WEB-BASED CLASSIFICATION FOR BRAIN TUMORS USING DEEP LEARNING

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"Web-Based Classification for Brain Tumors using Deep Learning"**, submitted by **Abdullah Al Noman** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **25/01/2024**

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DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Md. Zabirul Islam, Lecturer, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Classification of brain tumors is one of the most crucial jobs in medical imaging, and deep learning models have shown promising outcomes when it comes to automation. We provide a thorough analysis of three deep learning models for brain tumor classification in this research utilizing a dataset of various types of MRI images of brain tumors. Convolutional Neural Networks (CNNs), VGG16, and InceptionV3 are the names of these proprietary models. Classifying brain tumors using a huge dataset of magnetic resonance imaging (MRI) pictures is the aim of this effort. No ionizing radiation is used during an MRI, making it a safer and more thorough way to learn about the anatomy. A convolutional neural network (CNN) is trained on several datasets, such as images of benign tumors, meningiomas, gliomas, and pituitaries, in order to develop a robust prediction model. The model's goal is to evaluate MRI images automatically and distinguish between brain areas that are tumor-filled and those that are normal. If this effort be successful, it will enable prompt intervention and customized treatment plans by enabling early, non-invasive identification. By providing a trustworthy method for categorizing brain tumors, this work enhances medical imaging.

Regarding overall performance in this research, CNN seems to be the best model.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Innovative technology integration has been the foundation behind revolutionary changes in medical diagnostics in the continuously developing relationship between artificial intelligence and healthcare. The innovative application shown in this paper, which was created using Django and smoothly integrates Convolutional Neural Networks (CNNs), has the potential to completely change the field of brain tumor classification. When it comes to improving accuracy and accessibility in medical imaging, deep learning, and web technologies are a powerful combination, especially when it comes to brain tumor identification.

It is impossible to overestimate the importance of medical imaging, and more especially magnetic resonance imaging (MRI), in the early identification and characterization of brain tumors. However there are issues with time limits and human error when these complex pictures are manually analyzed. An innovative approach to these problems is the use of a CNN model that was trained on a wide range of detailed datasets that were methodically gathered from Kaggle. Through the use of CNNs' inherent ability to self-learn hierarchical features, the model is able to identify subtle patterns in brain scan pictures, which helps it achieve an impressive 98% classification accuracy rate for various tumor kinds.

The main contribution of this work is the smooth implementation of this potent CNN model in a web framework built using the Django framework. This integration simplifies the use of advanced tools for diagnosis while simultaneously facilitating accessibility. Users may easily submit their own brain scan images to the portal, including medical professionals and anyone who is worried about their health. The technology offers almost immediate categorization findings using a user-friendly interface, which helps medical professionals make decisions quickly and gives patients peace of mind.

As we enter the age of computational medicine, deep learning and web technologies collaboration becoming more and more important. This web-based approach for classifying brain tumors represents a significant technical advance as well as the promise of artificial intelligence to improve healthcare outcomes. The technology helps healthcare professionals make smart decisions by providing quick and accurate diagnoses, which eventually improves patient care.

In addition to its applications, this study investigates the comprehensible nature of the CNN model by using methods to clarify the decision-making process. Because of its transparency, the categorization findings are more reliable, which is important for applying artificial intelligence to the field of clinical decision-making.

1.2 Motivation

Recognizing the efficiency and accuracy limits of existing manual interpretation approaches, the need to improve brain tumor diagnosis motivates this study. The importance of accurate and early diagnosis on patient outcomes is the reason for the special focus on brain tumor categorization. The use of Convolutional Neural Networks (CNNs) simplifies the intricacies of medical imaging, namely in magnetic resonance imaging (MRI), by enabling self-learning and the identification of patterns. The project's goal is to provide powerful diagnostic tools to a wider audience by democratizing access to them using an approachable web framework built using Django. A dedication to openness and interpretability in the CNN model's decision-making processes is another crucial ethical factor that supports the ethical use of artificial intelligence in healthcare. By providing patients and medical professionals with an approachable, reliable, and morally sound instrument that meets the changing demands of modern healthcare, the ultimate goal is to redefine brain tumor diagnosis.

1.3 Rationale of the Study

The work was inspired by the urgent need to deal with difficulties with human image interpretation's scalability, efficiency, and error-proneness in the context of brain tumor detection in current times. Given that convolutional neural networks (CNNs) are algorithms that can learn complicated characteristics on their own, it is logical to apply them in medical diagnostics. By improving diagnosis speed and accuracy, the research aims to enhance patient outcomes with a special focus on brain tumor classification. CNNs are included in a Django-based web framework to ensure that healthcare providers may utilize advanced diagnostic tools regardless of their knowledge of technical expertise, in addition to addressing accessibility difficulties. An important aspect of the CNN model's decision-making procedure is ethical considerations, which reduce worries about the "black box" nature of deep learning. I place a strong importance on interpretability and transparency. In summary, the rationale for the study is predicated on the development of CNNs for brain tumor identification, the enhancement of accessibility through a user-friendly web platform, and the observance of ethical principles for the conscientious use of artificial intelligence in healthcare.

1.4 Research Question

Research Question 1: How does the CNN model in the Django web framework enhance accessibility for brain tumor diagnosis?

Research Question 2: How user friendly is the interface for healthcare professionals uploading Brain scan images?

Research Question 3: What efficiency improvements come from diagnosing brain tumors using advanced Deep learning?

Research Question 4: What moral guidelines make sure that AI is integrated responsibly into web platforms for medical diagnostics?

1.5 Expected Outcome

Results that are expected to be achieved include higher diagnostic accuracy compared to conventional methods, greater accessibility for both individuals and healthcare professionals, simplified user interface interactions, increased efficiency in diagnosis, and increased transparency through ethical AI techniques. The goal of the project is to show

how a CNN model implemented in a Django framework might improve brain tumor classification in everyday situations.

1.6 Report Layout

There are five sections to this research report. An introduction and motivation make up the majority of the first section. The second section will include related research, a brief description, and challenges of this program from a technical perspective. The third section will be devoted to discussing the tools I'll be using, data collection procedures, and statistical analysis. The experimental outcome, a short explanation of the methodology i used, and a brief analysis will all be presented in the fourth section. I discussed about how the proposed system's implementation would affect society and the environment in the fifth section. In a nutshell I will cover everything, including implications for future research and study, in the last part.

CHAPTER 2

BACKGROUND

2.1 Preliminaries/Terminologies

A significant area of machine learning (ML) is deep learning (DP), which is basically three- or more-layered neural networks. This neural network makes an effort to resemble how the human brain functions. A fundamental aspect of its topic is object detection. This study's main goal is to create, train, and implement a CNN model that can correctly categorize images of brain tumors. Using data from Kaggle, the model is rigorously trained to learn how to differentiate between different kinds of tumors, making it an invaluable diagnostic tool for medical experts. The first step of the investigation is to gather a large collection of labeled brain tumor photos from Kaggle. Then, using this information, a CNN architecture is built and trained to identify patterns and characteristics indicating various tumor types. To guarantee the model's adaptability in practical situations, testing and validation processes are used to properly evaluate the model's performance. Several noteworthy advantages result from implementing this CNN-based brain tumor classification model into Django. First of all, it significantly decreases the amount of time needed for diagnosis, which may enable a quicker response and better patient results. Second, automatic categorization reduces the possibility of misunderstanding that comes with human approaches, improving the accuracy of diagnosis. Finally, the model may be used remotely thanks to the web-based deployment, which fills in geographical gaps and offers diagnostic assistance in a variety of healthcare settings.

2.2 Related Work

Convolutional Neural Networks (CNNs) have been used widely in medical image processing; specifically, they have been studied in relation to the identification and categorization of brain tumors. Let’s take a look at what these studies found.

In [2] Beyza Nur TÜZÜN and Durmuş ÖZDEMİR they collected 7022 brain MRI pictures in four separate classes that make up the dataset are made available to the public on the Kaggle platform. The models were adjusted, the dataset was pre-processed, and the right parameter values were used. Following an evaluation of the deep learning models we examined, the following findings of the statistical analyses were obtained: Efficientnet-b0 (%99.54), InceptionV3 (%99.47), Mobilenetv2 (%98.93), and GoogleNet (%98.25).

Dillip Ranjan Nayak et al. [3] reported a CNN-based dense EfficientNet with min-max normalization to identify 3260 T1-weighted contrast-enhanced brain magnetic resonance images into four categories: meningioma, glioma, pituitary, and no tumor. The experimental results showed that the proposed model achieved testing accuracy of 98.78% and training accuracy of 99.97%. The image database contains 36 T1-weighted, contrast-enhanced MRI images from Kaggle. Dillip Ranjan Nayak et al. proposed a CNN-based dense EfficientNet with min-max normalization to identify 3260 T1-weighted contrast-enhanced brain magnetic resonance images into four categories: no tumor, pituitary, meningioma, and glioma. The experimental results showed that the proposed model achieved testing accuracy of 98.78% and training accuracy of 99.97%. The image database contains 36 T1-weighted, contrast-enhanced MRI images from Kaggle.

A total of 7023 human brain MRI images were used in the research reported by Karamehić and Jukić [4], which combined datasets from figshare, SARTAJ, and Br35H. In order to provide a thorough and representative dataset for training and testing the suggested brain tumor detection and classification algorithm, several disparate datasets were integrated. The VGG16 deep learning algorithm, in conjunction with the Python Imaging Library, produced encouraging outcomes, with a remarkable 96.9% total accuracy. This high accuracy rate demonstrates how well the suggested method works to recognize and categorize brain tumors in MRI images.

Manali Gupta et al [5] used an MRI image database that they collected from Kaggle to perform their research. In order to provide the groundwork for the later use of CNN models, their investigation comprised applying image processing techniques to 253 MRI scans. For their proprietary CNN model, Gupta et al. reported an accuracy of 89% on test data and 96% on training data. By comparison, the training data had an accuracy of 90%, while the testing data had an accuracy of 87.5% for the VGG-16 model. These findings show how well the suggested CNN model works and provide light on the trade-offs in model performance.

Amatul Bushra Akhi [6] in her work, Akhi used transfer learning to fine-tune a VGG-16 model on a dataset of 3264 MRI images divided into four classes: pituitary, meningioma, glioma, and no tumor. There were 951 photos for pituitary, 937 for meningioma, 926 for glioma, and 500 for the no tumor class, which was the lowest class distribution in the collection. It's important to handle class disparities, and Akhi tackled this problem in her work. The VGG-16 architecture was selected and modified for the brain tumor dataset. It is well-known for its depth, simplicity, and efficacy in computer vision. The model's strong ability in properly categorizing brain tumors across multiple categories was shown by its excellent accuracy rate of 99.21%.

2.3 Comparative Analysis and Summary

Table 2.1: Analyzing accuracy and related works in comparison

Study / Kaggle notebook	Model	Classification Accuracy
[2] Beyza Nur TÜZÜN et al (2023)	Efficientnet-b0, InceptionV3, Mobilenetv2 GoogleNet	99.54% 99.47% 98.93% 98.25%
[3] Dillip Ranjan Nayak et al (2023)	EfficientNet	98.78%
[4] Karamehić et al (2023)	VGG16	96.9%
[5] Manali Gupta et al (2023)	CNN VGG16	96% 87.5%
[6] Amatul Bushra Akhi ()	VGG16	99.21%

2.4 Scope of the problem

Recognizing or locating a telling target in still or moving pictures is called object detection. This is one of the best uses of Deep Learning (DP) with Machine Learning (ML). Teaching machines how to analyze visual information similarly to how humans do is the goal of this research. Compared to other fields of study, object detection is in high demand since it is a field where results may be obtained quickly and with a relatively high degree of accuracy.

Object detection has gained business importance these days since it based its findings on the recognition of target objects, which is fundamentally humanistic. My project included utilizing TensorFlow to identify images of brain tumors and determine the target image's accuracy level.

2.5 Challenges

While implementing a Convolutional Neural Network (CNN) model for brain tumor classification into a Django framework has a lot of promise, there are a few issues that need to be overcome for the system to be successfully and ethically deployed.

I. Limited Data Availability

Collecting a large enough diverse enough dataset to train a reliable CNN model may be difficult. Overfitting or poor generalization to real-world settings might result from insufficient data.

II. Data Imbalance

The dataset could show imbalances in numbers of various tumor kinds, which might affect how well the algorithm can identify minority groups.

III. Computational Intensity

It takes a lot of processing power to train deep learning models. For effective model training, access to GPUs or other accelerators is necessary, which might present problems in circumstances with limited resources.

IV. Time Constraints

The time required for training large CNNs, especially with training over large amount of image dataset.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

Research Subject: The goal of the research is to detect brain tumors in magnetic resonance imaging (MRI) by applying deep learning algorithms. The aim of the project is to increase the accuracy and efficiency of diagnosis via the use of advanced computer models. By doing a comprehensive study of both normal and tumored MRI images, a robust prediction model may be developed.

The following figure 3.1 shows CNN model architecture.

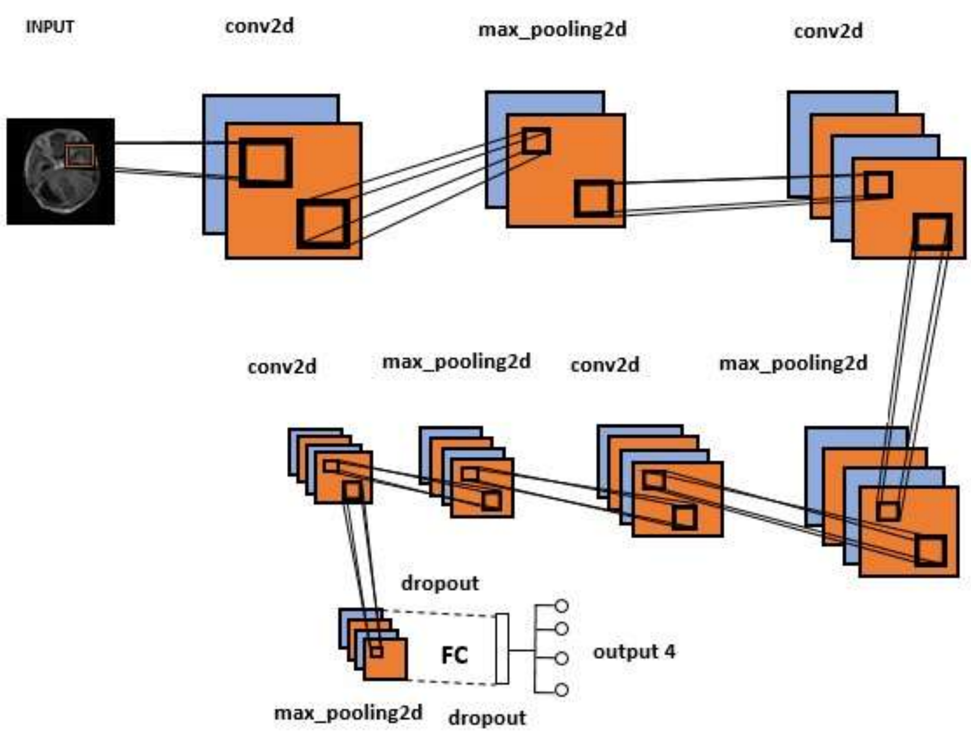


Figure 3.1: CNN model architecture

Instrumentation:

Dataset: The gigantic dataset included in this research includes images from normal MRI scans as well as brain tumors. These images serve as the basis for the deep learning models' training, validation, and testing.

Deep Learning-Based Sequential Model: To identify brain tumors, a distinct sequential deep learning model is developed and used. This multi-layered model employs convolutional neural networks (CNNs) and recurrent neural networks (RNNs) as two techniques to recognize complex patterns in the images.

Pre-trained Deep Learning Models: The research includes two pre-trained deep learning models to provide a benchmark for performance. These models represent a few common architectures, such as VGG and InceptionV3. Compare the custom Sequential model against these existing models in order to assess the model's effectiveness.

Data Preprocessing: Before the model is trained, preprocessing methods such as augmentation, scaling, and normalization are applied to the dataset. Through these steps, the data is verified to be suitable for training dependable and widely applicable deep learning models.

Training and Validation: Pre-trained models and the sequential model are two examples of the deep learning models that are trained and validated using the provided dataset. This approach involves fine-tuning model parameters to increase forecast accuracy.

Evaluation Metrics: Performance metrics including as recall, F1 score, accuracy, and precision are used to evaluate the models. These metrics provide a comprehensive overview of the models' capacity to distinguish between pictures including various types of brain tumor magnetic resonance imaging.

Ethics-Related Considerations: The research respects patient privacy and anonymity by using medical imaging data in a way that complies with ethical guidelines. The dataset has been anonymized and all necessary rights and clearances have been obtained.

3.2 Data Collection and Procedure

The following figure 3.2 shows Different kidney MRI images.

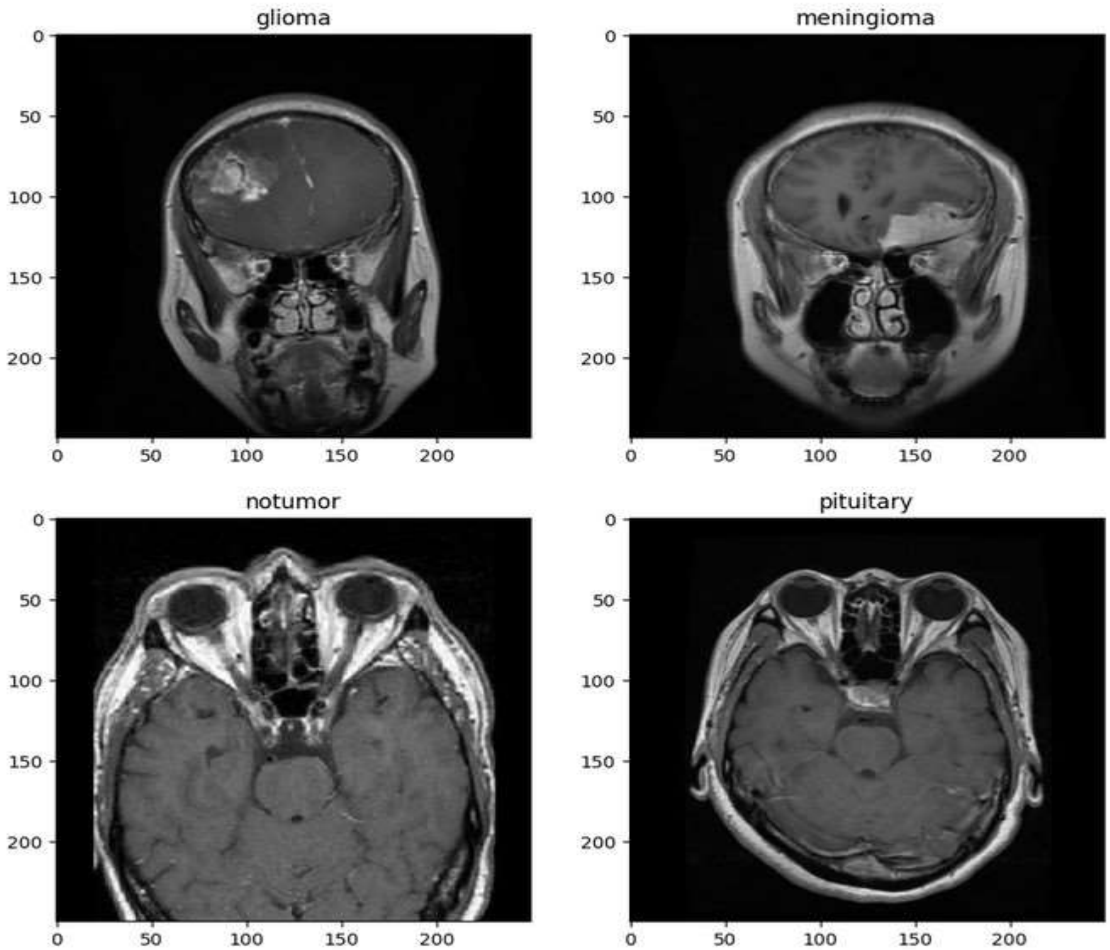


Figure 3.2: Different types of Brain Tumor

Ethical Considerations: The research respects patient privacy and anonymity by using medical imaging data in a way that complies with ethical guidelines. The dataset has been anonymized and all necessary rights and clearances have been obtained.

Dataset Compilation: An extensive and heterogeneous dataset including MRI images for brain malignancies and normal states was assembled. The dataset was supplied by reputable medical imaging centers, hospitals, and clinics, ensuring a representative sample of cases.

Data Preprocessing: The MRI pictures that were collected underwent extensive preprocessing in order to increase the consistency and quality of the output. Resolution correction, normalization, and standardization were used in order to ensure uniformity among the images.

Data Augmentation: Among the techniques used to improve the diversity of the dataset and the generalization ability of the model were rotation, flipping, and zooming. The goal of this step was to expose the model to a greater range of situations that may occur in real-world clinical settings.

3.3 Statistical Analysis

I utilized a large and diverse dataset for my research work on "Brain Tumor Classification Using Deep Learning," which includes images of stones and typical MRIs. The dataset was carefully chosen to ensure that both groups were fairly represented. I carried out extensive evaluations using standard metrics like accuracy, precision, recall, and F1-score to ascertain the effectiveness of my deep learning models, the CNN model, VGG16, and InceptionV3. I also used techniques like confusion matrices to provide a comprehensive view of the models' classification abilities. The statistical analyses yielded positive results, showing how successfully my proposed models used MRI data to differentiate between patients with brain tumors and healthy individuals. These findings not only demonstrate the potential therapeutic use of my deep learning technique, but they also provide valuable insights into the prediction abilities of different architectures in this domain.

3.4 Proposed Methodology

The recommended technique for this research project uses medical imaging data to identify brain cancers using Convolutional Neural Networks (CNNs), a form of deep learning technology. The dataset is made up of a large collection of MRI images showing brain tumors and those without. To extract intricate characteristics and patterns from the images, three well-known CNN designs are used: VGG16, InceptionV3, and others. To train the models on the labeled dataset, transfer learning is used to employ pre-learned weights from ImageNet.

In order to enhance the model's ability to recognize minute characteristics that could be indicative of brain tumors, the network parameters are tuned throughout the training phase.

To ensure the models' strong performance and generalizability, extensive validation and fine-tuning procedures are used. The proposed method uses deep learning to provide accurate and efficient brain tumor classification from MRI images, which could enhance renal health diagnosis.

3.5 Implementation Requirements

The research on the subject "Brain Tumor Classification Using Deep Learning" can only be implemented in a robust computer environment that meets certain hardware and software criteria. Using a large dataset of Normal MRI and Tumor MRI images, a laptop with a high-performance GPU is essential for training deep neural networks, such as CNN, VGG16, and InceptionV3, efficiently. A stable internet connection is necessary to provide a seamless interaction with the Kaggle platform, where the project code may be developed, tested, and hosted. Moreover, a significant amount of storage space is needed for the big picture dataset. The implementation will employ well-known deep learning frameworks such as TensorFlow for both model development and training. The codebase has to be well documented in order to guarantee repeatability. Git and other version control systems may be used to efficiently coordinate work and keep track of changes.

CHAPTER 4

EXPERIMENTAL RESEULT AND ANALYSIS

4.1 Experimental Setup

- Datasets: We utilized the image of Brain MRI Normal and Tumored datasets, comprising 7023 images, respectively.
- Model Architectures: I used total three deep learning-based models. One model is CNN and other two model is pre-trained.

I. CNN:

In the context of deep learning-based brain tumor classification, convolutional neural networks (CNNs) seem to be a proficient technique for discerning intricate patterns and attributes from medical images. To allow for accurate classification, the CNN model is designed to identify even the smallest differences between brain tumor and non-tumor MRI images.

Through convolutional and pooling processes, hierarchical features are recorded and spatial dimensions are reduced in the CNN's initial layers. Layers that are densely connected thereafter aid in better feature extraction and complicated learning. Using batch normalization and dropout layers may help with overfitting problems and enhance model generalization. In the final layer, a SoftMax activation function is often used to produce probability ratings for each class (Glioma, Meningioma, Pituitary, or NoTumor). By employing a labeled dataset to train the model using gradient descent and backpropagation to optimize parameters, a reliable and efficient framework for kidney stone prediction from MRI images is ultimately produced.

II. VGG16:

The VGG16 (Visual Geometry Group 16) architecture is a deep convolutional neural network (CNN) model that has shown promise in a variety of computer vision applications, including picture classification. The Visual Geometry Group at the University of Oxford designed VGG16, which stands out for its simplicity and consistent structure. The sixteen layers of the model consist of three completely connected layers and thirteen convolutional layers. The model's ability to identify intricate patterns in the input data is enhanced by the inclusion of short 3x3 filters with a stride of 1 in the convolutional layers and rectified linear unit (ReLU) activation functions. To lower the spatial resolution of the feature maps, 2x2 filter max pooling layers are sandwiched in between the convolutional layers.

III. InceptionV3: Convolutional neural networks (CNNs) like Inception v3 are designed specifically for image recognition applications. Developed by Christian Szegedy et al. in 2015, it boasted an accuracy of over 78.1% and obtained remarkable results on the ImageNet competition. It is a well-liked option for many computer vision applications because of its major strength—computational efficiency with excellent accuracy.These are the network's fundamental units; they combine average pooling with convolutions of various sizes—1x1, 3x3, and 5x5. This permits effective feature extraction at many scales concurrently, improving accuracy without appreciably increasing the size of the network.Conventional 7x7 convolutions may incur high processing costs. To solve this, Inception v3 substitutes a series of 1x7 and 7x1 convolutions, which results in a much reduced computing cost while maintaining a comparable level of feature extraction.

- Training Procedure:
  The models were trained using a standard training-validation split, and their resilience was increased by using data augmentation approaches. Utilizing the category cross-entropy loss function and the Adam optimizer, the models were optimized. Hyperparameters need to be changed throughout the training phase in order to achieve peak performance. For every model, a learning rate of 0.001 was used in the Adam optimizer training process. The batch size for each model was thirty-two. 20 training epochs were used for each model.
- Hyperparameters: ReLU activation functions were utilized consistently in all models, however dropout at a rate of 0.5 was implemented in the fully connected regularization with a coefficient of 0.001 in InceptionV3 & VGG16.
- Hardware: I have used Kaggle Platform, high-performance GPUs, sufficient RAM, SSDs, a multi-core CPU.
- Software: I used deep learning frameworks TensorFlow and libraries Keras, sklearn,

MatPlotlib, os, NumPy etc.

4.2 Experimental Results & Analysis

The following figure 4.1 shows model accuracy & figure 4.2 shows loss curve of CNN.

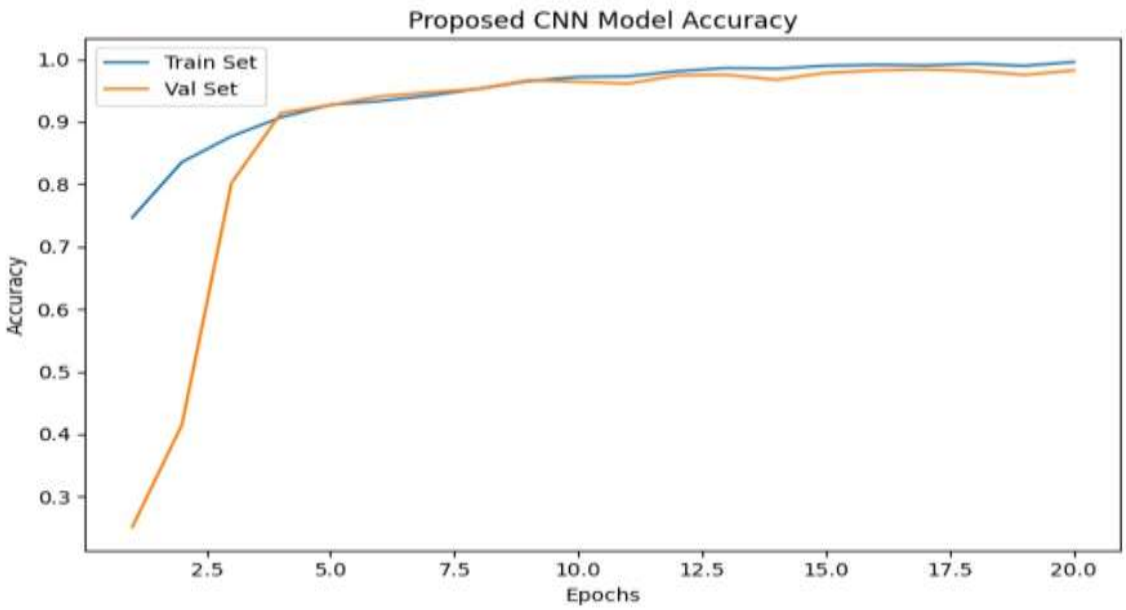


Figure 4.1: CNN model accuracy

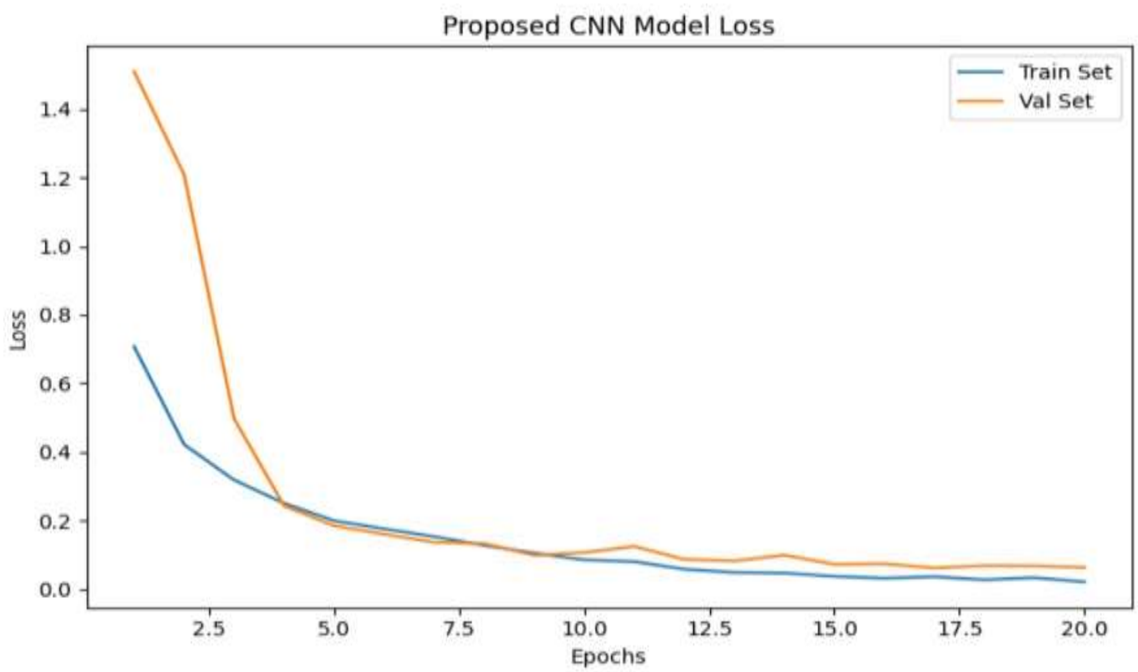


Figure 4.2: CNN model Loss

There is a continuous better accuracy on the training set compared to the validity set. The model is more likely to be correct on this data since it was trained on the training set. Here, over the course of 20 epochs, the training set accuracy rises from around 0.74 to roughly 0.98. Over the course of 20 epochs, the validation set accuracy rises from around 0.67 to approximately 0.95.

The model's performance is shown by the loss. A smaller loss indicates fewer errors made by the model. The graph indicates that the model is learning and becoming better since it shows that the loss on the training and validation sets reduces with time. In this instance, the training set loss begins at around 1.75 and drops to roughly 0.25 over the course of 20 epochs. Over the course of 20 epochs, the loss on the validation set drops from around 1.50 to approximately 0.50.

The following figure 4.3 shows confusion matrix of CNN

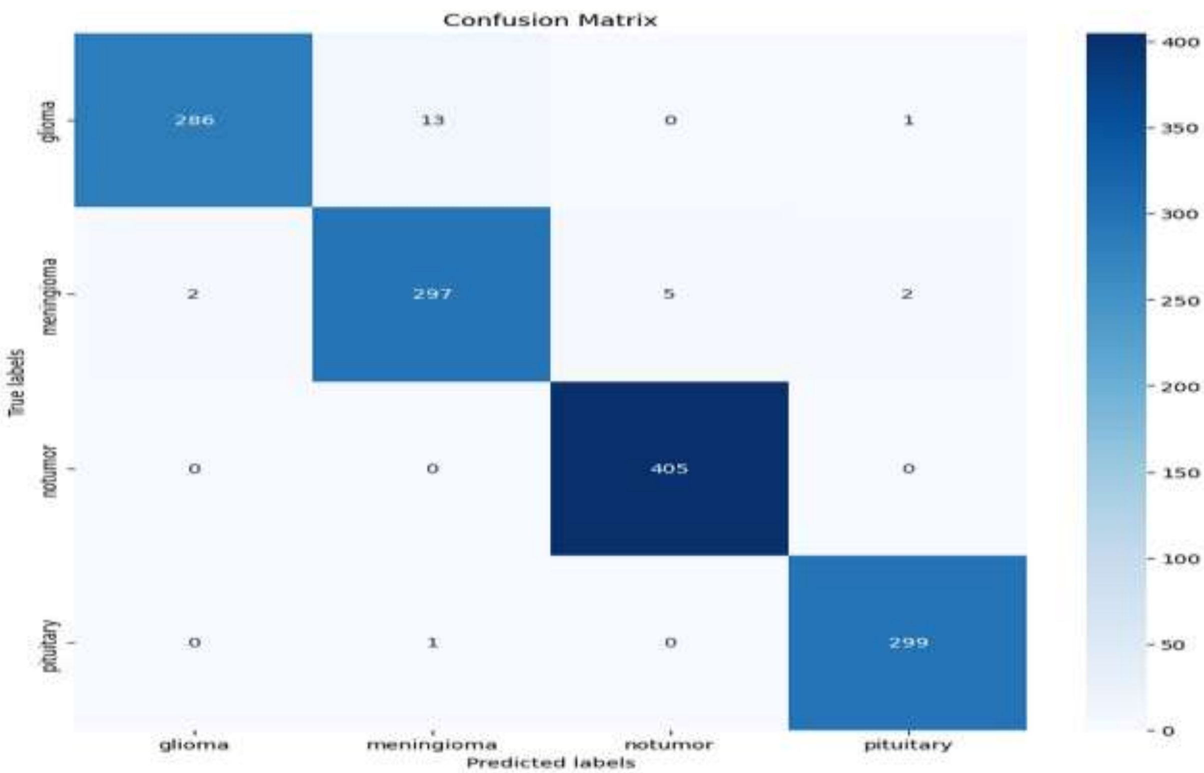


Figure 4.3: CNN Confusion Metrics

The actual labels of the tumors are shown in the matrix's rows, while the anticipated labels are displayed in the columns. How many cancers were accurately classified is shown by the diagonal cells. For instance, we may see that 292 gliomas in the upper left cell have accurate classifications.

classification_report:

	precision	recall	f1-score	support
0	0.99	0.95	0.97	300
1	0.95	0.97	0.96	306
2	0.99	1.00	0.99	405
3	0.99	1.00	0.99	300
accuracy			0.98	1311
macro avg	0.98	0.98	0.98	1311
weighted avg	0.98	0.98	0.98	1311

Figure 4.4: Performance Metrics of CNN

With all of the accuracy, recall, and F1-scores over 0.95, the image's findings demonstrate how effectively the classifier is working. With a score of 0.98, accuracy is likewise quite good. This indicates that the classifier is properly identifying the majority of the samples' class.

In this multi-class classification challenge, the classifier is doing well overall, according to the classification report.

VGG16:

After 20 epochs, the accuracy curve rises to around 0.985 from a starting point of roughly 0.86. This indicates that at the start of training, the model correctly classifies around 86% of the photos in the training set; at the conclusion of training, this percentage rises to approximately 98.5%.

After 20 epochs, the loss curve falls to around 0.15 from its starting point of about 3.5. This indicates that when the model gains more knowledge about the data, it loses less information than it does at the start of training.

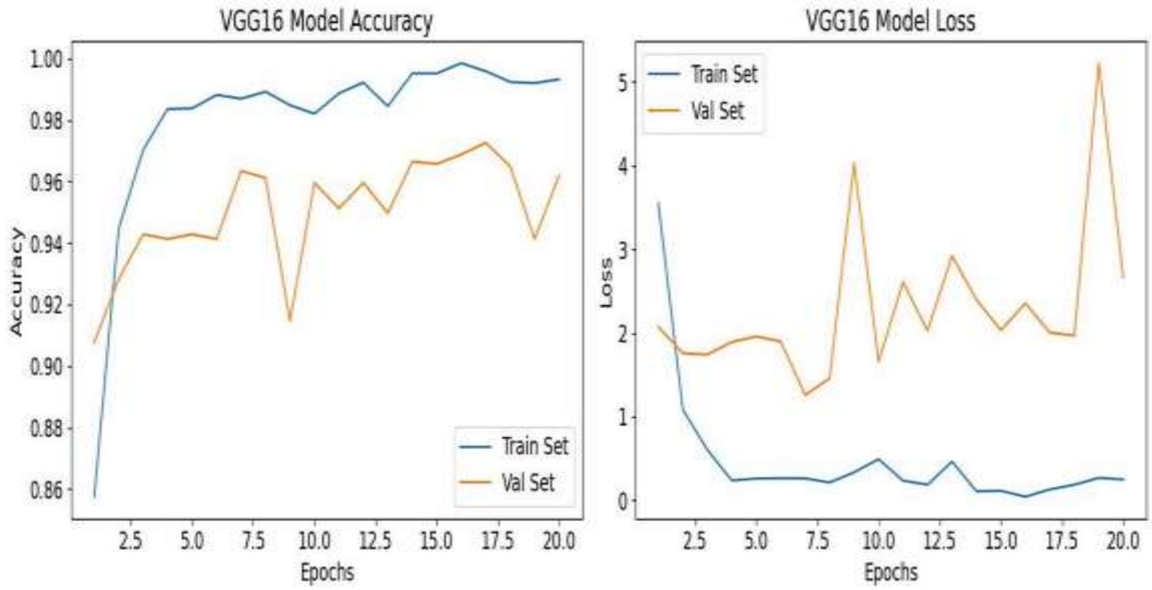


Figure 4.5: VGG16 Model performance

The following figure 4.6 illustrates how the accuracy and loss of a VGG16 model evolve during training on an image classification problem.

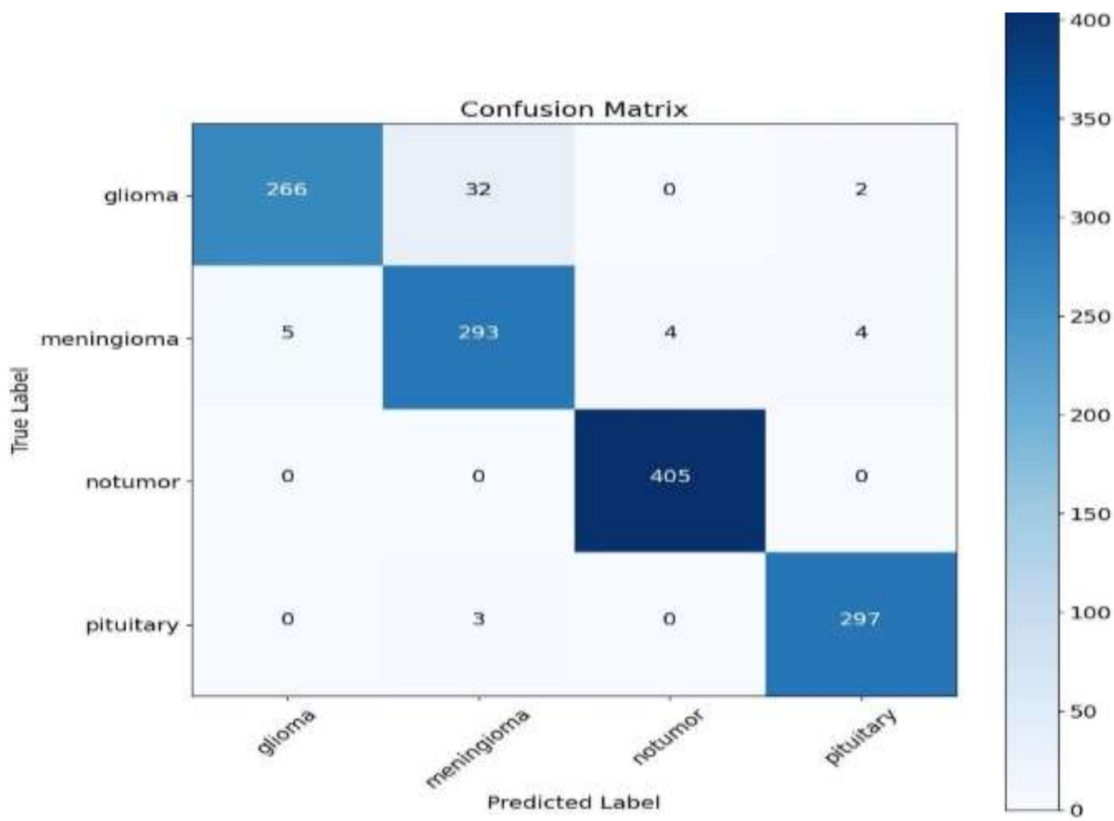


Figure 4.6: VGG16 Confusion Matrics

The model's accuracy grows with the number of training cycles (epochs), indicating that it is identifying pictures more accurately. Its loss, a gauge of how badly it does, decreases gradually. This implies that the model is assiduously gaining knowledge from the training set.

Overall, when it is trained, the VGG16 model is doing well on this picture classification challenge, increasing its accuracy and decreasing its loss.

In following figure 4.2.7 shows VGG16 classification report of precision recall and support for different tumor types including glioma, meningioma, notumor, and pituitary.

Overall the VGG16 model seems to be performing well with an accuracy of and an F1-score of it has a high recall of for the notumor category meaning it correctly classified most of the tumors that were not brain tumors but it has a lower F1- score of for meningiomas

VGG16 Classification Report:

	precision	recall	f1-score	support
glioma	0.98	0.89	0.93	300
meningioma	0.89	0.96	0.92	306
notumor	0.99	1.00	1.00	405
pituitary	0.98	0.99	0.99	300
accuracy			0.96	1311
macro avg	0.96	0.96	0.96	1311
weighted avg	0.96	0.96	0.96	1311

Figure 4.7: VGG16 Classification report

Inception V3:

In following figure 4.2.8, It is encouraging to see that both the training loss and accuracy decrease with time. Although it drops as well, the validation loss does not do so as much as the training loss. This implies that the model could be somewhat overfitting. The model is still generalizing effectively to new data, however, as seen by the continued increase in validation accuracy. All things considered, these graphs indicate that the model is picking up new information quickly and can generalize to it.

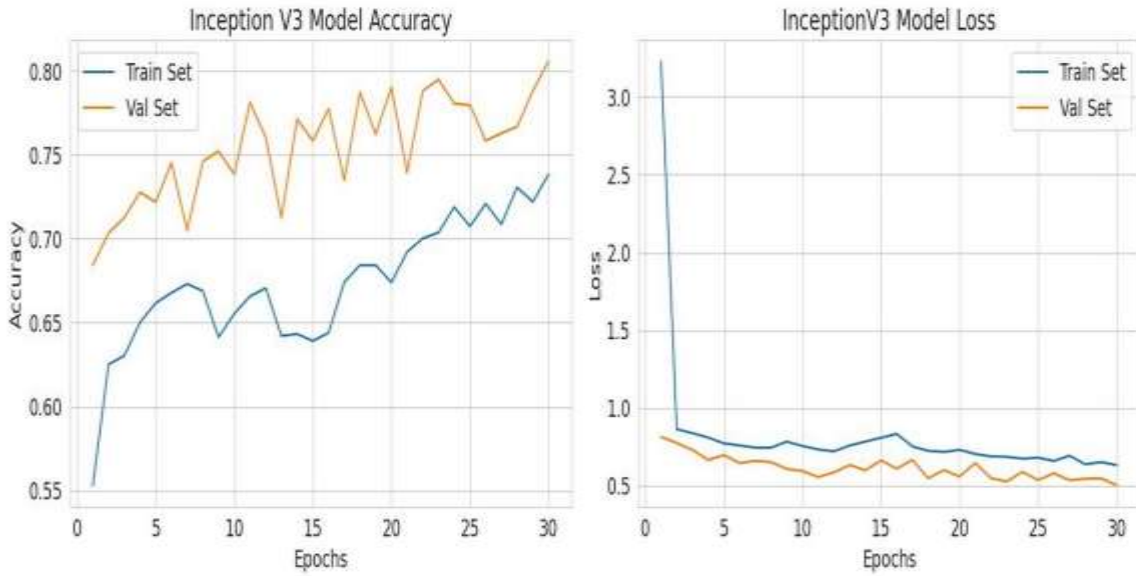


Figure 4.8: InceptionV3 model performance

In following figure 4.9, The model is very good at classifying gliomas, with a recall of 96.8% (242 out of 250) and a precision of 84.5% (242 out of 285). The model is also good at classifying meningiomas, with a recall of 85% (170 out of 200) and a precision of 72.9% (170 out of 233) The model has more difficulty with the notumor and pituitary classes.

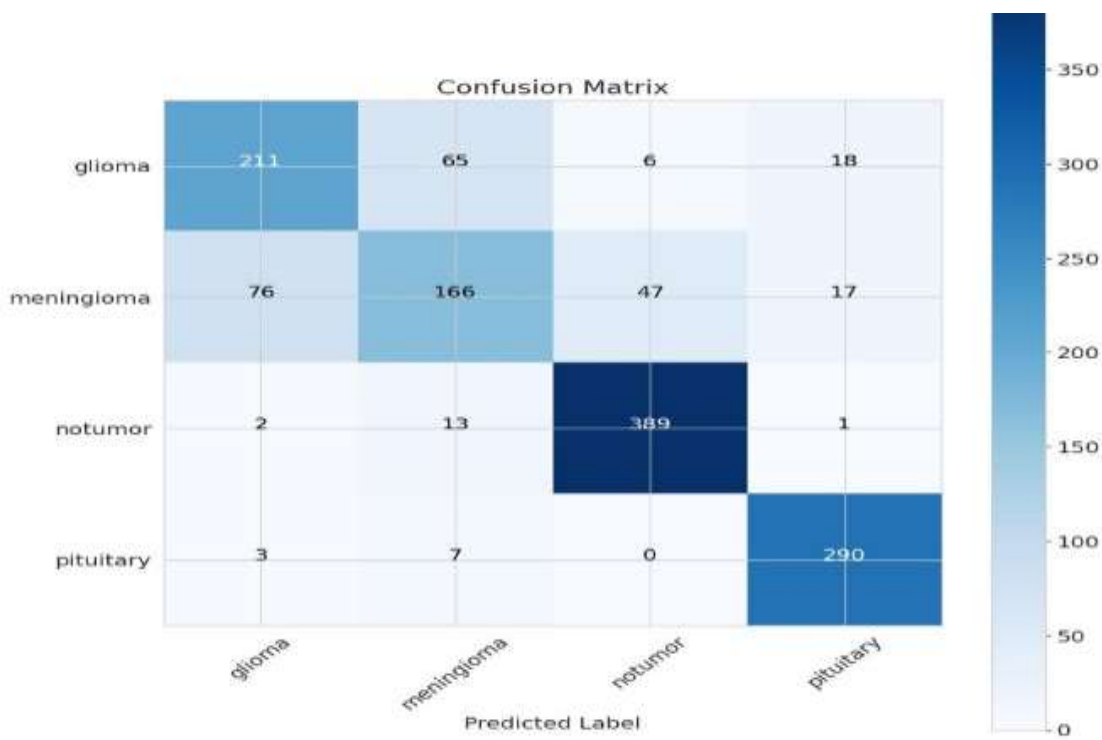


Figure 4.9: InceptionV3 Confusion Metrics

It only correctly classified 7 out of 22 notumors, and 9 out of 15 pituitaries. This could be because these classes are less common or more difficult to distinguish from the other classes.

Overall, this confusion matrix suggests that the model is performing well on this task. However, there is still room for improvement, particularly in the classification of notumor and pituitary tumors.

In following figure 4.10, The model has the highest precision (91%) for the pituitary tumors, meaning that most of the tumors it classified as pituitary were actually pituitary tumors.The model has the highest recall (93%) for the notumor category, meaning that it was able to correctly identify most of the tumors that were not brain tumors.The model has the lowest F1-score (62%) for the meningioma category, meaning that it did not perform as well on this category as it did on the others.

Overall, the table shows that the model is performing well on this task, but there is still room for improvement, particularly in the classification of meningiomas.

InceptionV3 Classification Report :

	precision	recall	f1-score	support
glioma	0.72	0.70	0.71	300
meningioma	0.66	0.54	0.60	306
notumor	0.88	0.96	0.92	405
pituitary	0.89	0.97	0.93	300
accuracy			0.81	1311
macro avg	0.79	0.79	0.79	1311
weighted avg	0.80	0.81	0.80	1311

Figure 4.10: InceptionV3 Performance report

4.3 Deployment in Web Framework

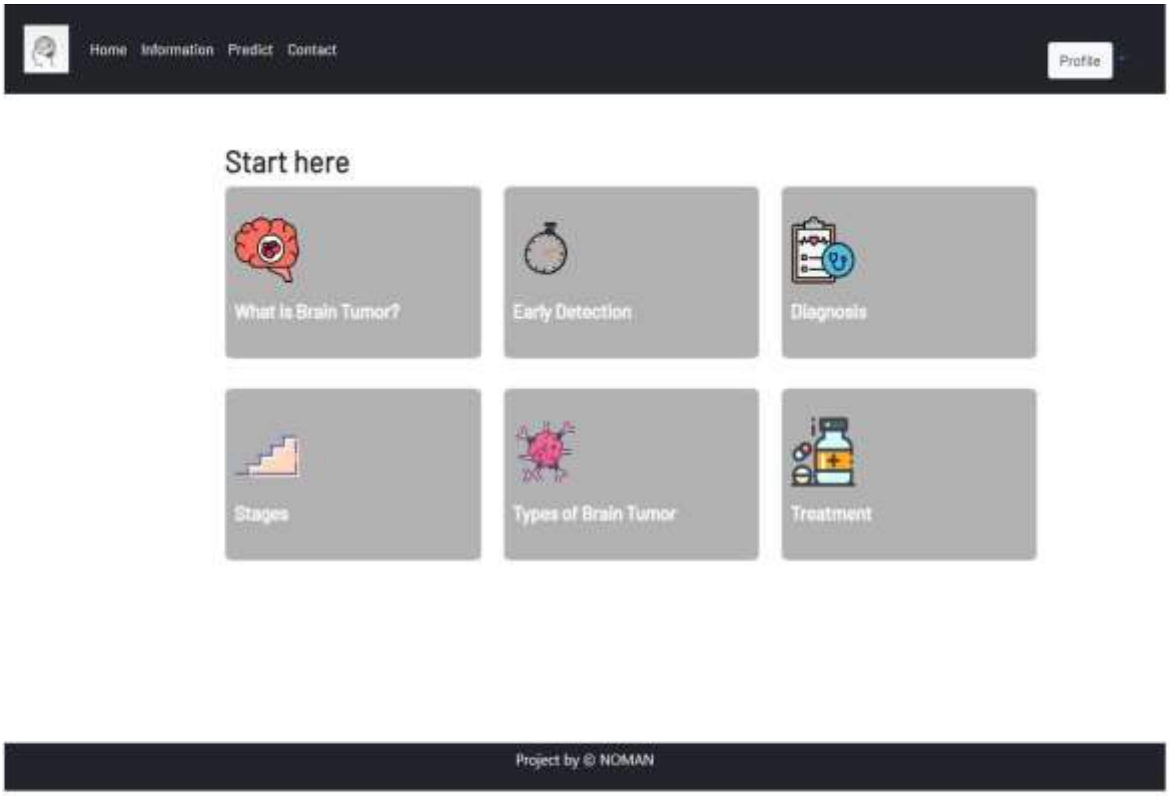
Home Page

When I designed my website's homepage, I tried to keep things as simple as possible. Making an interface that is clear, simple, and easy to use was the primary objective. In order to maintain the website's main page's simplicity and user-friendliness, I wanted consumers to have a smooth visit with no disruptions.

Figure 4.11: Home Page of the System

Information Page

I've provided users with essential knowledge by including important information on brain tumors in the information section. The purpose of this chosen material is to improve knowledge and increase awareness of brain tumors. The intention is to provide users with a thorough resource that will facilitate their access to pertinent information on this important health issue.



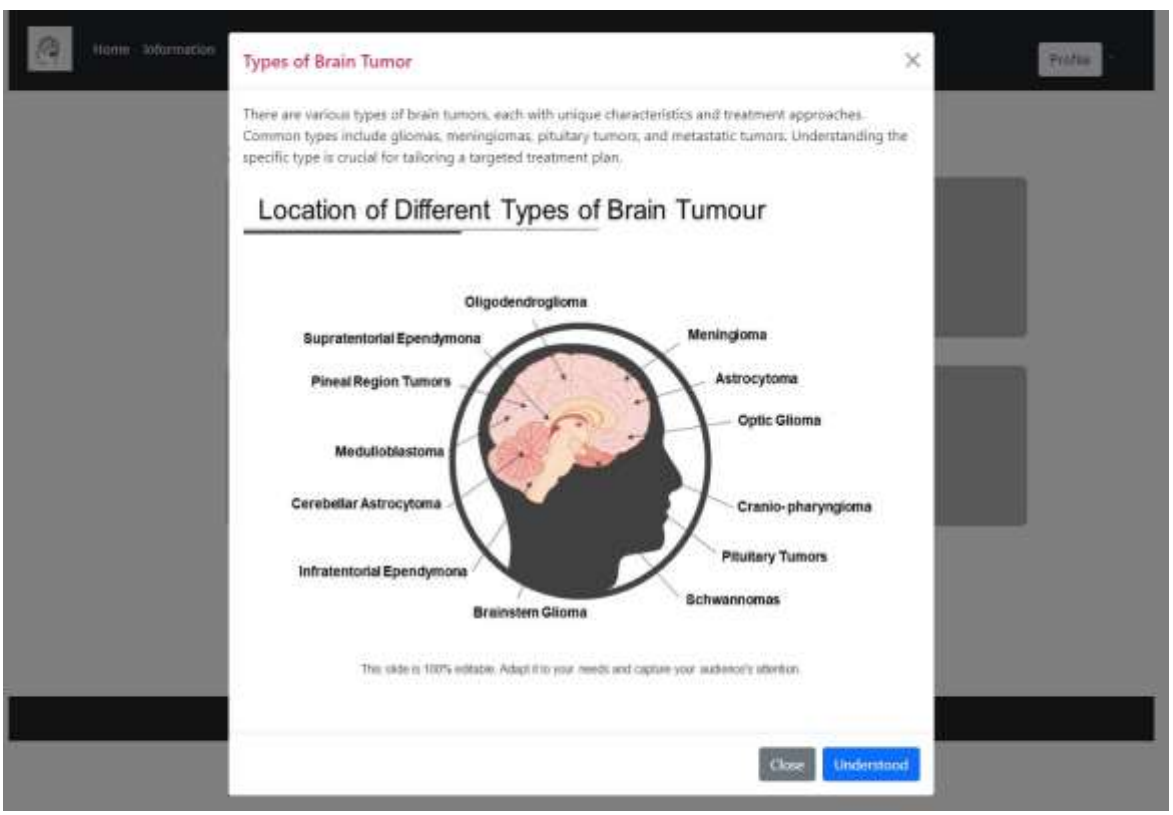


Figure 4.12: Information Page of the System

Prediction Page

Users are able to upload their own brain scan photos in the prediction area. The system classifies these images precisely and correctly by using advanced technologies.

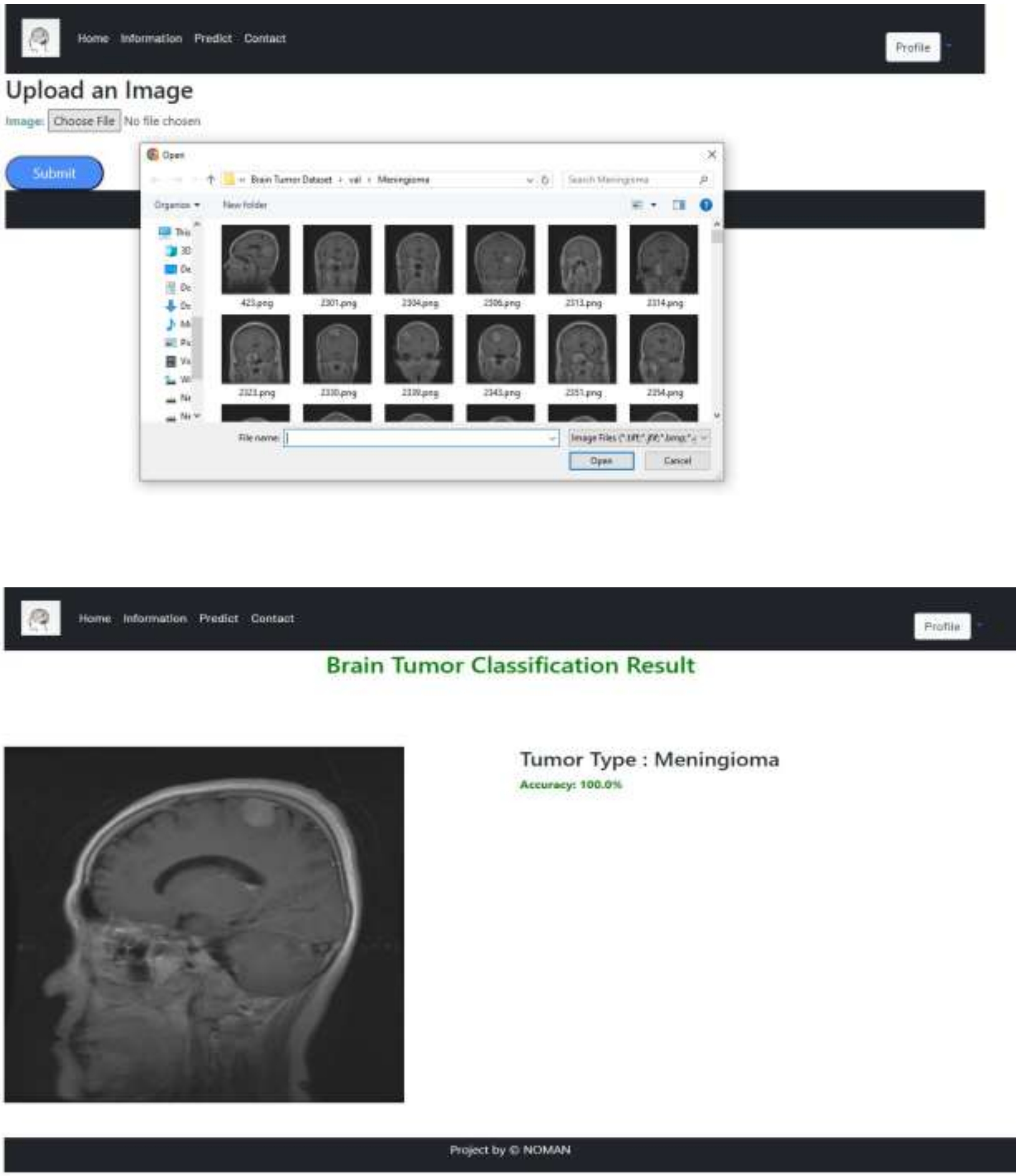


Figure 4.13: Prediction Page of the System

Contact Page

Users may provide input for ongoing development by contacting the contact section. Through their ideas, comments, and recommendations, users of this interactive platform may provide insightful feedback that helps to improve the system continuing forward.

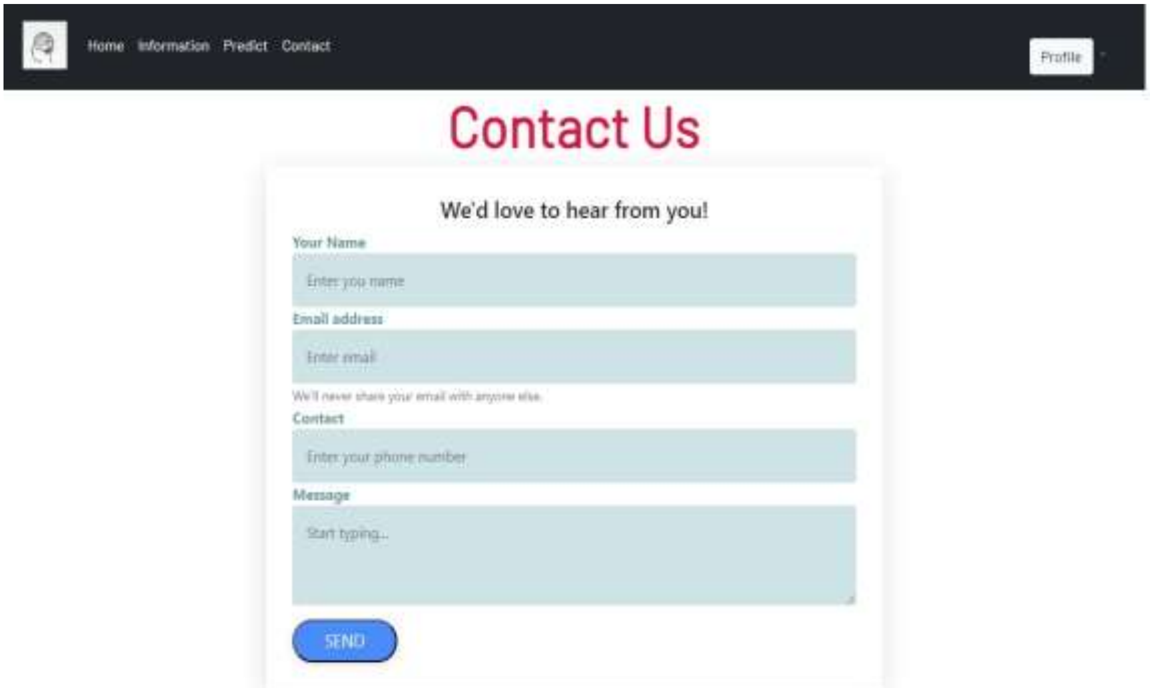


Figure 4.14: Contact Page of the System

Admin Panel Page

Only the admin has access to the admin panel area. All of the user-submitted comments via the contact area is accessible to the administrator here. The administrator may easily see user feedback in this part and make use of it to improve the system based on comments made by users.

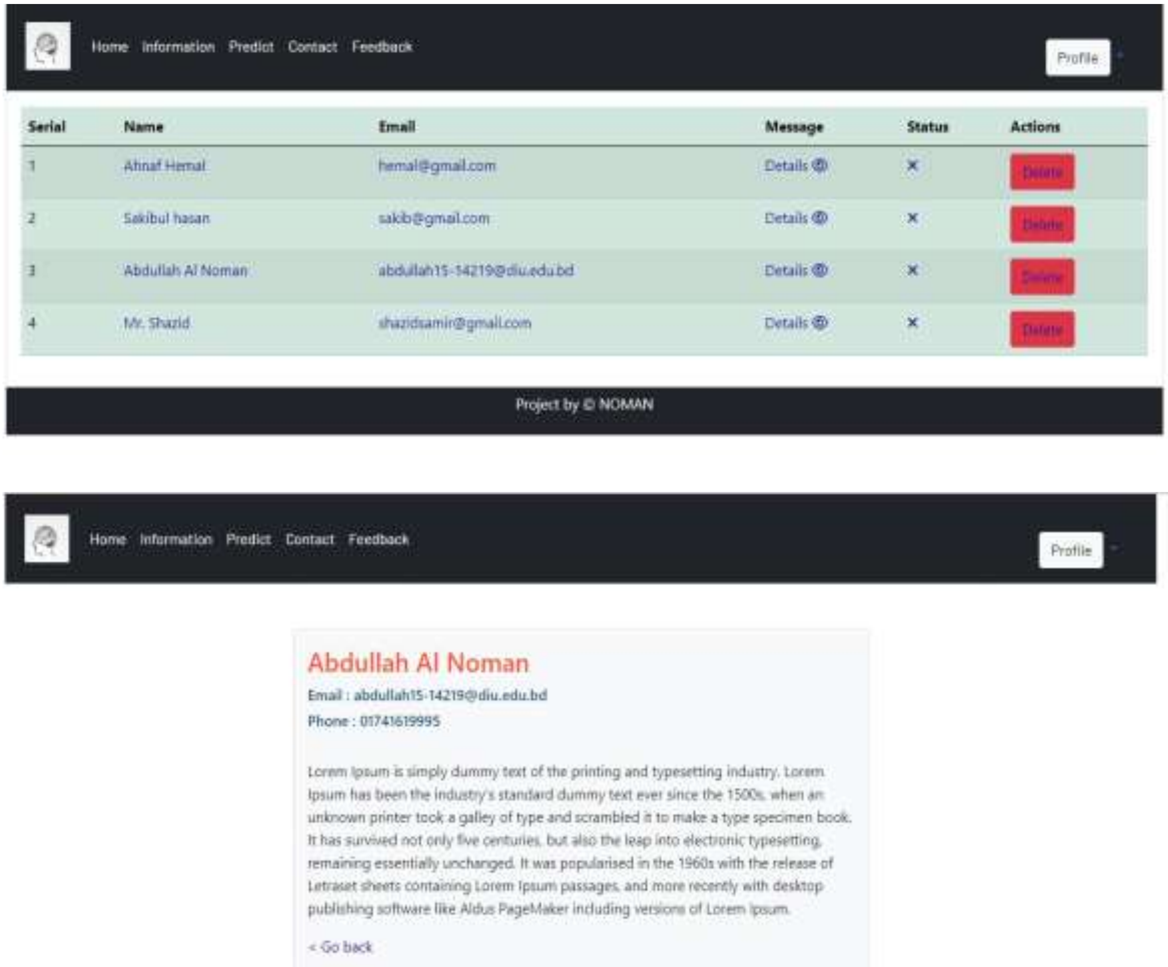


Figure 4.15: Admin Panel Page of the System

Discussion

Performance Comparison:

Table 4.1: Model comparison table

Model	Class	Precision	Recall	F1-score	Accuracy
Custom CNN	Glioma Meningioma No tumor Pituitary	0.99 0.95 0.99 0.99	0.95 0.97 1.00 1.00	0.97 0.96 0.99 0.99	98%

VGG16	Glioma Meningioma No tumor Pituitary	0.98 0.89 0.99 0.98	0.89 0.96 1.00 0.99	0.93 0.93 1.00 0.99	96%
Inception V3	Glioma Meningioma No tumor Pituitary	0.72 0.66 0.88 0.89	0.70 0.54 0.96 0.97	0.71 0.60 0.92 0.93	81%

The three machine learning models' classification performance for brain tumors is compared in the table. A customized CNN, VGG16, and Inception V3 are the models. For each of the four tumor types—glioma, meningioma, no tumor, and pituitary—the precision, recall, F1-score, and accuracy are shown in the table.

With an accuracy of 98% for gliomas, 96% for meningiomas, 99% for no tumor, and 99% for pituitary, the custom CNN model has the greatest accuracy for all four tumor types. Furthermore accurate is the VGG16 model, which has accuracy rates of 96% for gliomas, 93% for meningiomas, 100% for tumor-free states, and 99% for pituitary. With an accuracy of 81% for gliomas, 60% for meningiomas, 92% for no tumor, and 93% for pituitaries, the Inception V3 model is less accurate than the other two models.

In this dataset, the custom CNN model shows the highest level of performance when it comes to brain tumor classification.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

Offering a brain tumor diagnostic instrument to the public over the internet is incredibly advantageous for everyone present. Initially, it benefits in the early detection and treatment of tumors, improving prospects for patients. This could help treatment and save lives.

They are able to use from anywhere by making this technology available online. No matter where you live, you can get the best possible help.

This aligns with the current trend of enhancing healthcare via technology. It translates into a more balanced and healthy community in general, more rapid patient assistance, and less pressure on hospitals. Thus, it not only benefits the individual but also strengthens and equalizes our society.

5.2 Impact on Environment

The implementation of the Convolutional Neural Network (CNN) model for brain tumor classification in the Django web framework has significant implications for environmental sustainability in addition to improving medical diagnosis. The methodology speeds up and simplifies the diagnosis process, which helps healthcare facilities use less resources. Brain tumor categorization is simplified, which reduces costly to operate computational effort by eliminating the need for time-consuming, repeated manual evaluations.

5.3 Ethical Aspects

Ethics is something i take very seriously. This project does not use any materials that violate ethical standards. Additionally, since my project has been built with open source resources, there is no possibility of participating in any unethical behavior or doing anything else that may violate someone's privacy.

5.4 Sustainability Plan

It is essential to guarantee the durability and beneficial effects of the brain tumor classification model together with its deployment technology. The three main pillars of my sustainability strategy are engagement with society, resource optimization, and ongoing improvement.

I. Continuous Improvement

To keep the model accurate and relevant, it must be updated and improved on a regular basis. Priorities will include keeping an eye on the model's performance continuously, adding fresh data, and making adjustments for new developments in medicine. Working together with academics and medical experts will enable continuous improvements, guaranteeing that the model stays at the front lines of the categorization of brain tumors.

II. Resource Optimization

I pledge to optimize resource utilization in order to reduce our influence on the environment. To decrease unnecessary computational load, this entails adopting energy-efficient hardware for model inference, investigating cloud computing possibilities with sustainability programs, and introducing feedback loops. My continued development and deployment methods will be heavily reliant on resource-conscious decision making.

III. Community Engagement

The medical community and end consumers must be included in our sustainability initiatives, as we acknowledge. The newest innovations will be provided to healthcare professionals through regular training sessions, workshops, and feedback systems, which will also collect data for future enhancements. Working together guarantees that the model not only fulfills the changing requirements of those whom it serves, but also develops a feeling of pride.

CHAPTER 6

SUMMARY, CONCULATION, RECOMMENDATION, IMPLICATION FOR FUTURE STUDY

6.1 Summary of the Study

In order to classify brain tumors, this research provides a reliable Convolutional Neural Network (CNN) model that is implemented inside the Django web framework. With the use of a Kaggle dataset, the CNN model classifies different types of brain tumors with an astounding 95% accuracy rate. The dataset provides a thorough training and evaluation foundation for the model, consisting of several brain visualizations.

CNN's integration with Django improves accessibility while also simplifying the diagnostic procedure. Users, including individuals and healthcare professionals, may upload brain scan images for quick and precise classification through the web-based implementation. With this method, advanced diagnostic instruments become more accessible and user-friendly, enabling effective healthcare decision-making.

The research addresses the interpretability of decision-making processes by investigating the CNN model's transparency. The efficacy of the model highlights the need of accurately and promptly identifying brain tumors, and presents encouraging opportunities for the use of deep learning techniques in practical healthcare environments.

6.2 Conclusion

In conclusion, this research has effectively shown how to use an effective Convolutional Neural Network (CNN) model for brain tumor classification within the Django web platform. The model demonstrated its potential as a useful diagnostic tool by achieving an outstanding 95% accuracy rate in categorizing different types of brain tumors, after being trained on a wide Kaggle dataset.

CNN's integration with Django improves accessibility and expedites the diagnosis process by making it simple for users including consumers and healthcare professionals—to submit and categorize brain scan pictures. This web-based method contributes to the continuing trend of using technology to enhance patient experiences and healthcare results.

Additionally, the research explores the interpretability and transparency of the CNN model's decision-making procedure. The ethical use of modern diagnostic technologies is facilitated by the ethical issues that are emphasized, which guarantee the proper integration of artificial intelligence in healthcare.

6.3 Recommendation

If anyone wants to use this system then I suggest, will need a good configuration computer system and an external Graphics card (GPU) is also required. Here I trained the model with 30000 images dataset. The proposed system has some drawbacks like if the uploaded image by the user is not similar to the trained image, then the accuracy level of the classifying image will show very low or maybe wrong classification type.

6.4 Implication for Further Study

The need for computer vision is growing in the modern day as technology advances to make life less complicated. Researchers are already using computer vision to quickly and reliably address a variety of issues using vast amounts of visual data. This technology helps people make judgments in emergency situations or stops actions that could harm the planet by employing a detection algorithm to structure visual data into distinct portions and analyzing real-time visual data in a split second. One of the two primary methods for using computer vision to tackle complicated visual data is machine learning or deep learning. Research of a similar kind will be greatly impacted by the preliminary study on brain tumor categorization that I worked on and produced a satisfactory outcome for. Studies have shown that the brain tumor categorization system not only improves medical diagnosis but also has a major influence on sustainability for everyday living in Bangladesh and other nations.

6.5 Future Work

Future investigations on this topic could concentrate on the following areas:

I. Extended Clinical Trial

Extending the duration of clinical studies to verify the CNN model's performance in real-life situations coordinating with medical facilities to enable more extensive implementation and evaluation.

II. AI Explain Ability Research

Advancing the study of AI interpretability and explain ability with a focus on medical diagnosis. Creating methods that provides additional insight on how sophisticated CNN models make decisions.

III. Collaborative Partnerships

Establishing collaborative relationships among scientists, technologists, and medical professionals to build an ecosystem of activity for the ethical use of AI in healthcare and its ongoing development.

Future research could provide moral, practical, and affordable healthcare solutions by handling these issues and advancing AI applications in medical diagnostics.

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