

Comparative Study of Transfer Learning Models for Early Diagnosis of Brain Tumours Using MRI Images

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Abstract: *Early and accurate diagnosis of brain tumours is essential for improving treatment planning and patient outcomes. Recent advances in deep learning and transfer learning have enabled the development of automated systems for medical image analysis, particularly for brain tumour classification using magnetic resonance imaging (MRI). This study presents a comparative analysis of transfer learning models for the early diagnosis of brain tumours using a publicly available MRI dataset comprising 7,023 images categorized into glioma, meningioma, pituitary tumour, and no tumour classes. The methodology incorporates image preprocessing techniques, including resizing, normalization, brain region extraction, RGB conversion, and data augmentation, to enhance data quality and model generalization. Three pre-trained convolutional neural network architectures, namely VGG-16, InceptionV3, and MobileNetV2, were evaluated using accuracy, precision, recall, and F1-score. Experimental results demonstrate that VGG-16 achieved the best classification performance with an accuracy of 96.00%, precision of 94.00%, recall of 99.99%, and F1-score of 98.00%, outperforming the other models. The findings indicate that transfer learning-based approaches can provide reliable and efficient support for automated brain tumour diagnosis and assist clinical decision-making by accurately classifying MRI images.*

Keywords: Brain Tumour Classification, MRI Imaging, Transfer Learning, VGG-16, InceptionV3, MobileNetV2, Deep Learning, Medical Image Analysis, Preprocessing, Diagnostic Automation

I. INTRODUCTION

Health plays a vital role in human well-being, and the early detection of serious diseases is essential for effective treatment and improved survival rates[1]. Neurological disorders affecting the central nervous system are among the most challenging health conditions, requiring accurate and timely diagnosis[2]. The brain and spinal cord make up the central nervous system of Homo sapiens. The brain controls most biological activities, such as analyzing, integrating, organizing, determining, and issuing directions to the body. The structural complexity of the human brain is remarkable. Certain CNS problems, including stroke, infection, brain tumours, and headaches, are difficult to diagnose, analyze, and treat. Brain tumours are abnormal cell growths within the rigid skull that encloses the brain. Any growth in this confined space can cause serious complications and brain damage. Brain tumours are the tenth leading cause of mortality in both adults and children. Various tumour types have poor survival rates depending on their texture, location, and shape[3]. Brain tumours are classified as primary tumours, which originate in brain tissue, and secondary tumours, which spread from other parts of the body to the brain through the bloodstream. Given the intricate nature of the brain, which contains approximately 100 billion nerve cells and controls the nervous system, the possibility of a brain tumour diagnosis often causes significant anxiety among patients. Among primary brain tumours, glioma and meningioma are considered particularly lethal, with glioma being the most common type in humans [4].



Brain tumours are generally categorized as benign and malignant. Benign tumours are non-cancerous, less aggressive, and typically do not spread to other parts of the body[5]. In contrast, malignant tumours are cancerous and can spread rapidly. Malignant tumours are further classified into primary malignant tumours, which originate in the brain, and secondary malignant tumours, which develop elsewhere in the body and subsequently spread to the brain. Common brain tumour types include meningioma, pituitary tumours, and glioma. Meningioma develops in the membranes surrounding the brain and spinal cord, glioma originates from glial cells, and pituitary tumours arise from abnormal cell growth in the pituitary gland. Brain tumours remain one of the most life-threatening disorders, making early detection and treatment essential for improving patient outcomes. Deep learning algorithms offer a promising solution for the automatic detection and classification of brain tumours[6]. However, accurate classification remains challenging because tumours vary significantly in size, shape, and intensity.

Brain magnetic resonance imaging (MRI) provides detailed structural information due to its high spatial resolution and excellent soft tissue contrast. Consequently, MRI has become one of the most widely used imaging modalities for brain tumour detection and analysis. Numerous automated approaches have recently been proposed for brain tumour detection and classification using MRI images.

Transfer learning is a fundamental concept in machine learning and deep learning that involves applying knowledge gained from one task to improve performance on a related task[7][8]. In neural networks, transfer learning utilizes pre-trained models developed on large and diverse datasets and adapts them to new tasks through fine-tuning. In this study, transfer learning models including InceptionV3, VGG16, VGG19, and EfficientNetB4 were employed for brain tumour classification [9]. Transfer learning has emerged as a powerful approach in medical image analysis because it effectively addresses the challenge of limited labelled medical datasets [10][11][12]. By transferring knowledge acquired from general image recognition tasks to domain-specific applications, transfer learning improves model efficiency, reduces training requirements, and enhances classification accuracy[13].

1.1 Significance and contribution

This study contributes significantly to medical image analysis by enabling accurate and automated brain tumour diagnosis from MRI images using transfer learning. By comparing VGG-16, InceptionV3, and MobileNetV2 on a multi-class MRI dataset, it identifies the most reliable model while highlighting the balance between accuracy and computational efficiency. The proposed approach supports real-time clinical diagnosis and early tumour detection.

- A balanced MRI brain tumour dataset of 7,023 images across four classes (glioma, meningioma, pituitary tumour, and no tumour) was used for multi-class classification.
- A robust preprocessing pipeline, including resizing, normalization, brain region cropping, RGB conversion, and data augmentation, was applied to improve input quality.
- The study compares three pre-trained CNN models—VGG-16, InceptionV3, and MobileNetV2—to determine the most effective architecture for tumor classification.
- Performance was evaluated using accuracy, precision, recall, and F1-score for comprehensive assessment.
- Computational efficiency was also considered, identifying MobileNetV2 as a lightweight option for resource-limited environments.
- The findings provide a foundation for real-time clinical diagnostic systems and future extensions to 3D MRI analysis and cross-hospital validation.

1.2 Justification and Novelty

The justification for this study arises from the growing need for accurate and automated tools for early brain tumour detection, as manual MRI analysis is time-consuming and prone to human error. This research addresses this challenge by employing transfer learning with pre-trained deep CNN models to improve diagnostic accuracy and efficiency. The novelty of this study lies in the comparative evaluation of VGG-16, InceptionV3, and MobileNetV2 on a balanced multi-class MRI dataset. Unlike many previous studies that focus on binary classification or a single architecture, this



work systematically compares multiple models using a consistent preprocessing pipeline and evaluation metrics. Furthermore, by including the lightweight MobileNetV2 alongside deeper models such as VGG-16 and InceptionV3, the study highlights the trade-off between classification performance and computational efficiency, supporting practical deployment in resource-constrained clinical environments.

1.3 Structure of the paper

The study is structured as follows: Section II presents related work on the application of deep and transfer learning techniques in brain tumour classification using MRI images. Section III details the methodology, including dataset preparation, preprocessing steps, and model implementation. Section IV presents the experimental results and performance evaluation of the transfer learning models. Section V concludes the study and highlights key findings, contributions, and future research directions.

II. LITERATURE REVIEW

This section discusses several review articles related to the early diagnosis of brain tumours using MRI images through transfer learning approaches. Table I highlights the author, methods, dataset, key findings, and limitations/future work, offering a comparative overview of the DL and transfer learning models employed for brain tumour classification.

Singla and Gupta, (2025) The fine-tuned transfer learning model achieved a test accuracy of 98.9% with minimal loss, demonstrating strong capability in distinguishing brain tumour cases from healthy subjects. Confusion matrix analysis revealed high sensitivity and specificity with very few false positives and false negatives. The results highlight the model's potential for automated and reliable brain tumour detection, while future work may focus on larger datasets and 3D MRI scans to further enhance diagnostic performance[14].

Singh et al., (2024), This study utilizes a publicly available MRI brain tumour dataset from Kaggle to evaluate several pre-trained deep learning models, including Inception ResNet V2, Inception V3, ResNet50, VGG16, Xception, and VGG19. Transfer learning was applied to fine-tune the models for tumour classification. Among the evaluated architectures, VGG19 achieved the highest validation accuracy of 92.37%, outperforming VGG16 (89.83%), ResNet50 (81.34%), Inception V3 (74.56%), Xception (70.67%), and Inception ResNet V2 (62.39%). The results highlight the effectiveness of VGG19 for accurate brain tumour classification from MRI images[15].

Swetha and Seenu, (2024) This study proposes a brain tumour detection method using MRI images based on DenseNet and ResNet101 architectures. Data augmentation and Principal Component Analysis (PCA) are employed to improve model robustness and reduce feature dimensionality. Transfer learning is applied to enhance classification performance while minimizing computational complexity. Experimental results demonstrate that DenseNet outperforms ResNet101 and conventional approaches in terms of accuracy, precision, and F1-score, highlighting its effectiveness for accurate brain tumour detection[16].

Kanagapriya et al., (2024) The approach consists of three stages: image preprocessing, segmentation, and classification. Preprocessing enhances MRI image quality through brightness adjustment, sharpening, contrast enhancement, and noise reduction. Segmentation techniques, including thresholding, Canny edge detection, and watershed segmentation, are used to identify tumour regions. Deep learning models are then employed for feature extraction and tumour classification. Comparative results show that EfficientNetB0 achieved the highest accuracy (95%), followed by EfficientNetB7 (93%), VGG16 (92%), ResNet50 (89%), and CNN (88%). Model performance was evaluated using accuracy, precision, recall, and F1-score, highlighting the effectiveness of deep learning in brain tumour diagnosis[17].

Vijayalakshmi et al., (2023) deep models with a transfer learning approach for accurate classification of tumours. A collection of MRI brain images with and without tumors are trained using pre-trained deep models. A comparative analysis is using five pre-trained models VGG-16, VGG-19, RESNET50, INCEPTIONV3, and EFFICIENTB0. From the comparison study, it is observed that InceptionV3 with an accuracy of 94% is achieved. This study shows the power of deep models and transfer techniques in accurately classifying the brain tumours for our custom dataset[18].



Table I: Summary of background study of Transfer Learning Models for Early Diagnosis of Brain Tumours Using MRI Images

Author	Methods	Dataset	Key Findings	Limitations & Future Work
Singla & Gupta (2025)	Transfer Learning (CNN, fine-tuned model)	Not specified (likely MRI-based dataset)	Accuracy ~98.9%, high sensitivity/specificity; low false positives/negatives	Suggests using 3D MRI and diverse datasets to improve robustness
Singh et al. (2024)	Transfer learning with multiple DL models (e.g., VGG16, Xception, InceptionResNetV2)	Kaggle Brain Tumour MRI dataset	VGG19 showed best accuracy (92.37%)	Some models underperformed; explore architecture optimization
Swetha & Seenu (2024)	DenseNet, ResNet101, PCA, Transfer Learning	MRI images	DenseNet outperforms ResNet101; PCA improves training speed and effectiveness	Suggests evaluating on larger datasets and multi-centre validation
Kanagapriya et al. (2024)	CNN, ResNet50, VGG16, EfficientNetB7, EfficientNetB0	Brain MRI dataset	EfficientNetB0 achieves best accuracy (95%) among all compared models	More experiments with different pre-processing and segmentation strategies recommended
Vijayalakshmi et al. (2023)	VGG16, VGG19, ResNet50, InceptionV3, EfficientB0	Custom MRI dataset	InceptionV3 achieves best performance (94%) among all	Limited to a specific dataset; future work could explore ensemble approaches

III. METHODOLOGY

The methodology adopted for early brain tumour diagnosis using MRI images is illustrated in Figure 1. The process begins with the collection and labelling of MRI datasets containing tumour and non-tumour images. The acquired images undergo preprocessing steps, including resizing, normalization, brain region extraction, and RGB formatting to ensure consistency and compatibility with the deep learning model. Data augmentation techniques such as rotation, flipping, and zooming are applied to increase dataset diversity and improve model generalization. The dataset is then divided into training, validation, and testing subsets. A pre-trained VGG-16 convolutional neural network is fine-tuned using the processed MRI images for tumour classification. Finally, the model performance is evaluated using accuracy, precision, recall, and F1-score to assess its diagnostic effectiveness and reliability.



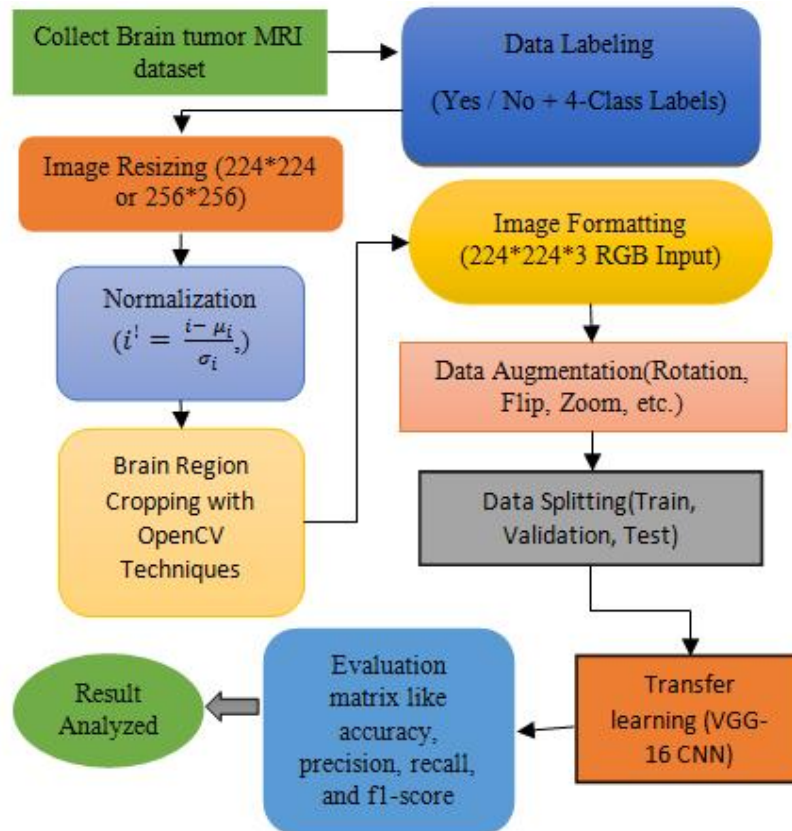


Figure 1:Flowchart for Transfer Learning-Based Early Diagnosis of Brain Tumours Using MRI Images

The following steps of proposed methodology are briefly discussing in below:

3.1 Data collection

The dataset used in this study data is collected from Kaggle’s “Brain Tumour MRI Dataset”.The dataset is split into training and testing datasets comprising 7023 human brain MRI images in total with5712 instances of images in training and 1311 in testing. The images are classifiedinto four classes: glioma, meningioma, no tumour, and pituitary. Each class has 1300 to 1500 images which is well balanced for training and testing machine learningmodels without requiring extensive data balancing techniques. The images in the dataset were of diverse sizes. Therefore, all the images were resized to 224x224 pixels during the training of the models. Different augmentationtechniques like rescaling, rotation, shearing, zooming, and horizontal flipping were applied to increase the dataset size and create variation.

3.2 Data Labelling

The pre-processing of the image database is categorized into two segments, Yes and No, based on the existence of the tumour in an MRI images and the remaining 98 brain MRI images are malignant tumours. Generally, in our work, we, we split our dataset into three segments required for training, testing, and validation. The MRI brain image dataset in shown in fig 2.



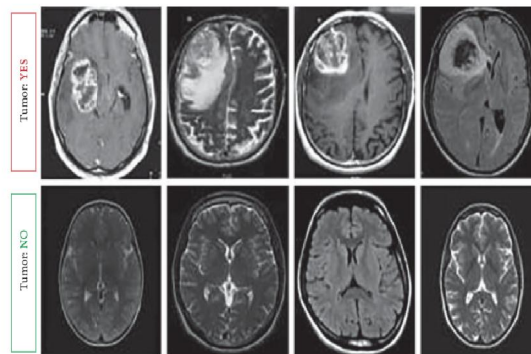


Figure 2: Sample dataset of brain MRI images

3.3 Image Resizing

All the MRI images were resized to a consistent dimension of 256×256 pixels. Resizing ensures uniformity across the dataset and is essential for processing the images through deep learning models, which require fixed input shapes. This resizing not only standardizes the dataset but also reduces memory consumption and computational complexity during training.

3.4 Normalization of Pixel Intensity

To reduce variations due to differences in image acquisition conditions, pixel values in each image were normalized. This was done using the statistical formula $i^{\wedge} = \frac{[i - \mu]}{\sigma}$, where i represents the original pixel intensity, μ is the mean intensity, and σ is the standard deviation. This transformation standardizes the images, bringing them to a similar scale, which in turn helps improve the training efficiency and convergence of deep learning models.

3.5 Brain Region Cropping

Before feeding the images into the model, unnecessary background regions were removed to focus on the region of interest, i.e., the brain area. This was achieved through image processing techniques using OpenCV, including thresholding and contour detection. These operations isolated the main brain region and cropped out irrelevant sections of the image, improving the model's ability to extract meaningful features related to tumours.

3.6 Image Formatting for Model Input

After normalization and cropping, the images were formatted to meet the input specifications of the selected pre-trained models. Most CNN architectures such as VGG-16, ResNet-50, and InceptionV3 require images of size 224×224 with three colour channels. Even though MRI images are typically grayscale, they were converted to RGB format by duplicating the grayscale channel across all three colour channels, thus resulting in an image size of $224 \times 224 \times 3$.

3.7 Data Augmentation

Given the limited size of the dataset, data augmentation techniques were employed to artificially expand the training set and improve generalization. The augmentation strategies applied included rotation, horizontal and vertical flipping, zooming, affine transformations, and perspective changes. These augmentations created varied versions of the original images, making the model more robust to image distortions and reducing the risk of overfitting.



3.8 Data splitting

The dataset was divided into three subsets: training, validation, and testing. Although the paper does not specify the exact split ratio, commonly used configurations such as 70% for training, 15% for validation, and 15% for testing were likely used. This division ensured that model performance could be evaluated effectively on both seen and unseen data.

3.9 Classification with Machine learning and deep learning models

In this section discuss the VGG-16 CNN model:

VGG-16 CNN Model

The model to be tested by the authors for the classification of brain tumours was the VGG-16 CNN model[19]. Because of the small image dataset and to avoid overfitting problems, our model is fine-tuned by freezing some of the convolution (Conv) layers. VGG-16 is a CNN model with sixteen convolution layers developed in 2014 by researchers. The model accepts brain MRI images as input with a dimension of $224 \times 224 \times 3$. It incorporates Conv layers with kernels (filters) of fixed 3×3 filter size and 5 maxpooling layers of dimension 2×2 in size within the network. It also includes extensively ReLU activation functions and 2 fully connected layers with a softmax output layer. VGG-16 model is a broad network that contains approximately 138 million hyperparameters. It stacks multiple convolutional layers to construct deep neural networks that improve the ability to learn invisible handcrafted features. The hyperparameters are essential as they control the overall behaviour of the model. Its aim is to minimize the predefined loss function and to obtain better results for a specific dataset. The hyperparameters to tune are the neuron and epoch counts, softmax activation function, learning rate, and optimizer. The number of convolution layers is the second step of the hyperparameter to undergo tuning. Thus, with an increase in ConvNet depth, the capacity to learn hidden features increases at a lower cost.

The convolution operation applied within VGG-16 can be expressed mathematically as in (Equation(1)):

$$O(i, j) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} I(i + m, j + n) \cdot K(m, n) \text{-----(1)}$$

where $O(i, j)$ is the output feature map at position (i, j) is the input image, K is the convolution kernel (filter), and $M \times N$ is the size of the kernel (e.g., 3×3 in VGG-16). This operation is repeated across all input channels and stacked filters.

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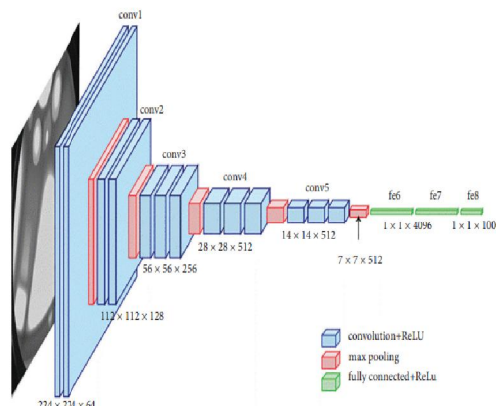


Figure 3: VGG-16 Model Architecture



Explanation of the VGG-16 Architecture in fig 3

Input Layer

Size: $224 \times 224 \times 3$ (standard RGB image), but in your specific image, it's shown as $224 \times 224 \times 64$, which could suggest grayscale image expanded to match RGB channel depth or processed as feature maps (e.g., brain MRI scan).

Convolutional Blocks (conv1 to conv5)

Each convolutional block in the VGG-16 model consists of multiple 3×3 convolutional layers with ReLU activation, followed by a max pooling layer that reduces the spatial dimensions. This structure helps the network extract detailed features while minimizing computational load.

Block	Layer Outputs	Feature Maps	Explanation
conv1	$224 \times 224 \rightarrow 112 \times 112$	64 filters	Two 3×3 convs \rightarrow downsample via maxpool
conv2	$112 \times 112 \rightarrow 56 \times 56$	128 filters	Two 3×3 convs \rightarrow downsample
conv3	$56 \times 56 \rightarrow 28 \times 28$	256 filters	Three 3×3 convs \rightarrow downsample
conv4	$28 \times 28 \rightarrow 14 \times 14$	512 filters	Three 3×3 convs \rightarrow downsample
conv5	$14 \times 14 \rightarrow 7 \times 7$	512 filters	Three 3×3 convs \rightarrow downsample

Each convolution uses 3×3 filters with stride = 1 and padding to preserve spatial resolution before pooling.

Fully Connected Layers (fc6, fc7, fc8)

In the VGG-16 model, the flattened output from the final convolutional layer is passed through three fully connected layers: fc6 and fc7 each with 4096 neurons, and fc8 with 1000 neurons for classification. For brain tumour detection, fc8 is typically modified to have 2 or 4 neurons, depending on whether binary or multiclass classification is needed, with a softmax activation to output class probabilities.

Activation Functions and Dropout

- ReLU: activation is used after each convolution and fully connected layer.
- Dropout: is often applied (not shown in the figure) after fc6 and fc7 to reduce overfitting.

3.10 Evaluation metrics

Image classification plays a prominent role in healthcare applications to detect and predict deadly cancerous tumours in human body organs. The most popular image classification models are VGG 16, Inception-v3 model.

To evaluate the performance of the proposed model, crucial metrics such as F1-Score, Precision, Recall, and Accuracy are considered, As shown in equations (1-4), these metrics provide an understanding of False Negatives(FN), True Negatives(TN), False Positives(FP), and True Positives(TP) The confusion matrix is listed in below[15]:

- True Positive (TP), represents the number of MRI scans with brain tumours correctly identified as having a tumour.
- False Positive (FP), indicates MRI scans without tumours that were incorrectly classified as tumour-positive.
- False Negative (FN), Denotes MRI scans with tumours that were incorrectly classified as tumour-negative.
- True Negative (TN), represents MRI scans without tumours correctly classified as tumour-negative. Following performance measures are as follows:



Accuracy

The model's accuracy is a measure the effectiveness of the classifier's ability to predict sample data correctly. It is determined as the ratio of accurate forecasts to all predictions (see Equation (2)). The accuracy of the model offers an overall evaluation of its correctness

$$Accuracy = \frac{TP + TN}{TP + Fp + TN + FN} \dots\dots (2)$$

Precision

Precision, on the other hand, is the ratio of True predictions to the overall correct predictions. It shows how well the classifier identified positive samples (see Equation (3)).

$$Precision = \frac{TP}{TP + FP} \dots\dots (3)$$

Recall

Recall, also known as sensitivity, measures the classifier's quality in making accurate positive predictions. This is determined by dividing the overall positive samples by the actual positive forecasts(see Equation (4)).

$$Recall = \frac{TP}{TP + FN} \dots\dots\dots (4)$$

F1-score

The F1-Score is a performance metric used to assess the accuracy of a classifier by taking both precision & recall. It is specifically required when the class distribution is imbalanced. The F1-Score is calculated as the harmonic mean of recall and precision, offering a single metric that balances both measures. (Equation (5))

$$F1 - Score = \frac{2(Precision * Recall)}{Precision + Recall} \dots\dots (5)$$

ROC

The ROC Curve is a graphical tool used to evaluate the performance of a classification model, particularly in binary classification scenarios. It provides a visualization of the sensitivity and specificity of the model, showing their variation as thresholds are changed. The ROC curve is plotted with the false positive rate on the x-axis and the True Positive Rate (TPR) on the y-axis. An optimal classifier, characterized by a TPR of one and a false positive rate of zero, lies in the upper left corner of the graph. The curve takes shape around this point, illustrating the performance of the model across different thresholds.

In addition, the area under the receiver operating characteristic (ROC) curve, commonly referred to as the "area under the curve", succinctly summarizes the overall model performance in a single metric. The AUC value ranges from 0 to 1, with values closer to 1 indicating the increased discriminative ability of the model. The ROC curve and AUC value serve as essential tools for comparing models and understanding classification model performance. A higher AUC value generally indicates superior model performance, while the curve illustrates the model's performance strengths and weaknesses at various thresholds[20].

These matrices are utilized to determine the machine and deep learning models.

IV. RESULT ANALYSIS AND DISCUSSION

The experimental results of the transfer learning models applied for early diagnosis of brain tumours using MRI images are discussed in this section. The experiments were carried out on a computing system equipped with a 3.6 GHz Intel Core i7 processor, 32 GB of RAM, and an NVIDIA GPU, running the Windows 11 operating system. The VGG-16 CNN model was fine-tuned and evaluated using standard performance metrics, including accuracy, precision, recall, and F1-score. These metrics were used to assess the model's effectiveness in classifying brain MRI images. The results of the evaluation are summarized in Table II, providing insight into the model's classification capabilities for early brain tumour detection.



Table II: Performance of Transfer Learning Models on Brain MRI Dataset for Early Diagnosis of Brain Tumours

Performance Measures	VGG-16 CNN
Accuracy	96.00
Precision	94.00
Recall	99.99
F1-score	98.00

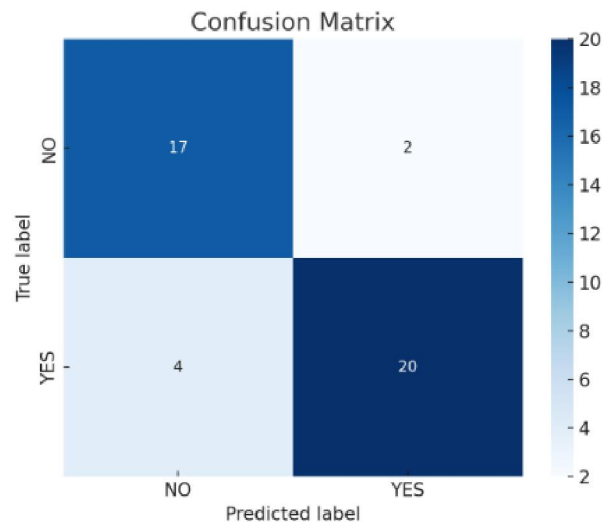


Figure 4 : Confusion matrix of VGG-16 CNN model

The confusion matrix in fig 4 illustrates the performance of a binary classification model applied to MRI brain tumour detection. Out of the total samples, the model correctly predicted 17 cases as "NO" (true negatives) and 20 cases as "YES" (true positives). However, it misclassified 2 "NO" cases as "YES" (false positives) and 4 "YES" cases as "NO" (false negatives). The high number of correct predictions indicates that the model performs well overall, especially in detecting tumour cases. The relatively low number of false classifications suggests strong specificity and sensitivity, making the model a potentially reliable tool for early brain tumour diagnosis.

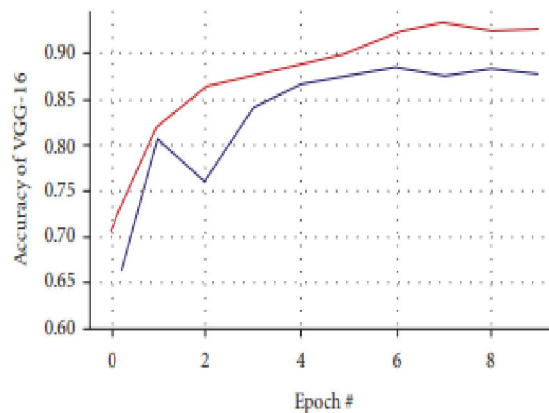


Figure 5: Accuracy curve of VGG-16 CNN model

The graph in fig 5 illustrates the testing and validation accuracy of the VGG-16 model over a span of 10 epochs. The red line represents training accuracy, while the blue line represents validation accuracy. Initially, both accuracies



increase significantly, indicating that the model is effectively learning from the data. After the third epoch, training accuracy continues to improve steadily, peaking around 91%, while validation accuracy rises more gradually and stabilizes around 87%. The slight gap between the two curves suggests mild overfitting, where the model performs slightly better on training data than on unseen validation data. Overall, the performance trend demonstrates that the VGG-16 model is well-optimised and maintains strong generalization capability for brain tumour classification using MRI images.

4.1 Comparative Analysis and Discussion

The comparative analysis for early diagnosis of brain tumours using MRI images is presented in this section. The performance of transfer learning models VGG-16 CNN, InceptionV3 (InceptionV3), and MobileNetV2 (MNv2) is evaluated based on performance metrics such as accuracy, precision, recall, and F1-score, as illustrated in Table III.

Table III: Comparative Study of Transfer Learning Models for Early Diagnosis of Brain Tumours Using MRI Images

Performance Measures	VGG-16 CNN	IncV3[21]	MNv2[22]
Accuracy	96.00	93.60	82.61
Precision	94.00	93.50	81.11
Recall	99.99	94.20	80.32
F1-score	98.00	93.60	80.71

Table III presents a comparative evaluation of VGG-16 CNN, InceptionV3, and MobileNetV2 for brain tumour classification using MRI images. Among the models, VGG-16 achieved the best performance with 96.00% accuracy, 94.00% precision, 99.99% recall, and 98.00% F1-score, demonstrating superior capability in identifying brain tumours. InceptionV3 also produced competitive results, while MobileNetV2 showed comparatively lower performance but offers advantages for resource-constrained environments. Overall, VGG-16 emerged as the most effective model for accurate brain tumour diagnosis. The proposed framework utilizes a fine-tuned VGG-16 model with transfer learning to enhance classification performance on MRI images. Preprocessing steps, including resizing, normalization, brain region extraction, and data augmentation, improve data quality and model generalization. By retaining pre-trained feature representations and adapting the classification layers to the target dataset, the model achieves robust and reliable tumour detection. Performance is assessed using accuracy, precision, recall, and F1-score, demonstrating the framework's effectiveness for supporting clinical decision-making.

V. CONCLUSION AND FUTURE WORK

The application of transfer learning techniques in brain tumour classification has demonstrated significant potential for supporting early and accurate diagnosis using MRI images. Advanced deep convolutional neural networks can effectively extract discriminative features from medical images, reducing the dependence on manual interpretation and improving diagnostic efficiency. The comparative analysis of transfer learning models indicates that VGG-16 achieved the highest classification performance, attaining an accuracy of 96.00%, precision of 94.00%, recall of 99.99%, and F1-score of 98.00%. These results highlight the model's strong capability in correctly identifying tumour cases while minimizing misclassification. The incorporation of preprocessing operations, including image resizing, normalization, brain region extraction, and data augmentation, further enhanced model robustness and generalization. Overall, the findings demonstrate that transfer learning-based approaches can serve as reliable and efficient tools for automated brain tumour detection, providing valuable assistance for clinical decision-making and improving the prospects of early intervention and treatment planning.

Future work may focus on the integration of advanced architectures, ensemble learning strategies, and attention mechanisms to further improve classification performance. Additionally, the use of larger multi-centre datasets, 3D MRI volumes, and cross-hospital validation can enhance model generalizability and support real-world clinical deployment.



REFERENCES

- [1] R. V. S. S. B. R, R. R. Al-Fatlawy, S. M. Sundaram, E. A. Rathnakumari, and M. Sudha, "Quantum variational-based support vector machine for early detection of sepsis," in 2024 4th International Conference on Mobile Networks and Wireless Communications (ICMNWC), Tumkuru, India: IEEE, 2024, pp. 1–5, December. doi: 10.1109/ICMNWC63764.2024.10872228.
- [2] S. Mahmud, "AI AND DATA ANALYTICS FOR ENHANCING HOME HEALTHCARE: OPTIMIZING PATIENT OUTCOMES AND RESOURCE ALLOCATION," *Front. Appl. Eng. Technol.*, vol. 2, no. 01, pp. 01–23, February, 2025.
- [3] V. K. Dhakshnamurthy, M. Govindan, K. Sreerangan, M. D. Nagarajan, and A. Thomas, "Brain Tumour Detection and Classification Using Transfer Learning Models," *Eng. Proc.*, vol. 62, no. 1, pp. 1–8, 2024, doi: 10.3390/engproc2024062001.
- [4] A. Amarnath, A. Al Bataineh, and J. A. Hansen, "Transfer-Learning Approach for Enhanced Brain Tumour Classification in MRI Imaging," *BioMedInformatics*, vol. 4, no. 3, pp. 1745–1756, 2024, doi: 10.3390/biomedinformatics4030095.
- [5] M. M. Billah, R. Bakhshizada, D. Das, T. T. Tanha, and R. Rahman, "Brain Tumour Classification using EfficientNet," *Int. J. Comput. Appl.*, vol. 187, no. 86, pp. 0975 – 8887, March, 2026.
- [6] K. V. Durga, D. Muduli, K. Rahul, A. V. S. C. Naidu, M. J. Kumar, and S. K. Sharma, "Automated Diagnosis of Brain Tumour Based on Deep Learning Feature Fusion Using MRI Images," in 2023 IEEE 3rd International Conference on Applied Electromagnetics, Signal Processing, & Communication (AESPC), 2023, pp. 1–6. doi: 10.1109/AESPC59761.2023.10390081.
- [7] P. Kaushik, P. Rawat, D. Batra, P. Johnvelin, B. Sardana, and S. S. S, "Early Brain Tumour Detection using AI: A Systematic Review," in 2025 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI), 2025, pp. 1–6. doi: 10.1109/IATMSI64286.2025.10984506.
- [8] M. R. Anand and A. K. S, "Temporal Fusion Transformer Forecasting and MILP Prescriptive Optimization for Hospital Pharmacy Supply Chain Orchestration," in 2025 9th International Conference on Electronics, Communication and Aerospace Technology (ICECA), IEEE, Nov. 2025, pp. 1206–1213, Nov. doi: 10.1109/ICECA66444.2025.11382695.
- [9] B. Taha, F. R. Liza, M. Moniruzzaman, and M. Samsuzzaman, "Comparative Analysis of Fine-Tuned MobileNet versions to Detect Brain Tumours from MRI images," in 2022 4th International Conference on Sustainable Technologies for Industry 4.0 (STI), 2022, pp. 1–6. doi: 10.1109/STI56238.2022.10103254.
- [10] A. E. Ahmed et al., "Comprehensive Evaluation of Vision Transformer in MRI-based Brain Tumour Detection," in 2024 International Conference on Computer and Applications (ICCA), 2024, pp. 1–6. doi: 10.1109/ICCA62237.2024.10927847.
- [11] R. Jahangir, T. Sakib, M. F.-U.-A. Juboraj, S. B. Feroz, and M. M. I. Sharar, "Brain Tumour Classification on MRI Images with Big Transfer and Vision Transformer: Comparative Study," in 2023 IEEE 9th International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE), 2023, pp. 46–51. doi: 10.1109/WIECON-ECE60392.2023.10456372.
- [12] M. R. Anand and K. Abhilash, "Transforming Energy-Intensive Smart Factories with AI: TCN-based Forecasting and DQN-Driven Operational Optimization for Healthcare Manufacturing," in International Conference on Intelligent Computing, Information and Control Systems (ICOIICS-2025), Nepal: IEEE, 2025, pp. 508–515, November. [Online]. Available: https://scholar.google.com/citations?view_op=view_citation&hl=en&user=Wm2jcU0AAAAAJ&citation_for_view=Wm2jcU0AAAAAJ:zYLM7Y9cAGgC
- [13] A. Poudyal, N. Devkota, and G. Budha, "MRI-based Brain Tumour Classification using Transfer Learning: A Comparative Analysis," *Int. J. Comput. Appl.*, vol. 186, pp. 975–8887, 2024, doi: 10.5120/ijca2024923988.



- [14] S. Singla and R. Gupta, "Leveraging Transfer Learning and Image Processing for Brain Tumour Classification from MRI Data," in 2025 3rd International Conference on Advancement in Computation & Computer Technologies (InCACCT), 2025, pp. 134–138. doi: 10.1109/InCACCT65424.2025.11011464.
- [15] A. Singh, P. Priyadarshi, A. Panwar, A. K. Dubey, and A. Jain, "Comparative Analysis of Transfer Learning Based Deep Learning Models for Brain Tumour Detection," in 2024 International Conference on Artificial Intelligence and Emerging Technology (Global AI Summit), 2024, pp. 840–845. doi: 10.1109/GlobalAISummit62156.2024.10947808.
- [16] K. Swetha and A. Seenu, "Deep Learning Approaches for Brain Tumour Detection in MRI Scans: A Comparative Study of DenseNet and ResNet101 Architectures," in 2024 International Conference on Smart Systems for Applications in Electrical Sciences (ICSSES), 2024, pp. 1–5. doi: 10.1109/ICSSES62373.2024.10561400.
- [17] S. K. Kanagapriya, V. V. Kaveri, S. Saraswathi, and V. Meenakshi, "Revolutionising Brain Tumour Diagnosis with Enhanced Deep Learning and Transfer Learning Algorithms," in 2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM), 2024, pp. 1–10. doi: 10.1109/ICONSTEM60960.2024.10568647.
- [18] M. Vijayalakshmi, N. Keerthika, V. Kiruthika, E. Sathish, and A. Sasithradevi, "Transfer learning approach for brain tumour classification using MRI images," in International Conference on Computer Vision and Internet of Things 2023 (ICCVIoT'23), 2023, pp. 266–271. doi: 10.1049/icp.2023.2886.
- [19] J. Jain, M. Kubadia, M. Mangla, and P. Tawde, "Comparison of Transfer Learning Techniques to Classify Brain Tumours Using MRI Images †," Eng. Proc., vol. 59, no. 1, 2023, doi: 10.3390/engproc2023059144.
- [20] M. Z. Khaliki and M. S. Başarslan, "Brain tumour detection from images and comparison with transfer learning methods and 3 - layer CNN," Sci. Rep., no. 0123456789, pp. 1–10, 2024, doi: 10.1038/s41598-024-52823-9.
- [21] E. H. Ibrahim, S. E. Abo-youssef, K. El-bahnasy, and K. A. Mohamed, "Early Diagnosis of Brain Tumour Using Machine Learning Approaches," vol. 10, no. ML, pp. 1089–1100, 2025.
- [22] N. Ullah, J. A. Khan, M. S. Khan, W. Khan, and I. Hassan, "Applied Sciences An Effective Approach to Detect and Identify Brain Tumors Using Transfer Learning," 2022.

