Identification and Detection of Brain Tumors using Machine learning and Deep Learning methods

MSc Research Project

Data Analytics

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MSc Project Submission Sheet

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Identification and Detection of Brain Tumors using Machine learning and Deep Learning methods

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Abstract

The challenge of addressing critical ailments such as tumors without manual intervention is substantial. Brain tumors, with their potential to induce cerebral pressure, hemorrhage, and mortality, underscore the gravity of the issue. In this study, we propose a novel approach using machine learning and deep learning techniques for the accurate detection of various brain tumor types. Our methodology encompasses machine learning tools, including SVM and Naive Bayes, as well as deep learning frameworks like CNN, VGG, and Inception. Leveraging a diverse dataset representing different brain tumor scenarios, we rigorously evaluate our models using metrics such as accuracy, precision, recall, and F1-score. This research offers a promising pathway toward enhanced diagnostic automation in the context of brain tumor detection.

1 Introduction

Brain tumours are uncontrolled, rapid cell growths in the brain tissues. Since this tumour has the potential to cause bleeding and ultimately mortality, it should be identified as soon as possible (hemanth et.al). Over a million people in America have brain tumours, and the survival rate is around 36%.The research by (Siddaiah.et.al) emphasises the difficulties in diagnosing, localising, and categorising brain tumours using magnetic resonance imaging (MRI) and manual tumour identification. Brain tumours are a hazardous ailment, with an increasing number of people dying as a result of them. The importance of an automated brain tumour diagnosis system with high tumour detection and localization accuracy is emphasised in the research.
Brain tumors can be benign or malignant, and they affect people of all ages, with varying impacts.Brain cancer is caused by abnormal cells called glial cells and is a growing health problem worldwide.It is important to detect the entire affected cancerous tissues for further treatments. The most common medical imaging technique used for brain tumor diagnosis is Magnetic Resonance Imaging Scanning (MRI scan), which is effective for detection and classification of different types and grades of tumors in clinical diagnosis(H. T. Zaw et al.)

1.1 Literature Review

Brain tumors pose a significant health concern globally, and early detection is crucial for timely intervention and improved patient outcomes. Machine learning (ML) and deep learning (DL) techniques have gained substantial traction in recent years for their potential in aiding the identification and detection of brain tumors. This literature review provides an overview of studies and advancements in using ML and DL methods for the early identification and detection of brain tumors.

Traditional Machine Learning Approaches for Brain Tumor Detection:

Many early studies utilized traditional ML algorithms for brain tumor detection. Techniques such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and decision trees were applied to features extracted from medical imaging modalities like Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET). These studies often involved handcrafted feature extraction methods and achieved promising results in distinguishing between tumor and healthy brain tissue.

Feature Extraction and Selection Techniques:

Researchers focused on optimizing feature extraction and selection to enhance the performance of ML models. Techniques like Principal Component Analysis (PCA), Wavelet Transform, and Histogram of Oriented Gradients (HOG) were employed to extract discriminative features from imaging data. Feature selection methods, such as Recursive Feature Elimination (RFE) and mutual information-based selection, helped in identifying the most informative features for classification.

Deep Learning for Brain Tumor Detection:

The emergence of DL revolutionized brain tumor detection. Convolutional Neural Networks (CNNs) emerged as a dominant approach for feature learning directly from imaging data. CNNs have shown exceptional performance in automated segmentation, classification, and detection of brain tumors. Various architectures, including U-Net, DeepMedic, and 3D CNNs, have been proposed and fine-tuned for different types of brain tumor detection tasks.

Multi-Modal Fusion for Improved Accuracy:

Incorporating multi-modal data, such as combining MRI, CT, and PET scans, has gained traction. Fusion of multi-modal information often improves the accuracy and robustness of brain tumor detection systems. Researchers have developed integrated models that combine data from different imaging modalities to achieve better performance compared to using individual modalities.

Data Augmentation and Transfer Learning:

Data scarcity is a common issue in medical imaging datasets. Data augmentation techniques, such as rotation, scaling, and flipping, have been applied to mitigate this challenge and enhance model generalization. Additionally, transfer learning, where models pre-trained on large datasets are fine-tuned for brain tumor detection, has been effective in utilizing features learned from non-medical domains.

Challenges and Future Directions:

Despite significant advancements, challenges like interpretability, data privacy, and generalization to diverse populations remain. Future research should focus on developing explainable AI models, leveraging advanced DL architectures like transformers, and incorporating genetic or molecular data for a more comprehensive understanding of brain tumors.

1.2 Research Question

RQ: *To what extent can transfer learning technique VGG, in comparison to traditional machine learning and deep learning methods, enhance the accuracy of brain tumor detection, aiming to minimize mortality rates through early identification and intervention?*

Research Objectives

Table 1: This shows the objectives of the Brain Tumor Detection

Objective	Description	Metrics
Obj 1	Literature review of recent papers	-
Obj 2	Exploratory Data Analysis	-
Obj 3	Implementation, evaluation and results of Machine Learning methods - Support Vector Classification and Naïve Bayes	Accuracy,precision,recall, the F1 score
Obj 4	Implementation, evaluation and results of Data Learning methods – CNN, Inception,VGG	Accuracy, precision, recall, the F1 score
Obj 5	Comparison of developed methods	-

The document is structured as follows: Section 2 delves into a comprehensive exploration of various techniques for brain tumor detection, serving Objective 1. Sections 3 and 4 provide a detailed analysis of data and design considerations, contributing to the fulfillment of Objective 2. Section 5 covers the implementation process, evaluation methodology, and results obtained, addressing Objectives 3 and 4. Finally, Section 6 concludes the research, discussing its findings and outlining future research directions to fulfill Objective 5.

2 Related Work

2.1 Introduction

This section presents an exploration of the existing literature concerning tumor detection. It is organized into distinct papers that share common methodologies for detecting tumors and other diseases. Subsection 2.2 provides an overview of literature reviews focusing on machine learning techniques, including SVM and Naive Bayes classification and transfer learning methods, employed in detecting various types of tumors. In Subsection 2.3, a comprehensive analysis is presented, discussing the application of deep learning methods such as CNN, VGG, and Inception for tumor detection.The subsection 2.4 gives a clear review on Deep Learning and Machine learning techniques in other disease detection. This section answers the objective 1

2.2 Machine Learning models

Brain tumor detection is a crucial task in healthcare, requiring efficient and accurate methods. Image segmentation plays a pivotal role in identifying abnormal tumor regions within brain MRI scans (Hemanth et al., 2019). To address this challenge, the study proposes an automatic segmentation approach utilizing Convolutional Neural Networks (CNNs) and data mining techniques.The proposed method employs CNNs to achieve both segmentation and classification, demonstrating its effectiveness in detecting and classifying brain tumors (Hemanth et al., 2019). By leveraging data mining techniques, the study aims to extract significant patterns and relationships from the data, contributing to accurate detection and prevention at an early stage.

The paper by H. T. Zaw et al., 2019) discusses the detection of brain tumors, specifically grade-4 tumor, Glioblastoma multiforme (GBM), using Naïve Bayes classification.The most common medical imaging technique used for brain tumor diagnosis is Magnetic Resonance Imaging Scanning (MRI scan), which is effective for detection and classification of different types and grades of tumors in clinical diagnosis.The paper by (H. T. Zaw et al., 2019) has taken Naïve Bayes classifier based prediction algorithm for tumor detection by Testing 50 MRI images with an overall accuracy of 94%

Amin et al.,(2022) have stated that Brain tumors are a critical health concern due to their potential to rapidly grow and lead to life-threatening consequences if not detected and treated early (Amin et al., 2022). Despite substantial efforts, accurate segmentation and classification of brain tumors remain challenging tasks. Variability in tumor location, shape, and size adds complexity to the detection process.The survey covers a range of topics including brain tumor anatomy, publicly available datasets, enhancement techniques, segmentation, feature extraction, classification, and the application of deep learning techniques, transfer learning, and quantum machine learning in brain tumor analysis (Amin et al., 2022)

Özyurt et al. (2019) proposes a hybrid method using Neutrosophy and Convolutional Neural Network (NS-CNN) to classify brain tumor region areas as benign and malignant.The CNN features were classified using SVM and KNN classifiers.The paper evaluates the proposed NS-EMFSE-CNN method in terms of Sensitivity, Precision, Accuracy, and Youden index scales.The SVM classifier was found to be more successful than the KNN classifier with an accuracy of 93.1%

2.3 Deep learning models

Rohith et al.(2023) proposes a method for detecting brain tumors using the VGG-16 model, which has been successfully applied to this task and achieved high levels of accuracy.The proposed method involves pre-processing the images to enhance contrast and remove noise, extracting features from the images using the VGG-16 model, and building a SVM classifier to distinguish between images with and without tumors. The results show that the VGG-16 model is highly effective in detecting brain tumors, achieving an accuracy of over 95%.

The literature provided by Alla SSM, Athota (2022) discusses the use of magnetic resonance imaging (MRI) for brain tumor evaluation and the challenges of manual segmentation due to the enormous amount of data generated by MRI. The novelty of this work is the use of Transfer Learning in conjunction with deep learning-based CNNs.The application of transfer learning was investigated by using three types of CNNs (Inception-V3, VGG-16, and VGG-19) to achieve reasonable accuracy, with fine-tuning of the final layers to improve the accuracy of the models.VGG-19 achieved 97% accuracy, and VGG-16 achieved 96% accuracy, which is better than the accuracy of Inception-V3 (89%). The results show that applying transfer learning to a CNN achieves high accuracy in less time and with a smaller dataset.

The authors, Arabahmadi et al. (2022), conducted a comprehensive review of existing efforts in this domain and identified gaps and potential future directions. The paper concludes that deep learning methods, particularly CNN, have shown promising results in accurately analyzing large datasets and identifying anomalies in medical images.

Pokharel et al. (2022) proposed a system that implements the machine learning approach to predict the presence of a tumor in the brain or close to the brain based on the MRI images of patients using Convolutional Neural Network.The paper proposes a deep learning strategy for detecting the existence of a brain tumor from MRI data based on the VGG-16 architecture.The model is found to be predicting the occurrence of Brain Tumor with 95.7% accuracy and 1.3% loss.

The paper by Kora et al. (2021) proposes a deep neural network framework for brain tumor detection using MRI scans. The study uses transfer learning based architectures such as VGG-16, Inception-v3, and Xception models for binary classification. The accuracy of the VGG-16 architecture is found to be the highest at 98.16%.

Siddaiah et al. (2022) proposes paper that aims to develop a system that can detect brain tumors from MRI scans of patients using the VGG-19 architecture of Convolutional Neural Networks.They have also utilized the 'exponentially weighted average' of the gradients to speed up the gradient descent algorithm and achieved succuss in developing satisfactory VGG-19 model.

The paper by R. Pillai et al. (2023) presents the results of using three different pre-trained transfer learning models (VGG16, InceptionV3, and ResNet50) for detecting brain tumors in a dataset of 251 MRI scans.The highest accuracy was achieved with the VGG16 model, which had an accuracy of 91.58%.

P.S. Lakshmi Veeranki et al. (2023) focused on stating that the VGG-16 model outperforms the CNN model in terms of accuracy for the detection and classification of brain tumors.Data augmentation techniques have also been used to artificially increase the dataset size to prevent the overfitting issue. The study includes a comparison of the two models in terms of their performance, and the results show that VGG-16 is the best-trained model.

The paper by Swamy (2020) proposes the use of Magnetic Resonance Imaging (MRI) to detect brain tumors and Convolutional Neural Network (CNN) algorithm to accurately estimate the severity of the tumor. This paper focused on proposing a methodology for brain tumor detection using MRI and CNN algorithm.

Brain tumor detection and classification are vital for effective treatment planning. The study proposes a multi-phase approach involving segmentation, feature extraction, and the application of various deep learning techniques for brain tumor classification (Sadad et al., 2021). The utilization of deep neural networks showcases their potential in achieving accurate brain tumor identification.Various deep learning models, including MobileNet V2, Inception V3, ResNet50, DenseNet201, and NASNet, are applied for tumor classification (Sadad et al., 2021). The study highlights the capabilities of these models and their contributions to accurate brain tumor classification.

Gliomas are challenging to segment due to their irregular shape and diffused boundaries. This study proposes a deep learning-based approach for brain tumor segmentation using multiple modalities of MRI (Sajid et al., 2019). The proposed hybrid convolutional neural network architecture incorporates various techniques to achieve accurate segmentation.
The study's proposed approach combines patch-based CNN architecture with dropout regularization and batch normalization for brain tumor segmentation (Sajid et al., 2019). The results demonstrate improved performance compared to state-of-the-art techniques.

Brain tumor detection is a critical task, and the study proposes a fusion-based approach to achieve accurate classification. The proposed method combines the GrabCut method for segmentation and deep learning features obtained from Transfer Learning models (Tanzila et al., 2020). The fusion of these features aims to enhance the accuracy of brain tumor classification.The study's approach involves preprocessing, segmentation, feature extraction using deep learning models, and fusion of features for classification (Tanzila et al., 2020). The study showcases the potential benefits of integrating traditional and deep learning techniques in brain tumor diagnosis.

2.4 Other Disease diagnosis using machine learning and deep learning techniques

Cancer diagnosis is a critical medical field where accurate classification is essential for effective treatment planning. Traditional methods, including the Asymmetry, Border, Color, and Diameter (ABCD) method, have limitations in achieving high performance (Munir et al., 2019). As a response to these challenges, deep learning techniques have gained attention for their potential to provide improved diagnostic tools.
The review outlines a comprehensive overview of cancer diagnosis techniques, ranging from traditional methods to deep learning techniques (Munir et al., 2019). The basics of deep learning and its applications in medical imaging, including preprocessing, image segmentation, and post-processing, are discussed. The review also focuses on various deep learning models such as convolutional neural networks (CNNs), generative adversarial models (GANs), and recurrent neural networks (RNNs), highlighting their potential contributions to cancer diagnosis. The incorporation of Python codes for experimentation enhances the accessibility of these advanced techniques.

Breast cancer diagnosis is of paramount importance, and mammograms are commonly used for screening and identifying abnormalities (Kavitha et al., 2022). This research presents an optimal multi-level thresholding-based segmentation technique, combined with a deep learning-enabled Capsule Network (CN), for breast cancer diagnosis using digital mammograms.
The proposed model involves preprocessing, segmentation using the thresholding technique, and the utilization of a Capsule Network for classification (Kavitha et al., 2022). The study demonstrates the effectiveness of the proposed approach on benchmark datasets, achieving high accuracy levels in breast cancer diagnosis.

The early detection of lung cancer is essential for improving patient outcomes. This study introduces an image preprocessing technique for lung CT images, followed by the application of deep learning techniques for accurate diagnosis (Sadad et al., 2019). The proposed approach aims to reduce misclassification and enhance the accuracy of lung cancer detection.
The study combines image preprocessing, clustering, and deep learning to achieve accurate lung cancer detection (Sadad et al., 2019). The proposed framework demonstrates impressive accuracy levels compared to existing systems, emphasizing the potential of deep learning in medical image analysis.

Skin cancer is a significant health concern that demands early detection. This review examines deep learning techniques for skin cancer detection, emphasizing lesion parameters like symmetry,

color, size, and shape (Sajid et al., 2021). The review provides insights into the state-of-the-art achievements in skin cancer diagnosis.
Various deep learning techniques, such as convolutional neural networks (CNNs), are explored for skin cancer detection (Sajid et al., 2021). The review presents a detailed analysis of relevant research, frameworks, and techniques for advancing skin cancer diagnosis.

Breast cancer detection and classification play a crucial role in early diagnosis and improved patient outcomes. This study introduces a deep learning-assisted efficient AdaBoost algorithm for breast cancer detection (Zheng et al., 2020). The study's proposed model demonstrates enhanced accuracy in breast cancer detection.
The study incorporates deep learning techniques, including convolutional neural networks (CNNs) and Adaboost algorithm, for breast cancer detection (Zheng et al., 2020). The study highlights the potential of these techniques in improving the efficiency and accuracy of breast cancer diagnosis.

Authors	**Classification of Studies**	**Adapted Models**	**Experiment Outcomes**
Özyurt et al.	Deep Learning	Convolutional Neural Network	Improved brain tumor detection using a CNN with fuzzy entropy
Kora et al.	Transfer Learning	Transfer Learning Models	Enhanced brain tumor detection through transfer learning approach
Siddaiah et al.	Deep Learning	VGG-19	Successful brain tumor detection using a VGG-19 deep learning model
Grampurohit et al.	Deep Learning	Deep Learning Models	Accurate brain tumor detection achieved using various deep learning models
Arabahmadi et al.	Survey	Deep Learning	Comprehensive survey of deep learning techniques for brain tumor detection
Zaw et al.	Machine Learning	Naïve Bayes Classification	Brain tumor detection demonstrated using a Naïve Bayes classification approach

Table 2: Literature review analysis of major contributed papers

3 Research Methodology

3.1 Introduction

The paper follows Knowledge Discovery in Databases (KDD) methodology for detection of brain tumor.The primary objective of this technical paper is to detect brain tumor using medical images.The technical paper uses the data that is publicly avaible from kaggle.Brain tumors can be cancerous (malignant) or noncancerous (benign). When benign or malignant tumors grow, they can cause the pressure inside skull. This can cause brain damage,Hemorrhage and it can be life-threatening.

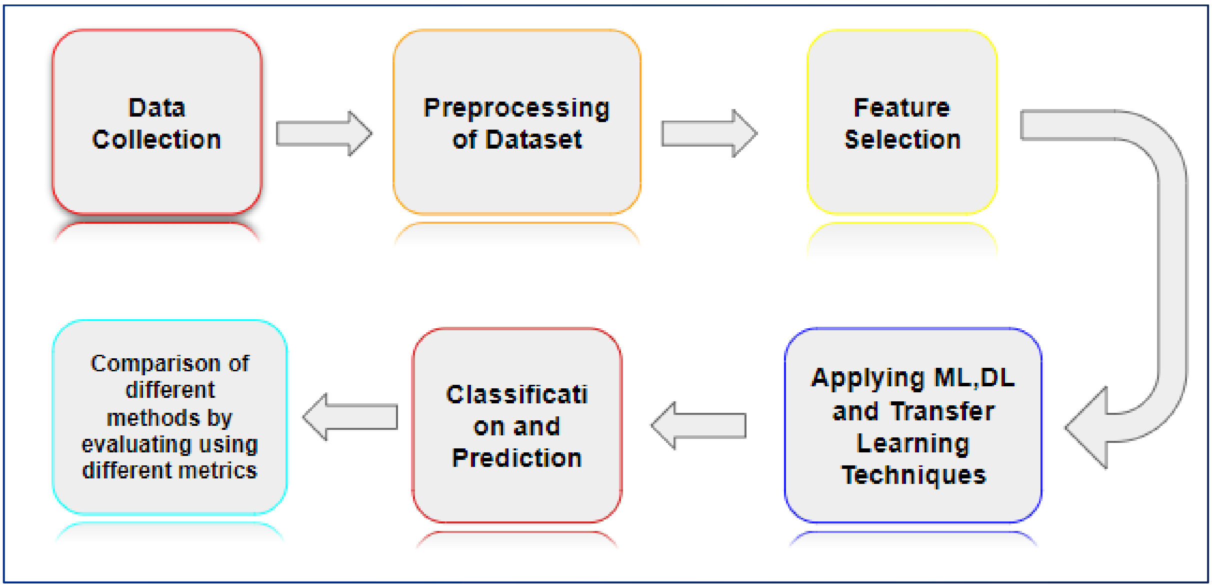

Figure 1: Describes Brain Tumor Detection methodology

3.2 Data collecting

The first phase in our process entails the careful collecting of a broad and representative dataset of medical images. This dataset contains 7023 images of human brain MRI images which are classified into 4 classes: glioma - meningioma - no tumor and pituitary. This experimental work in the diagnosis of brain tumors using Magnetic Resonance Imaging (MRI) involves detecting the tumor, classifying the tumor.

3.3 Data Preprocessing

To improve the performance of the model, it is necessary to do in-depth preprocessing on the data before feeding it into the machine learning pipeline.Data augmentation techniques such as rotating, flipping, and zooming are used to improve the model's ability to generalize to data that it has not before seen and to boost its capacity to manage fluctuations in the data set that it is being trained on.

3.4 Data Splitting

In order to conduct an accurate evaluation of the trained model's performance, the preprocessed dataset is split into two sets: the training set and the testing set. These sets are referred to as the training and testing sets, respectively. The training set receives around 68%

of the data and the testing set receives the remaining 32% of the data.The training set is used to provide the model with the opportunity to learn from labeled data. The testing set gives an objective evaluation of the final model's performance in determining whether or not hemorrhages have occurred.

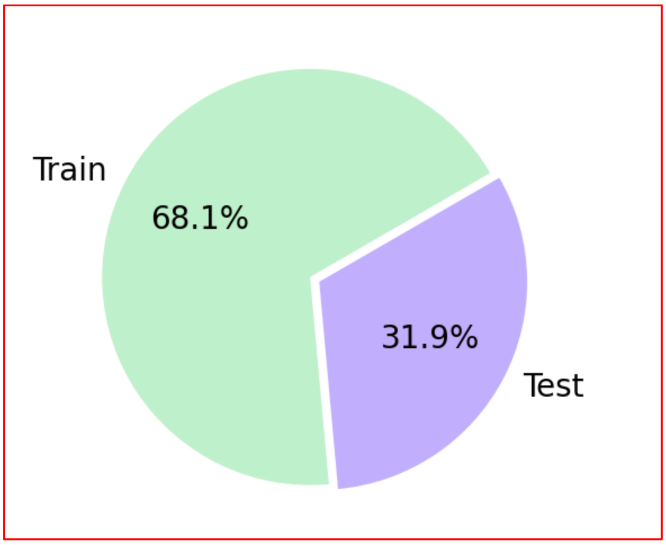

Fig 2: Data Splitting

3.5 Machine Learning methods selection

In order to achieve precise bleeding detection with this project considering ML techniques, SVC and Naives Bayes methods will be selected after thorough consideration. SVC and Naives Bayes are two methods that are worth considering as potential options because they have shown success in a variety of image recognition applications. These models are characterized by their deep structures and skip-connections, which promote improved feature extraction and gradient propagation. As a result, the model is able to capture complicated patterns and delicate features indicative of hemorrhages, which is important information.

3.6 Deep Learning method selection

In the realm of Deep learning methodologies, their efficacy and computational efficiency have garnered significant attention, leading to notable reductions in processing times. VGG, referred to as Visual Geometry Group, embodies a combination of simplicity and proficiency, rendering it proficient in comprehending intricate images. This attribute is particularly advantageous for discerning tasks, such as tumor identification, given its accessibility and capacity for knowledge transfer.

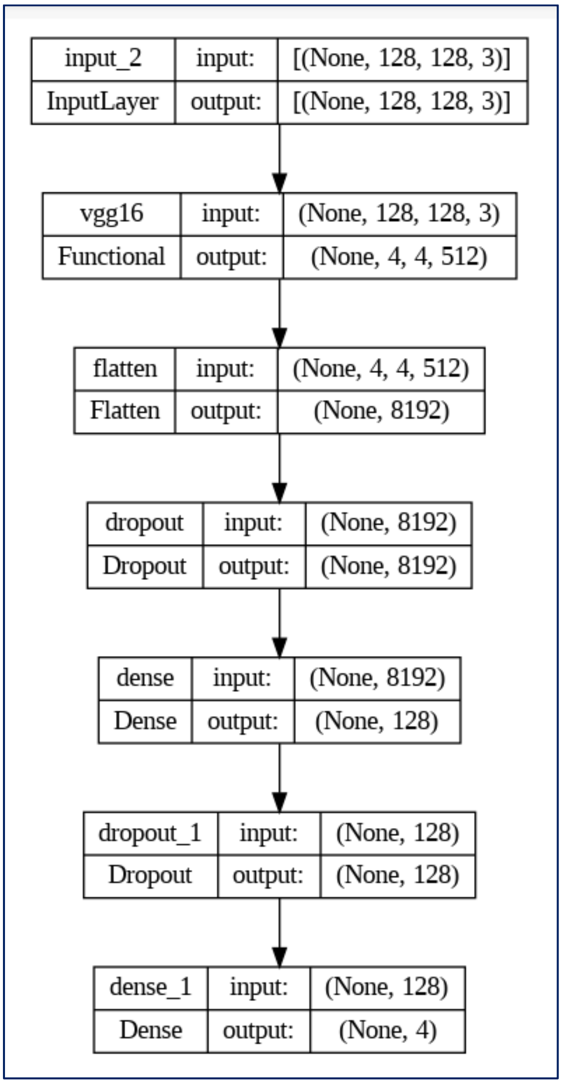

Fig 3: Layer structure of VGG

Convolutional Neural Networks (CNNs), akin to specialized analysts, excel in discerning intricate attributes within images, even amidst fluctuations in lighting or spatial orientation.The first layer is a Conv2D layer with 32 filters (also referred to as kernels), each having a size of 3x3 pixels

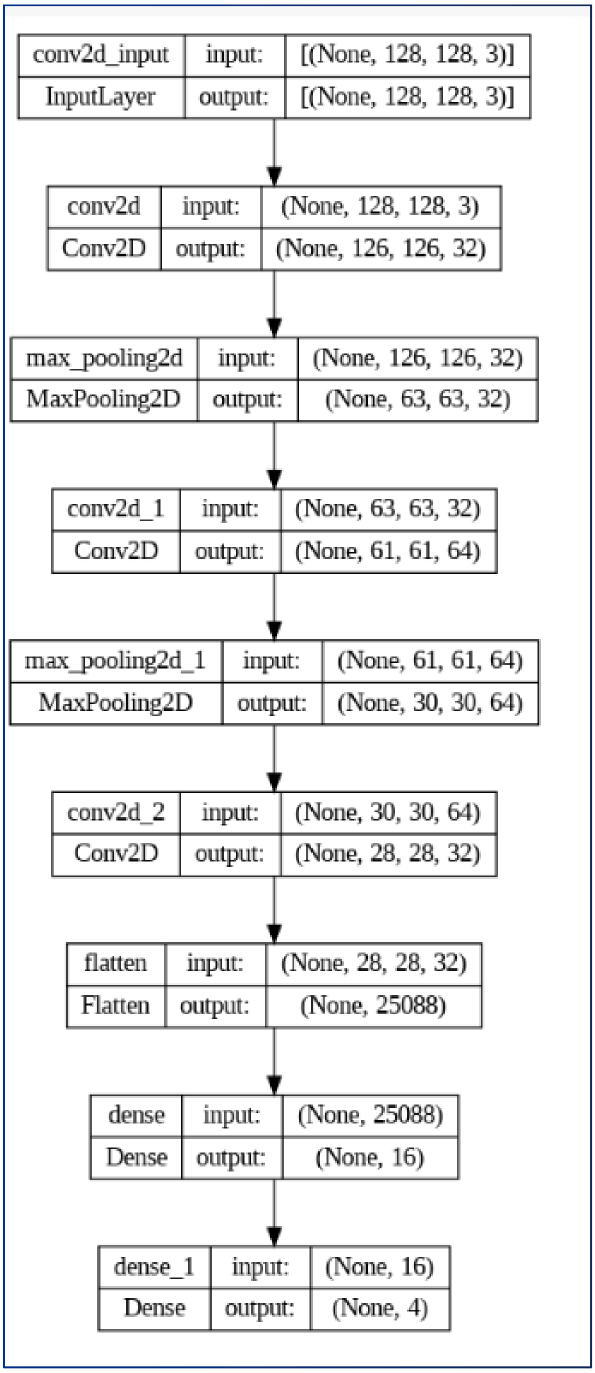

Fig 4: Layer structure of CNN

InceptionV3 is a convolutional neural network (CNN) architecture that was originally developed for image classification tasks. It's known for its effectiveness in capturing features at various scales using a combination of parallel convolutional branches with different kernel sizes.

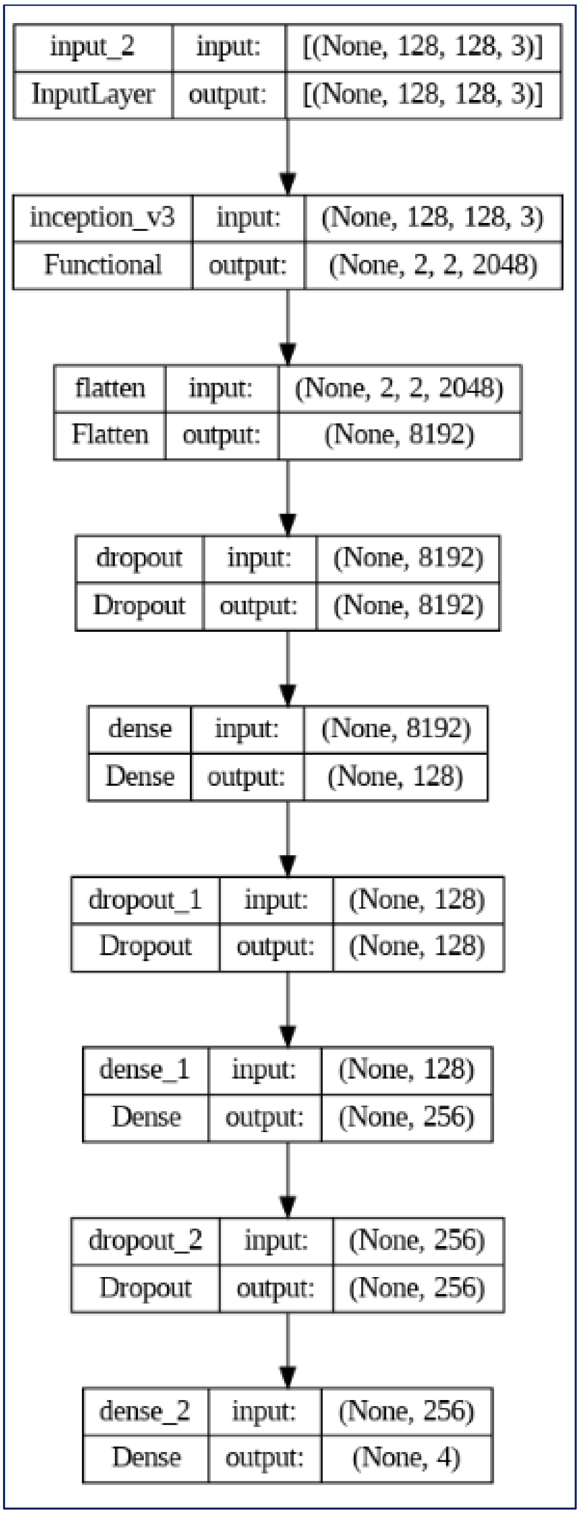

Fig 5: Layer structure of Inception

Conclusion

Combining Python with Machine learning and Deep learning methods provides a potent means of identifying and detecting tumor with high accuracy. By utilizing machine learning and deep learning algorithms to examine medical pictures, doctors can quickly identify brain tumor, allowing for more rapid intervention and enhanced patient care. With continued development, this technology may transform the realm of healthcare, sparing lives and easing the strain on medical experts. While the procedure may hold promise, it is vital to be vigilant and uphold moral principles, thus preserving patient confidentiality and ensuring the security of their data.

4 Design Specification

As stated by Özyurt et al. the classification of brain tumours is critical because if it is not done, it might be life-threatening. However, human labour is time-consuming, and deep learning algorithms have proven to be efficient enough to classify the images.According to Siddaiah et al., an automated approach for diagnosing brain tumours is required, and deep learning and machine learning techniques can be used to achieve this. Machine learning and deep learning techniques have been taken into consideration in this study since they produce outstanding results. The techniques used produce positive outcomes and are the best approaches to classifying photos.The flowchart below shows the workflow of the project

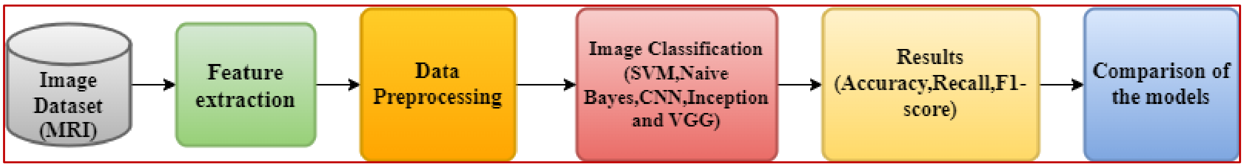

Fig:6 Flowchart of the work

5 Implementation, Evaluation and Results of Tumor Detection

5.1 Introduction

This section deals with the main implementation,evaluation and have the results of machine learning methods and deep learning methods used to detect tumor using image dataset. The machine learning methods like SVM and Naives Bayes and deep learning methods like CNN,VGG and Inception are being used in doing the execution.

5.2 Implementation, Evaluation and Results of Machine Learning methods

Machine learning methods as intelligent tools that allow computers to grasp insights from data, aiding in making predictions and classifications. These techniques have far-reaching uses, from spotting tumors in medical images to understanding human language.Here, 68% of data is used as training set and rest 32% is used as testr dataset and python is the language used for implementation.

5.2.1 Evaluation and Results of SVM (Support Vector Machine)

Total of 7023 images of Brain MRI images are considered and the number of Epochs 10 with 140 epoch steps.The implementation is done by Google colab and metrics used for proposed model are accuracy, recall,F1-score. The figure 7 below shows the evaluation and confusion matrix of SVC.

```
Training SVC...
SVC trained in 711.72 seconds
Accuracy for SVC: 0.82
Classification Report for SVC:
              precision    recall  f1-score   support

      glioma       0.76      0.79      0.77       300
  meningioma       0.73      0.60      0.66       306
     notumor       0.88      0.91      0.90       405
   pituitary       0.87      0.95      0.91       300

    accuracy                           0.82      1311
   macro avg       0.81      0.81      0.81      1311
weighted avg       0.82      0.82      0.82      1311

Confusion Matrix for SVC:
[[236  50   0  14]
 [ 49 185  50  22]
 [ 20  10 370   5]
 [  5   9   0 286]]
```

Fig 7: Evaluation and confusion matrix of SVC

The evaluation results of SVC demonstrate a noteworthy level of accuracy at 0.82. Specifically, when focusing on different types of brain tumors, the precision, recall, and F1 scores vary. For Glioma, the precision stands at 0.76, recall at 0.79, and the F1 score at 0.77. Conversely, Meningioma exhibits a precision of 0.73, a recall of 0.60, and an F1 score of 0.66. Meanwhile, the Notumor category demonstrates high precision at 0.88, recall at 0.91, and an impressive F1 score of 0.90. Similar results are observed for Pituitary, with precision, recall, and F1 score all at 0.88, 0.91, and 0.90, respectively.

5.2.2 Evaluation and Results of Naive Bayes

Total of 7023 images of Brain MRI images are considered and the number of Epochs 10 with 140 epoch steps.The implementation is done by Google colab and metrics used for proposed model are accuracy, recall,F1-score.The figure 8 below shows the evaluation and confusion matrix of Naive Bayes.

```
Training NaiveBayes...
NaiveBayes trained in 6.90 seconds
Accuracy for NaiveBayes: 0.60
Classification Report for NaiveBayes:
              precision    recall  f1-score   support

      glioma       0.53      0.84      0.65       300
  meningioma       0.34      0.23      0.28       306
     notumor       0.73      0.58      0.64       405
   pituitary       0.76      0.77      0.77       300

    accuracy                           0.60      1311
   macro avg       0.59      0.61      0.58      1311
weighted avg       0.60      0.60      0.59      1311

Confusion Matrix for NaiveBayes:
[[252  22   1  25]
 [127  71  87  21]
 [ 45 100 235  25]
 [ 55  13   1 231]]
```

Fig 8: Evaluation and confusion matrix of Naive Bayes

The evaluation of the Naive Bayes model yielded results within a quick 6.90 seconds as shown in above fig 8, showcasing a notable accuracy level of 0.60. When we examine its performance across various brain tumor types, we notice distinct variations in precision, recall, and F1 scores. For Glioma, the precision stands at 0.53, accompanied by a recall of 0.84 and an F1 score of 0.65. In contrast, Meningioma exhibits a precision of 0.34, a recall of 0.23, and an F1 score of 0.28. Meanwhile, the Notumor category displays precision at 0.73, recall at 0.58, and an F1 score of 0.64. For Pituitary, the precision, recall, and F1 score all align closely at 0.76, 0.77, and 0.77, respectively.

5.3 Implementation,Evaluation and Results of Machine Learning methods

Deep learning methods form a distinct category within machine learning. These algorithms feature intricate neural architectures tailored to unravel intricate data patterns, enabling independent learning and decision-making.

5.3.1 Evaluation and Results of CNN

Total of 7023 images of Brain MRI images are considered and the number of Epochs 10 with 140 epoch steps.The implementation is done by Google colab and metrics used for proposed model are accuracy, recall,F1-score.The figure 9,10 below shows the evaluation and confusion matrix of CNN respectively.

	precision	recall	f1-score	support
glioma	0.84	0.83	0.84	300
meningioma	0.75	0.74	0.75	306
notumor	0.94	0.92	0.93	405
pituitary	0.90	0.95	0.93	300
accuracy			0.87	1311
macro avg	0.86	0.86	0.86	1311
weighted avg	0.87	0.87	0.87	1311

Fig 9: Evaluation of CNN

The evaluation results for CNN revealasshown in Fig 9 an impressive accuracy level of 0.87. When scrutinizing its performance across various brain tumor types, distinct variations in precision, recall, and F1 scores become apparent. Glioma showcases a precision of 0.84, a recall of 0.83, and an F1 score of 0.84. Similarly, Meningioma exhibits strong metrics with a precision of 0.75, recall of 0.74, and an F1 score of 0.75. Notably, the Notumor category stands out with precision at 0.94, recall at 0.92, and an outstanding F1 score of 0.93. For Pituitary, the model's performance remains robust, boasting precision, recall, and F1 score all at impressive levels of 0.90, 0.95, and 0.93, respectively.

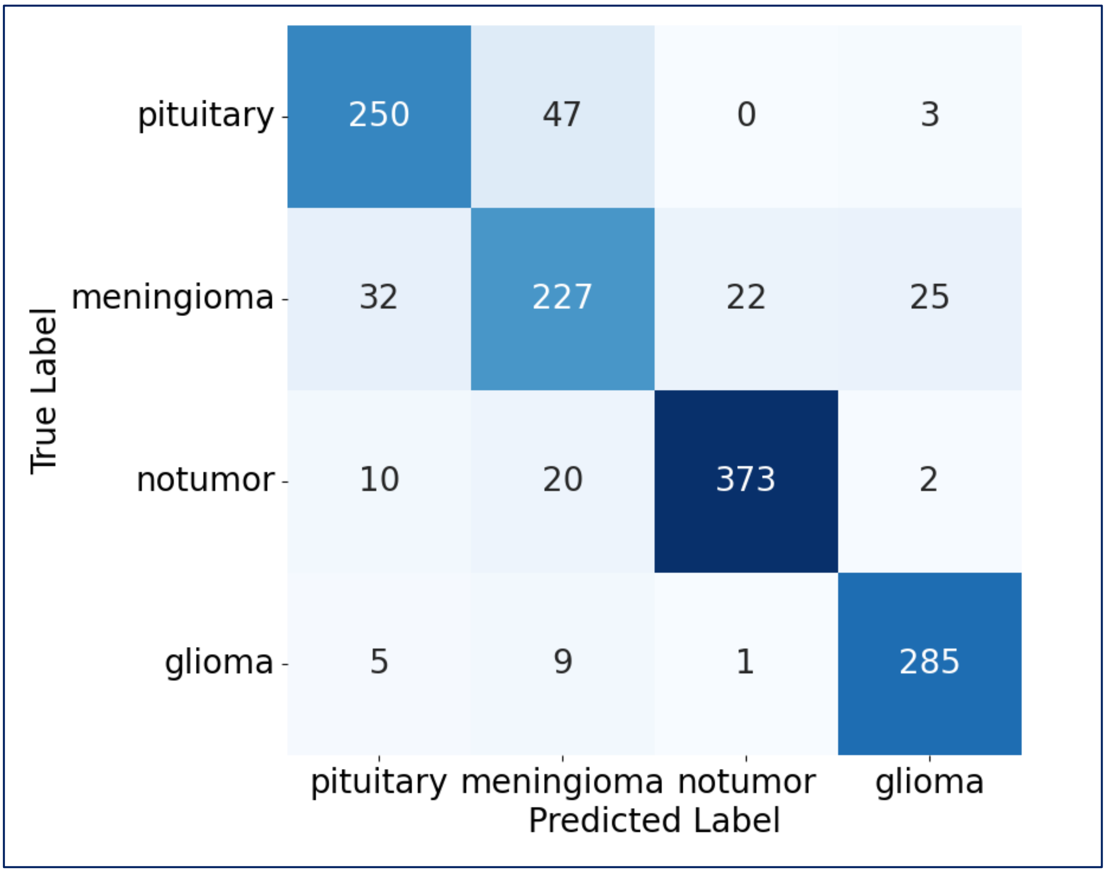

Fig 10: Confusion matrix of CNN

5.3.2 Evaluation and Results of Inception

Total of 7023 images of Brain MRI images are considered and the number of Epochs 10 with 140 epoch steps.The implementation is done by Google colab and metrics used for proposed model are accuracy, recall,F1-score.The figure 11,12 below shows the evaluation and confusion matrix of Inception respectively.

	precision	recall	f1-score	support
glioma	0.85	0.79	0.82	300
meningioma	0.76	0.74	0.75	306
notumor	0.95	0.94	0.94	405
pituitary	0.85	0.95	0.90	300
accuracy			0.86	1311
macro avg	0.85	0.86	0.85	1311
weighted avg	0.86	0.86	0.86	1311

Fig 11: Evaluation of Inception

When we assessed Inception's performance as observed in Fig 11, it delivered an impressive accuracy score of 0.86, which is on par with CNN's performance. Digging deeper into its capabilities across different types of brain tumors, we noticed distinct differences in precision, recall, and F1 scores. For Glioma, Inception achieved a precision of 0.85, a recall of 0.79, and an F1 score of 0.82. Similarly, when it came to Meningioma, Inception displayed strong metrics with a precision of 0.76, a recall of 0.74, and an F1 score of 0.75.

What's particularly noteworthy is how well Inception performed in the Notumor category, boasting a remarkable precision of 0.95, a recall of 0.94, and an exceptional F1 score of 0.94. Even in the case of Pituitary tumors, Inception continued to shine, delivering high precision, recall, and F1 scores, all impressively at 0.85, 0.95, and 0.90, respectively. These results underscore Inception's outstanding ability in tumor classification, positioning it as a strong contender alongside CNN.

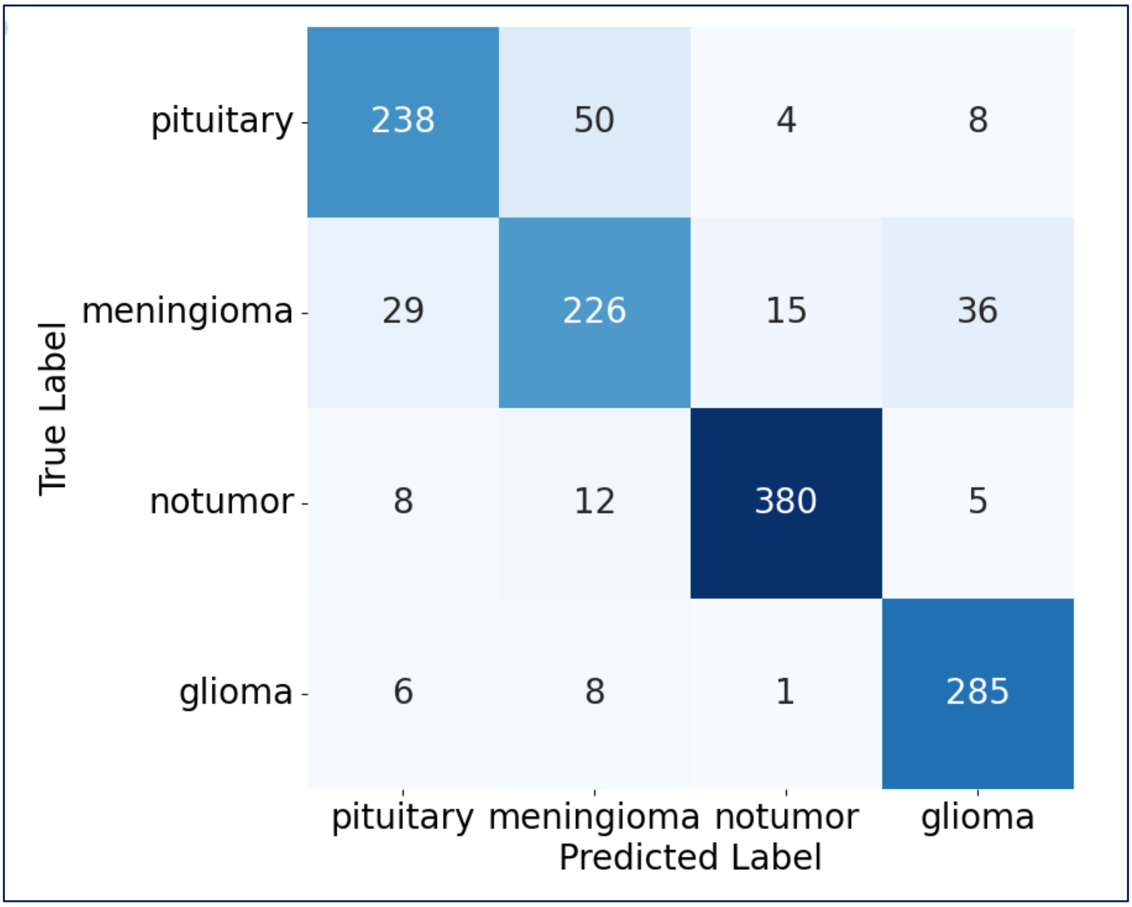

Fig 12: Confusion matrix of Inception

5.3.3 Evaluation and Results of VGG

Total of 7023 images of Brain MRI images are considered and the number of Epochs 10 with 140 epoch steps.The implementation is done by Google colab and metrics used for proposed model are accuracy, recall,F1-score.The figure 13,14 below shows the evaluation and confusion matrix of VGG respectively.

	precision	recall	f1-score	support
glioma	0.91	0.89	0.90	293
meningioma	0.86	0.85	0.86	297
notumor	0.97	0.97	0.97	396
pituitary	0.94	0.98	0.96	294
accuracy			0.93	1280
macro avg	0.92	0.92	0.92	1280
weighted avg	0.93	0.93	0.93	1280

Fig 13: Evaluation of VGG

The evaluation of VGG's performance reveals an exceptional accuracy level of 0.93, surpassing CNN, Inception, Naive Bayes, and SVC. When closely examining its performance across different brain tumor types, distinct variations in precision, recall, and F1 scores become evident. For Glioma, VGG achieves an impressive precision of 0.91, recall of 0.89, and an F1 score of 0.90. Similarly, in the case of Meningioma, VGG exhibits strong metrics with a precision of 0.86, recall of 0.85, and an F1 score of 0.86.

Remarkably, in the Notumor category, VGG stands out with the same value precision, recall and F1 score of 0.97. For Pituitary tumors, the model's performance remains robust, boasting precision, recall, and F1 score all at impressive levels of 0.94, 0.98, and 0.96, respectively. These results firmly establish VGG as a leading contender in brain tumor classification, surpassing its peers in accuracy and performance.

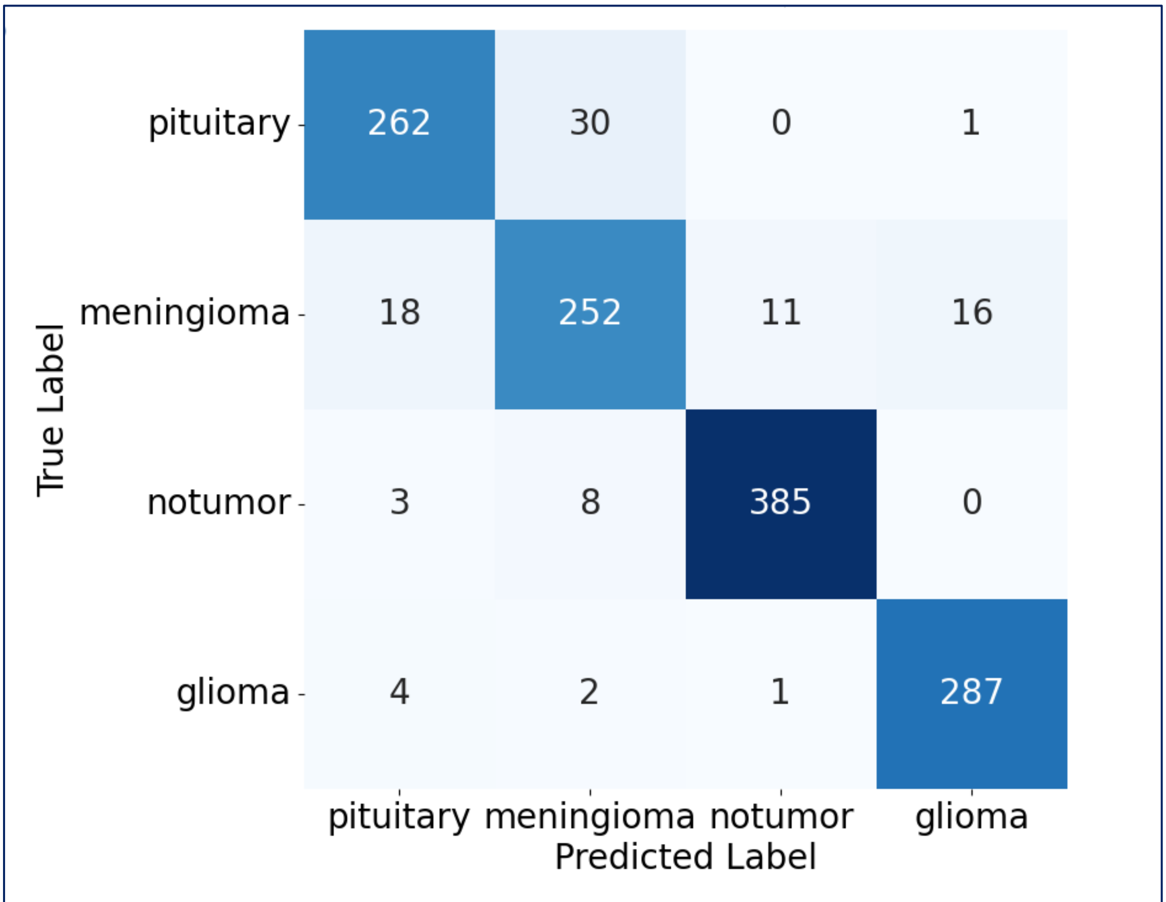

Fig 14: Confusion matrix of VGG

5.4 Discussion

In our investigation, distinct datasets were employed for training SVM, Naive Bayes, VGG, CNN, and Inception models. A thorough evaluation of model performance ensued, involving the assessment of accuracy, recall, and F1-score metrics. Results indicated SVM achieved an accuracy of 0.82, Naive Bayes attained 0.60 accuracy. Within the domain of deep learning, VGG exhibited a prominent accuracy of 0.92, whereas CNN and Inception yielded similar accuracies of 0.86.Hence this discussion answers the research question clearly.

6 Conclusion and Future Work

To detect Brain Tumor and its multiple stages, a range of machine learning and deep learning techniques were employed. The provided dataset underwent comprehensive testing using a variety of approaches including SVM, Naive Bayes, CNN, VGG, and inception. Assessment of each method's performance yielded reliable results.Notably, VGG exhibited exceptional accuracy at 0.92, surpassing all other methods.These results will help in minimising the mortality rate to an extent. Future endeavors may involve exploring alternative algorithms and incorporating an expanded dataset to enhance accuracy further.

References

1) G.Hemanth, M. Janardhan and L. Sujihelen, "Design and Implementing Brain Tumor Detection Using Machine Learning Approach," 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2019, pp. 1289-1294, doi: 10.1109/ICOEI.2019.8862553.
2) Gaikwad, Sharmila & Patel, Saarah & Shetty, Ajinkya. (2021). Brain Tumor Detection: An Application Based on Machine Learning. 1-4. 10.1109/INCET51464.2021.9456347.
3) Özyurt, F., Sert, E., Avci, E. and Dogantekin, E. (2019). Brain tumor detection based on Convolutional Neural Network with neutrosophic expert maximum fuzzy sure entropy. Measurement, 147, p.106830. doi:https://doi.org/10.1016/j.measurement.2019.07.058.4.
4) Pokharel, Monika & Rajkarnikar, Lisa & Karn, Gyanendra & Shrestha, Surendra. (2022). Detection of Brain Tumor using VGG-16 Architecture. 04. 60-65.
5) Arabahmadi M, Farahbakhsh R, Rezazadeh J. Deep Learning for Smart Healthcare-A Survey on Brain Tumor Detection from Medical Imaging. Sensors (Basel). 2022 Mar 2;22(5):1960. doi: 10.3390/s22051960. PMID: 35271115; PMCID: PMC8915095.
6) P.Kora, S. Mohammed, M. J. Surya Teja, C. Usha Kumari, K. Swaraja and K. Meenakshi, "Brain Tumor Detection with Transfer Learning," 2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Palladam, India, 2021, pp. 443-446, doi: 10.1109/I-SMAC52330.2021.9640678.

7) N. Siddaiah, C. Vignesh, T. Narendra, K. Pujitha and D. Madhu, "Brain Tumor detection from MRI scans using VGG- 19 networks," 2022 10th International Conference on Emerging Trends in Engineering and Technology - Signal and Information Processing (ICETET-SIP-22), Nagpur, India, 2022, pp. 1-6, doi: 10.1109/ICETET-SIP-2254415.2022.9791683.

8) H. T. Zaw, N. Maneerat and K. Y. Win, "Brain tumor detection based on Naïve Bayes Classification," 2019 5th International Conference on Engineering, Applied Sciences and Technology (ICEAST), Luang Prabang, Laos, 2019, pp. 1-4, doi: 10.1109/ICEAST.2019.8802562.

9) Swamy, G.. (2020). Brain Tumor Detection using Convolutional Neural Network. International Journal for Research in Applied Science and Engineering Technology. 8. 615-620. 10.22214/ijraset.2020.6100.

10) P. S. Lakshmi Veeranki, G. L. Banavath and P. R. Devi, "Detection and Classification of Brain Tumors using Convolutional Neural Network," 2023 7th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2023, pp. 780-786, doi: 10.1109/ICOEI56765.2023.10125652.

11) R. Pillai, A. Sharma, N. Sharma and R. Gupta, "Brain Tumor Classification using VGG 16, ResNet50, and Inception V3 Transfer Learning Models," 2023 2nd International Conference for Innovation in Technology (INOCON), Bangalore, India, 2023, pp. 1-5, doi: 10.1109/INOCON57975.2023.10101252.

12) S. Rohith, M. S. Prakash, R. Anitha, K. S. Kumar and K. Yogeswara Sai, "Detection of Brain Tumor using VGG16," 2023 8th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2023, pp. 1400-1405, doi: 10.1109/ICCES57224.2023.10192639.

13) Chakraborty, A., Basu, A., Raha, S. and Chakraborty, T. (2023). A Scientific Approach to Building an Image Classification model of brain MRI images for Brain Tumor detection. International Journal of Engineering Technology and Management Sciences, [online] 7(2), pp.164–171. doi:https://doi.org/10.46647/ijetms.2023.v07i02.021.
14) Alla SSM, Athota K. (2022) Brain Tumor Detection Using Transfer Learning in Deep Learning. Indian Journal of Science and Technology. 15(40): 2093-2102. https://doi.org/10.17485/IJST/v15i40.1307
15) Grampurohit, V. Shalavadi, V. R. Dhotargavi, M. Kudari and S. Jolad, "Brain Tumor Detection Using Deep Learning Models," 2020 IEEE India Council International Subsections Conference (INDISCON), Visakhapatnam, India, 2020, pp. 129-134, doi: 10.1109/INDISCON50162.2020.00037.
16) Sankaranarayaanan, M. S. Kumar, B. Chidhambararajan and P. Sirenjeevi, "Brain tumor detection and Classification using VGG 16," 2023 International Conference on Artificial Intelligence and Knowledge Discovery in Concurrent Engineering (ICECONF), Chennai, India, 2023, pp. 1-5, doi: 10.1109/ICECONF57129.2023.100838
17) Amin, J., Sharif, M., Haldorai, A. et al. Brain tumor detection and classification using machine learning: a comprehensive survey. Complex Intell. Syst. 8, 3161–3183 (2022). https://doi.org/10.1007/s40747-021-00563-y
18) Munir, K.; Elahi, H.; Ayub, A.; Frezza, F.; Rizzi, A. Cancer Diagnosis Using Deep Learning: A Bibliographic Review. Cancers 2019, 11, 1235. https://doi.org/10.3390/cancers11091235

19) Kavitha, T., Mathai, P.P., Karthikeyan, C. et al. Deep Learning Based Capsule Neural Network Model for Breast Cancer Diagnosis Using Mammogram Images. Interdiscip Sci Comput Life Sci 14, 113–129 (2022). https://doi.org/10.1007/s12539-021-00467-y

20) P. Mohamed Shakeel, M.A. Burhanuddin, Mohamad Ishak Desa, Lung cancer detection from CT image using improved profuse clustering and deep learning instantaneously trained neural networks, Measurement, Volume 145, 2019, Pages 702-712, ISSN 0263-2241, https://doi.org/10.1016/j.measurement.2019.05.027.

21) Sadad, T, Rehman, A, Munir, A, et al. Brain tumor detection and multi-classification using advanced deep learning techniques. Microsc Res Tech. 2021; 84: 1296–1308. https://doi.org/10.1002/jemt.23688

22) Dildar, M.; Akram, S.; Irfan, M.; Khan, H.U.; Ramzan, M.; Mahmood, A.R.; Alsaiari, S.A.; Saeed, A.H.M.; Alraddadi, M.O.; Mahnashi, M.H. Skin Cancer Detection: A Review Using Deep Learning Techniques. Int. J. Environ. Res. Public Health 2021, 18, 5479. https://doi.org/10.3390/ijerph18105479

23) J. Zheng, D. Lin, Z. Gao, S. Wang, M. He and J. Fan, "Deep Learning Assisted Efficient AdaBoost Algorithm for Breast Cancer Detection and Early Diagnosis," in IEEE Access, vol. 8, pp. 96946-96954, 2020, doi: 10.1109/ACCESS.2020.2993536.

24) Sajid, S., Hussain, S. & Sarwar, A. Brain Tumor Detection and Segmentation in MR Images Using Deep Learning. Arab J Sci Eng 44, 9249–9261 (2019). https://doi.org/10.1007/s13369-019-03967-8

25) Tanzila Saba, Ahmed Sameh Mohamed, Mohammad El-Affendi, Javeria Amin, Muhammad Sharif, Brain tumor detection using fusion of hand crafted and deep learning features, Cognitive Systems Research, Volume 59, 2020, Pages 221-230, ISSN 1389-0417, https://doi.org/10.1016/j.cogsys.2019.09.007.