A detailed project report on

"Brain Tumour Segmentation"

Submitted for the partial fulfilment of the requirement of paper in
B.Tech 5th Semester

"BEC 508: Design Project Phase - I"

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Declaration

This is to certify that the project work entitled “**Brain Tumour Segmentation**” is a bonafide work carried out by us bearing University Enrolment Number “U2151008, student of B.Tech. (C.S.E.), 5th Semester in the Department of Electronics and Communication, University of Allahabad, Prayagraj (INDIA), under the esteemed supervision of **“Dr. Pravin Kumar”**.
We declare that the work presented here is carried out by us and has not been submitted anywhere else for the award of any degree or certificate.

Signature

(Ayush Srivastava)

The work presented in this report has been done under my supervision.

Signature

(Dr. Pravin Kumar)

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ACKNOWLEDGEMENT

We would like to express our sincere gratitude to everyone who helped us finish this joint project report on **"Classification and Segmentation of Brain Tumours from MR Images Using Deep Transfer Learning."**

We would like to thank our supervisor sincerely, **Dr. Pravin Kumar,** for all of his help and support during the research process. His wealth of knowledge, insightful feedback, and unwavering encouragement have significantly enriched our understanding of the subject.

His commitment to excellence and passion for research has been a constant source of inspiration throughout this journey. His willingness to share expertise and provide constructive criticism has been invaluable in shaping the trajectory of this project.

Ayush Srivastava

ABSTRACT

Embarking on the intricate journey within the human brain, where uncontrolled cell growth manifests as brain tumours, we navigate the crucial juncture between early detection, cutting-edge medical imaging, and the transformative power of deep learning.

A brain tumour, characterised by uncontrolled and rapid cell growth, is **an abnormal mass of tissue in which the cells develop uncontrollably and suddenly.** There are two primary classifications for it: benign and malignant.

A patient's life expectancy and overall quality of life are greatly increased by the timely detection and effective treatment of these tumours. In the complex anatomy of the brain, image segmentation—especially in Magnetic Resonance Imaging (MRI)—is essential for accurately identifying aberrant tumours.

Recent developments in deep learning techniques have sparked a revolutionary era in medical imaging, particularly in the healthcare sector, where confidentiality is particularly important. With the aid of these methods, brain tumours can be precisely located, automatically detected, and classified from MRI scans.

This report conveys a novel experimental approach that uses Deep Transfer Learning and Convolutional Neural Networks (CNNs) to identify and locate brain tumours, as well as categorise them according to their type.

In contrast to conventional techniques, our research introduces a unified model for these tasks, promising a leap in diagnostic efficiency and accuracy.

INTRODUCTION

Within the complex terrain of the human brain, the development of cancerous growths, commonly referred to as brain tumours, poses a serious threat to the delicate balance of brain tissue. These tumours arise from uncontrolled cell growth, disrupting the normal functions of the brain and posing a considerable risk to overall health.

The development of brain tumours is associated with damage to specific genes on a cell's chromosomes, resulting in their impaired functionality. These genes typically control cell division rates, repair mechanisms for gene defects, and the activation of self-destructive processes in response to irreparable damage. Some individuals may be born with partial defects in these genes due to environmental factors contributing to additional damage. Alternatively, environmental injury may serve as the sole cause. The factors influencing why certain individuals in a specific environment develop brain tumours while others do not remain elusive.

When a cell undergoes rapid division and the internal regulatory mechanisms for its growth are compromised, it has the potential to evolve into a tumour. The body's immune system acts as a defence mechanism, ideally identifying and eliminating abnormal cells. However, tumours can produce substances that impede the immune system's ability to recognise these abnormal cells, ultimately overcoming internal and external barriers to their growth. [1]

In the context of a rapidly proliferating tumour, the local blood supply intended for normal tissue may prove insufficient to meet the increased demand for oxygen and nutrients. Tumours release angiogenesis factors that stimulate the growth of blood vessels, enhancing the nutrient supply to the tumour. This increased vascular network eventually renders the tumour dependent on these new vessels. Ongoing research in this domain is underway, yet further extensive investigations are warranted to translate this knowledge into potential therapeutic applications.

Classifying Brain Tumour Types:

Benign (non-cancerous): Characterised by slow growth, these tumours typically remain localised and seldom pose an immediate threat. While monitoring and treatment may be necessary, the prognosis is generally optimistic.

Malignant (cancerous): Marked by aggressive growth, these tumours spread rapidly, infiltrating healthy brain tissue and significantly compromising neurological function. Early detection and intervention play a pivotal role in mitigating their deleterious effects.

New cells replace the old, damaged cells when the majority of them are destroyed. Problems may arise if the old and damaged cells are not removed in the process of making new ones.

The process of accurately identifying and delineating these abnormal masses from healthy brain tissue is known as brain tumour segmentation.
This segmentation, crucial for both diagnosis and treatment, involves distinguishing various components of the brain, such as grey matter, white matter, and cerebrospinal fluid, from distinct tumour regions, including the core, enhancing areas, oedema, and necrosis.

The Significance of Early Diagnosis:

The cornerstone of effective brain tumour management lies in early detection.
The timely detection and intervention of tumours in their incipient stages substantially improve patient outcomes, emphasising the critical need for

accurate and easily accessible diagnostic tools. While traditional methods are valuable, their susceptibility to errors due to challenges in visually recognising and distinguishing tumours necessitates innovative approaches.

Impactful solutions are being offered by the context-appropriate integration of deep learning techniques to enhance medical diagnosis. The World Health Organisation (WHO) states that a correct diagnosis of a brain tumour entails its detection, location, and classification based on its type, grade, and malignancy. This experimental work involves the detection of the tumour, its classification according to its grade and type, and its location using Magnetic Resonance Imaging (MRI) for the diagnosis of brain tumours.

MRI: A Cutting-Edge Diagnostic Instrument:

Fortunately, the field has witnessed remarkable progress, with medical imaging, especially magnetic resonance imaging (MRI), emerging as an invaluable tool.

The preeminence of magnetic resonance imaging (MRI) has risen as a leading technology for visualising brain structures with unparalleled detail. Its exceptional contrast resolution for soft tissues surpasses the capabilities of CT scans, making it an invaluable tool for precise tumour detection and characterization.

Deep Learning and the Potential for Automation:

Deep learning has shown impressive results in a variety of image classification tasks thanks to its capacity to automatically extract hierarchical features from data. A deep learning technique called transfer learning makes use of models that have already been trained on big data sets to improve a model's performance on a particular task with a limited amount of data. Combining deep learning and transfer learning offers a viable way to increase efficiency and accuracy in the classification of brain tumours.

The advent of deep learning, particularly through convolutional neural networks (CNNs), represents a groundbreaking approach to medical image analysis. These intelligent algorithms adeptly learn intricate patterns within MRI data, facilitating automated tumour detection with remarkable accuracy and efficiency.
This research is dedicated to harnessing the potential of CNNs for a comprehensive approach to brain tumour diagnosis:

- By employing a singular, unified model, the objective is to streamline the diagnostic workflow, covering efficient detection, precise localization, and accurate classification of tumours.
- This innovative approach holds promise for outperforming traditional methods in terms of both accuracy and speed, ultimately contributing to improved patient care and prognosis.

The segmentation of brain tumours from MR images using deep transfer learning is the main focus of this work. Utilising neural network architectures that have been trained in the past on a variety of image datasets, the model seeks to acquire dependable characteristics that capture the complex patterns linked to various kinds of brain tumours. The objective is to develop a dependable, computerised approach that can help physicians correctly identify and classify brain tumours from MRI scans.

Research Objectives:

- Examine how to classify brain tumours from MRI scans accurately and efficiently using deep transfer learning techniques such as Convolutional Neural Networks (CNNs).
- Describe how the integration of EfficientNetV2B0, InceptionV3, ResNet50, and DenseNet121 into a unified deep transfer learning model improves diagnostic efficiency and accuracy for tasks like multi-class classification, precise location identification, and brain tumour detection. Compare the model's performance with that of other architectures.
- Review and evaluate the existing literature on deep transfer learning methodically, with a focus on its application to medical imaging analysis and, in particular, the classification of brain tumours from MRI scans. Making sure our study has a solid and well-informed foundation by combining knowledge from the literature.

LITERATURE REVIEW

A brain tumour is a mass that directly impacts human life and develops inside the brain from the tissues surrounding the brain or the skull. This mass is classified as either benign or malignant. These tumours inside the brain press against each other as they grow unevenly. Pressure has the effect of causing a variety of brain disorders that have an impact on the body. Human manifestations of these conditions include headaches, dizziness, fainting episodes, paralysis, and other symptoms. In contrast to benign growths, malignant tumours grow unevenly and cause tissue damage in their wake. Generally speaking, surgical methods are preferred when treating brain tumours.

Deep learning models have made a name for themselves in the field of biological applications lately. Deep learning is a network made up of many hidden layers. Furthermore, this model automatically completes the dataset's learning process. One deep learning model is the convolutional neural network (CNN) architecture.

The use of MRI scans for brain tumour diagnosis was proposed by J. Seetha et al. The tedious manual segmentation process of tumour vs. non-tumour is very time-consuming because the MRI scan typically generates a large amount of data. Even so, for a limited number of images, it provides accurate quantitative metrics. Consequently, the need for reliable and automated classification techniques to lower the human-death ratio emerges. The automated classification of brain tumours is often quite intricate due to significant spatial and structural discrepancies in the surrounding brain tumour areas.

Herein, a CNN classification-based automatic method for brain tumour detection is proposed. The work of N. Varuna Shree et al. focuses on minimising complexity and improving performance through the use of noise removal techniques, GLCM (grey-level co-occurrence matrix) feature extraction, and DWT-based brain tumour region growth segmentation.

After segmentation, noise that may accumulate is removed with the help of morphological filtering. MRI brain images are used to train and evaluate the probabilistic neural network classifier's accuracy and performance in locating tumours. [3,6]
Before replacing its fully connected layers and starting the classification process, a deep neural network was first pre-trained as a discriminator in a generative adversarial network (GAN) on various datasets to extract features. Brain tumours were successfully classified with a 95.6% success rate. To classify brain tumours with a 97.39% performance rate, Badža and Barjaktarović [8] put forward a basic CNN with two convolution layers for feature collection and two completely interconnected layers for classification.
The research that performs the best in classifying brain tumours was carried out by Rehman et al.[10] , according to the literature. For classification, they used transfer learning techniques (AlexNet, GoogleNet, and VGGNet), and with VGGNet, they achieved 98.69% classification performance.

In deep learning, the objective is to minimise the discrepancy between the expected and actual results. Another name for this is a cost function or loss function. Therefore, minimising the cost function by determining the weights' optimal value is the aim.
This is accomplished by processing numerous iterations with various weights. Finding the lowest cost is aided by this. This iterative machine learning optimisation technique for lowering the cost function is called gradient descent. This will aid in the accurate prediction-making process of neural networks.
A deep learning technique called transfer learning uses pre-trained model weights to conduct learning for a different task after a model has been trained on a large-scale dataset for the first task. The following is a summary of the benefits of transfer learning:

• <u>Quicker training</u>: Using the weights from the previously trained model shortens the training process's duration. Stated differently, the pace of learning is quickening.
• <u>Training using fewer data</u>: Less data can yield more dependable outcomes and better performances. because large amounts of data are used to train the model's weights.
• <u>Improved performance</u>: Adding one or more new fully connected layers to previously trained models can improve performance in transfer learning with a straightforward operation.

The literature contains several transfer learning models, including DenseNet, ResNet, VGG, GoogleNet, Inception, and others.
The deep transfer learning models EfficientNetV2B0, InceptionV3, ResNet50, and DenseNet121 were employed in this work to classify the types of brain tumours.

PROPOSED METHODOLOGY

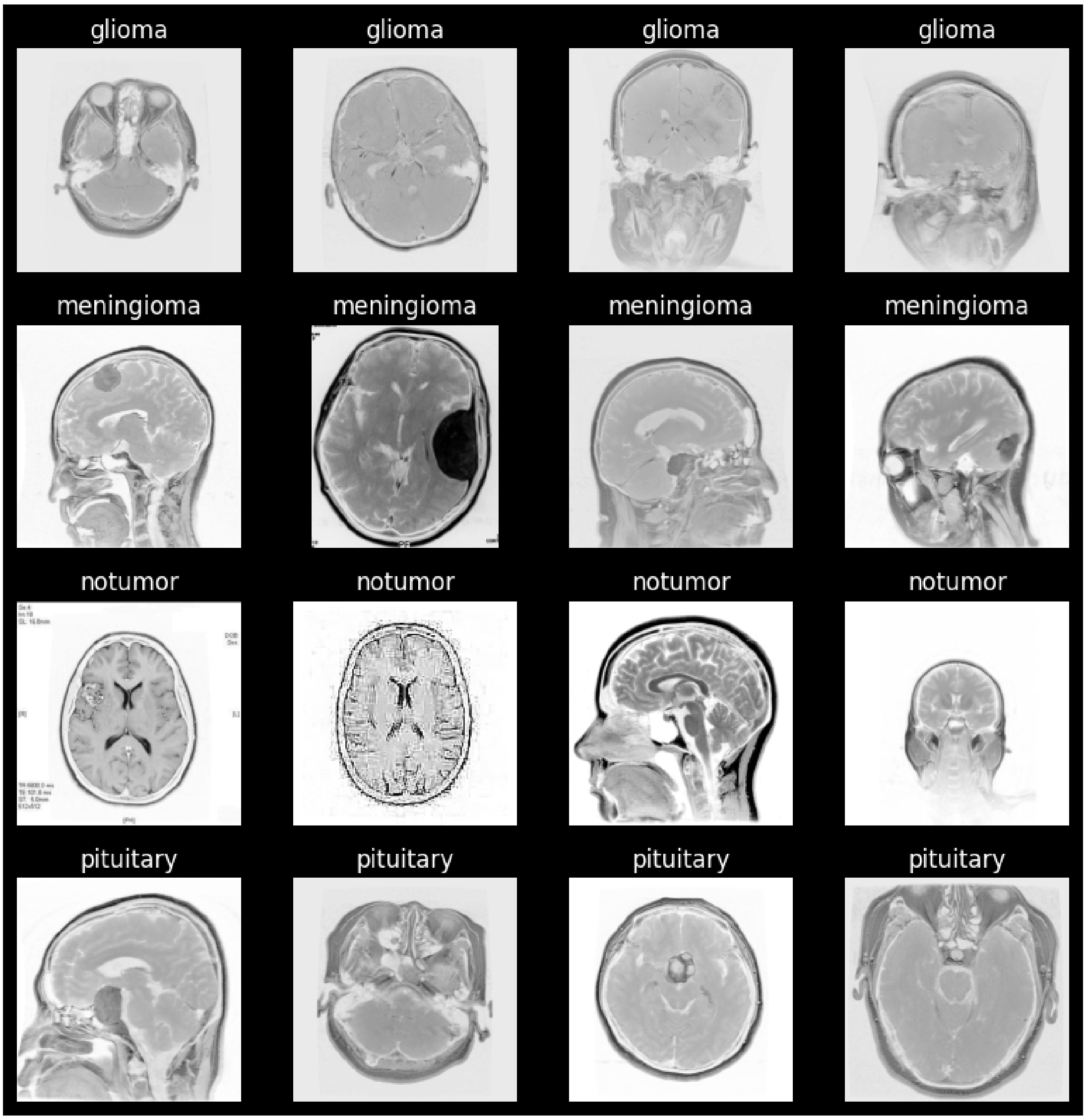
1. Dataset

This dataset is a combination of the following three datasets :
Figshare: This brain tumour dataset contains 3064 T1-weighted contrast-enhanced images from 233 patients with three kinds of brain tumours: meningioma (708 slices), glioma (1426 slices), and pituitary tumour (930 slices). Due to the file size limit of the repository, we spli the whole dataset into 4 subsets and archived them in 4.zip files with each .zip file containing 766 slices. The 5-fold cross-validation indices are also provided.

SARTAJ Dataset: The data set holds 3260 images on T1-weighted contrast-enhanced images that were cleaned and augmented. The best ANN model concluded with an accuracy of 78%, and the best CNN model consisting of 3 convolution layers had an accuracy of 90%. The VGG16 (retrained on the dataset) model surpasses other ANN, CNN, and TL models for multi-class tumour classification. This proposed network performs significantly better, with a validation accuracy of 94% and an F1-Score of 91.

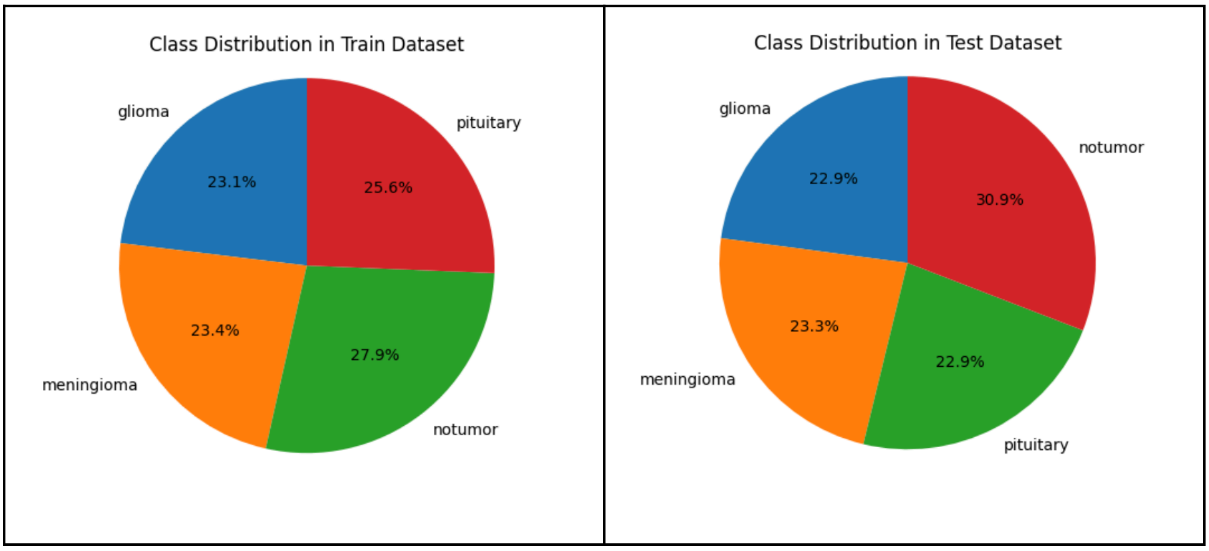
Br35H: To detect and classify brain tumours using CNN and Transfer learning as an asset of Deep Learning and to examine the tumour position (segmentation).
The dataset contains 3 folders: yes, no and pred, which contain 3060 brain MRI images. Yes contains 1500 Brain MRI images that are tumorous, No contains 1500 Brain MRI images that are non-tumorous.

```
[ ] # Get the class names for our multi-class dataset
    data_dir = pathlib.Path(train_dir)
    class_names = np.array([item.name for item in data_dir.glob('*')])
    print(class_names)

    ['glioma' 'meningioma' 'notumor' 'pituitary']
```



```python
# Display the information
print("Train Dataset:")
for name, count in zip(train_class_names, train_class_counts):
    print(f"Class: {name}, Count: {count}")

print("\nTest Dataset:")
for name, count in zip(test_class_names, test_class_counts):
    print(f"Class: {name}, Count: {count}")
```

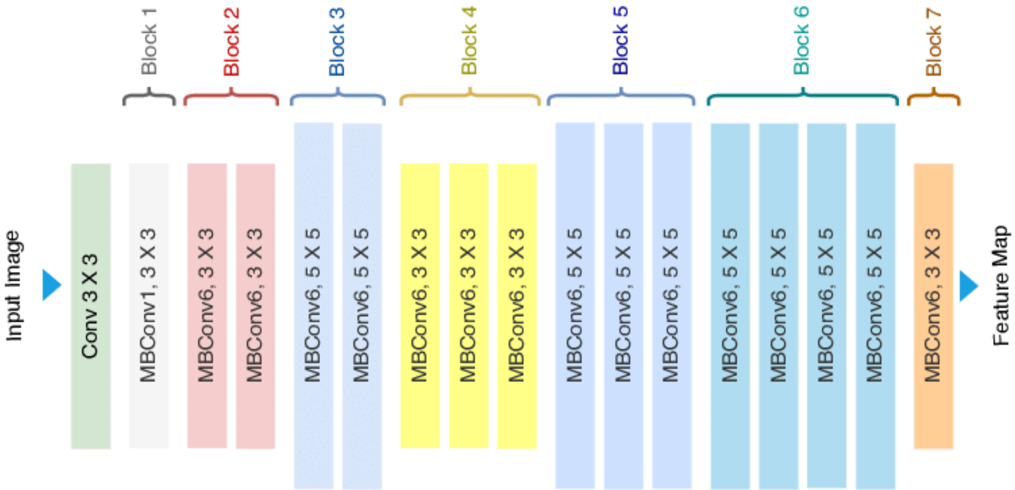
```
Train Dataset:
Class: glioma, Count: 1321
Class: meningioma, Count: 1339
Class: notumor, Count: 1595
Class: pituitary, Count: 1467

Test Dataset:
Class: glioma, Count: 300
Class: meningioma, Count: 306
Class: pituitary, Count: 300
Class: notumor, Count: 405
```



2. <u>Transfer Learning Models</u>:

Modules that are being used in the project:

- <u>**EfficientNetV2B0**</u>:
    1. **Efficient Architecture:** Known for its scalable and efficient architecture, EfficientNetV2 was created to outperform conventional convolutional neural networks (CNNs) in terms of accuracy while requiring fewer parameters.
    2. **Compound Scaling:** To maximise model performance under various resource constraints, it presents a novel compound scaling technique that uniformly scales network width, depth, and resolution.
    3. **Friendly to Mobile:** Because of its effective design, which keeps performance competitive while being computationally light, it is especially well-suited for mobile and edge devices.

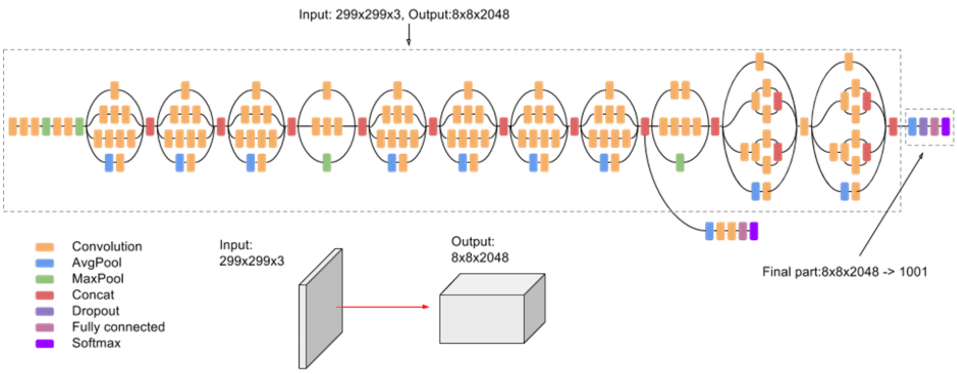


<u>Architecture of EfficientNetV2B0</u>

- <u>**InceptionV3:**</u>

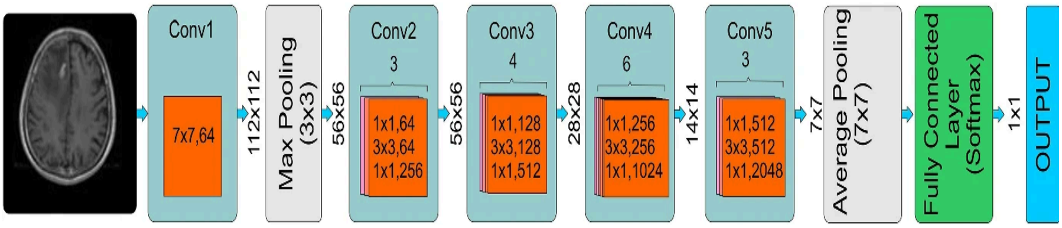
  Presented the idea of the "**inception module**," which records features at different scales by using several filters of varying sizes inside a single layer.

1. **Auxiliary Classifiers:** During training, auxiliary classifiers are incorporated at intermediate layers to support regularisation and gradient flow, which is advantageous for deeper architectures.
2. **Advanced Image Recognition:** Considered for its performance in the ImageNet Large Scale Visual Recognition Challenge, this algorithm is well-suited for tasks requiring advanced image recognition and feature extraction.



<u>Architecture of InceptionV3</u>

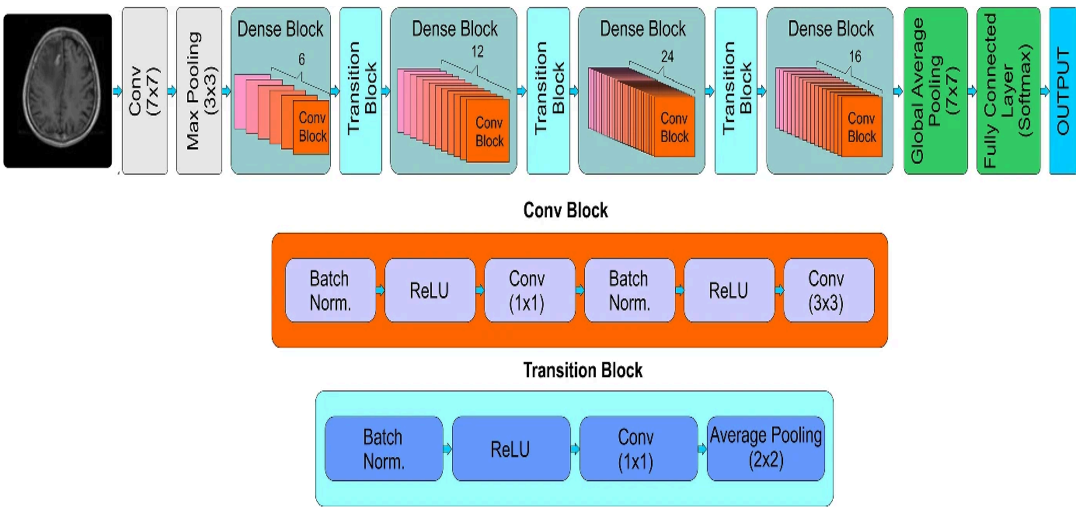
- **<u>ResNet50</u>:**
  1. **Residual Blocks:** Utilises residual blocks to introduce residual learning, which mitigates the vanishing gradient issue and permits the training of extremely deep networks by adding input to the output.
  2. **Deep Architectures:** Renowned for its capacity to manage extremely deep architectures, which qualifies it for uses needing a significant depth.
     Reached cutting-edge results on a range of image classification tasks, especially when using very deep neural networks.



Architecture of ResNet50

- **DenseNet121**

  1. **Dense Connectivity:** The feature promotes feature reuse and improves gradient flow by having intensely connected blocks where every layer accepts input from all previous layers.
  2. **Parameter Efficiency:** Because of the dense connectivity, there is more efficient use of parameters, which improves feature learning and model compactness.
  3. **Reduced Vanishing Gradient:** This makes direct connections between layers easier, which encourages gradients to flow through the network and solves the vanishing gradient problem.



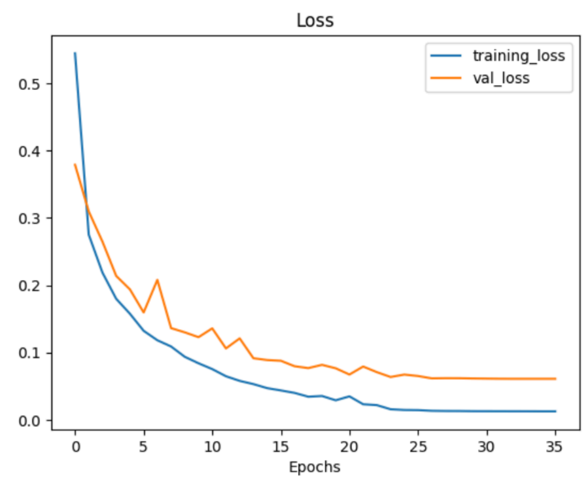
Architecture of DenseNet121

3. Implementation

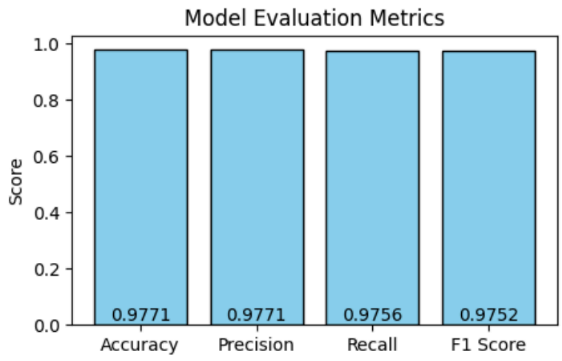
1. Problem Definition
2. Importing Libraries
3. EDA
4. Visualization and Analysis
5. Fine-tuning Deep Learning Models
    - ➢ EffcientNetB0
    - ➢ ResNet50
    - ➢ InceptionV3
    - ➢ DenseNet121
6. Comparing all Models
    - ➢ Accuracy
    - ➢ Precision
    - ➢ Recall
    - ➢ F1-score
7. Saving and Loading Best Model
8. Prediction on New MR Images

4. Performance Analysis

4.1 EfficientNetV2B0

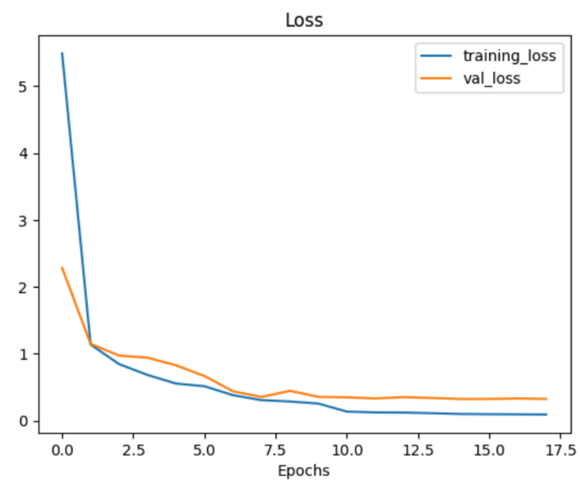


Log loss curve of EfficientNetB0

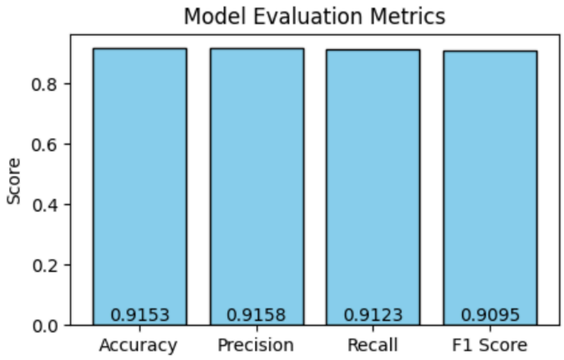


Model Metrics Evaluation

4.2 ResNet50

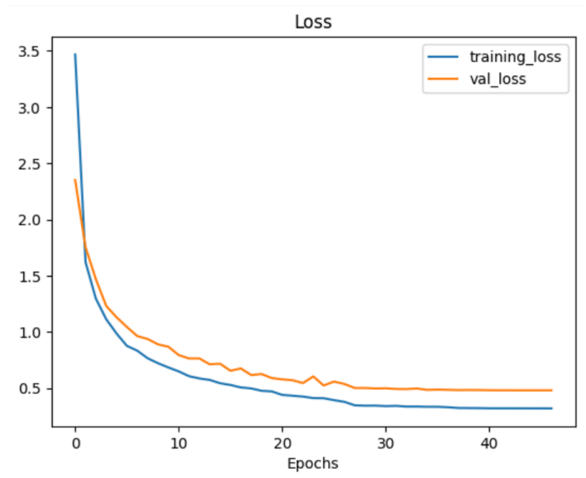
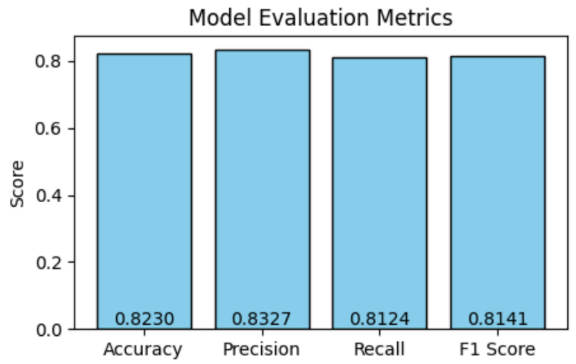


Log loss curve of ResNet50

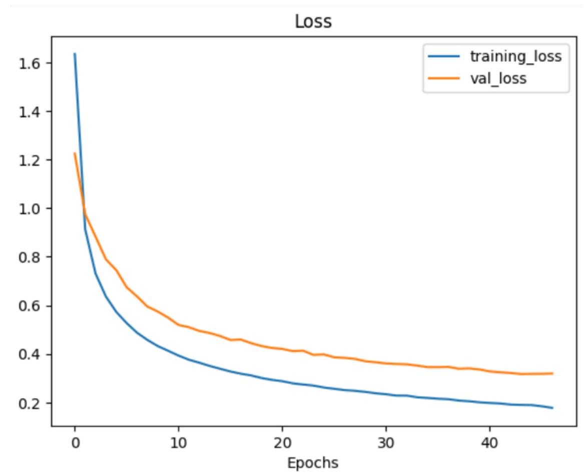
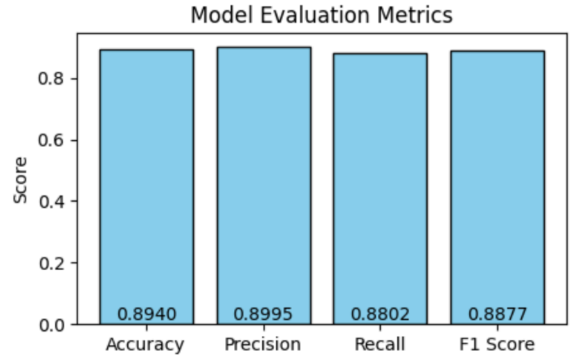


Model Metrics Evaluation

4.3 **InceptionV3:**

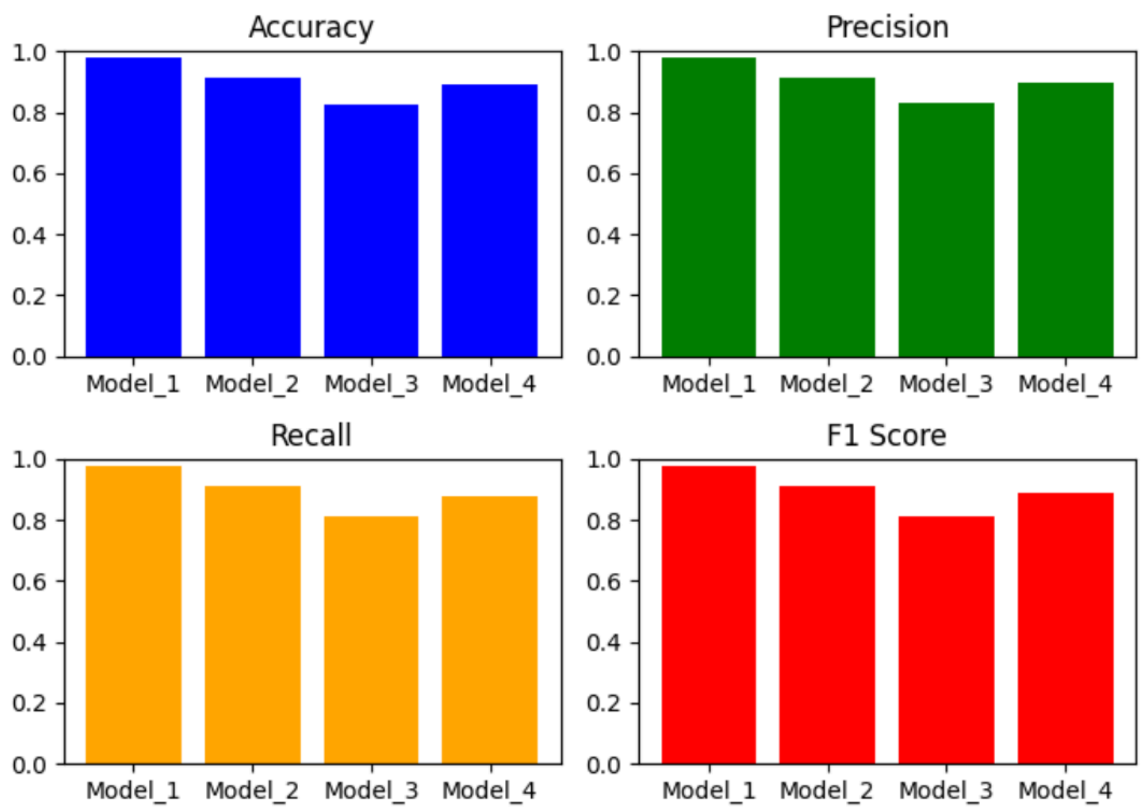
	
Log loss curve of InceptionV3	Model Metrics Evaluation

4. 4 **DenseNet121**

	
Log loss curve of DenseNet121	Model Metrics Evaluation

Results and Conclusion

1. Thoroughly assessed the performance of four distinct models by examining crucial metrics, including accuracy, precision, recall, and F1 score.
2. Illustrated the comparative outcomes through a graph, providing a clear and concise overview of how each model performed across the diverse set of metrics.



3. The analysis pinpointed that model_1 excelled among the four models, achieving a standout accuracy of approximately 97%.
4. The project's findings underscore the significance of model_1 as the most proficient choice, demonstrating its superior performance and reliability for the specific classification task at hand.

In summary, our study on deep transfer learning for brain tumor segmentation using MR images marks a significant advancement in medical imaging. By incorporating state-of-the-art architectures like EfficientNetV2B0, InceptionV3, ResNet50, and DenseNet121, we've demonstrated the potential for a unified model, enhancing diagnostic accuracy in the complex task of brain tumor categorization.

EfficientNetB0 emerged as the top performer among the four models, surpassing InceptionV3, ResNet50, and DenseNet121. With an accuracy of approximately 97%, it not only excelled in overall accuracy but also demonstrated outstanding precision, recall, and F1-score metrics. EfficientNetB0's exceptional performance positions it as a leader in medical image analysis, suggesting broader applications.

The addition of EfficientNetB0 significantly enhanced our combined model's diagnostic performance, showcasing its ability to identify subtle patterns in MR images. This breakthrough holds promise for automated brain tumor classification systems, benefiting patients and healthcare providers.

Moreover, this research emphasizes the importance of brevity and understanding, highlighting the role of deep transfer learning in brain tumor classification. This understanding enables the application of Explainable AI methods, ensuring transparency in the decision-making processes of these models for medical professionals.

Our work contributes to ongoing efforts to leverage cutting-edge technologies for more accurate and timely brain tumor diagnosis in the evolving healthcare landscape. Reflecting on this journey, it's evident that the integration of advanced neural network architectures has the potential to revolutionize medical diagnostics, offering a glimpse into a future where technological advancements are pivotal for healthcare improvements

Future Scope for Further Development

As we conclude this research endeavour on the "**Classification of Brain Tumors from MR Images Using Deep Transfer Learning**," numerous avenues present themselves for future exploration and enhancement. The following outlines potential directions for further development:

1. Development of an Integrated Diagnostic Application	Build upon the findings of this study to create an integrated diagnostic application that seamlessly incorporates the deep transfer learning models discussed.
2. Real-Time Image Processing and Diagnosis	Extend the capabilities of the developed application to support real-time image processing and diagnosis.
3. Sustained Model Optimisation and Fine-Tuning	Continue the research in order to improve and hone the deep transfer learning models so that they can be adjusted to new datasets and advances in technology.
4. User Input and Iterative Development	The application's ongoing relevance and efficacy will be guaranteed by constant improvement based on user experiences and changing medical requirements.

The developed application can develop into a strong and adaptable tool by following these future directions, which will help advance medical imaging and improve the accuracy of brain tumour diagnosis.

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