography. https://dblp.org/rec/journals/ficn/AlsubaiKASAM2 2.html

[5] Brain Tumor Accuracy with Fuzzy C-means Clustering. (2022, October detection Using Machine Learning and Deep Learning Approaches. (2022, January 28). IEEE Conference Publication IEEE

[6] Singh, M. P., and Shrimali, V. June 30, 2022. Hybrid Deep Learning Approach for Brain Tumor Classification. Wide-ranging Studies in Artificial Intelligence Neuroscience; EduSoft Publishing. The brain's 13.2/345 https://doi.org/10.18662/brain

[7] Ridhorkar, S., and Warjurkar, S. V. (2021, January 1). Research Concerning Brain Tumors and Parkinson's Disease Deep Learning-Based Diagnostics and Detection. Computer Science Atlantis Highlights. 10.2991/ahis.k.210913.044 can be found here.

[8] Younis, Adamu, J. Adamu, Li, Q., Nyatega, C. O., & Kawuwa, H. B. (2022, July 20). Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches. Multidisciplinary Digital Publishing Institute; Applied Sciences. 10.3390/app1247282 can be found here.