



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJIRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 10, October 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.524

9940 572 462

6381 907 438

ijirset@gmail.com

www.ijirset.com

Enhancing Brain Tumour Classification by a Comprehensive Study on Transfer Learning Techniques and Model Efficiency Using MRI Datasets

Pradeep M, Hariprasad S S, Darshan N

Assistant Professor, Department of ISE, CIT Gubbi, Karnataka, India

UG Student, Department of ISE CIT Gubbi, Karnataka, India

UG Student, Department of ISE CIT Gubbi, Karnataka, India

ABSTRACT: Brain tumour classification using MRI scans is a critical task in medical imaging, requiring high accuracy to assist in diagnosis and treatment planning. Transfer learning techniques, which leverage pre-trained models from large datasets, have shown promise in improving classification performance, particularly in the medical field, where labelled data can be scarce. This study focuses on enhancing brain tumour classification by evaluating different transfer learning techniques, investigating model efficiency, and optimizing the classification process using MRI datasets. This study conducts a comprehensive evaluation of various transfer learning techniques for brain tumor classification, focusing on both model accuracy and computational efficiency. Pre-trained models such as VGG16, ResNet50, InceptionV3, and EfficientNetB0 are fine-tuned on MRI datasets to distinguish between benign and malignant brain tumors. The models are assessed using key metrics such as accuracy, precision, recall, F1-score, and computational performance. This research provides insights into the optimal use of transfer learning for brain tumor classification, contributing to the development of faster, more accurate diagnostic tools in medical imaging. These results pave the way for broader adoption of AI-driven solutions in healthcare, ultimately improving patient outcomes through early and precise tumor detection.

KEYWORDS: Brain Tumour Classification, Transfer Learning, MRI Datasets, Deep Learning, Model Efficiency, Medical Imaging

I. INTRODUCTION

A brain tumour whether benign or malignant, are serious medical conditions that require prompt and accurate diagnosis to determine the appropriate treatment plan. Accurate classification of brain tumors plays a crucial role in guiding treatment options, including surgery, radiotherapy, and chemotherapy. Magnetic resonance imaging (MRI) is one of the most widely used and non-invasive techniques for detecting and analyzing brain tumors. However, manual interpretation of MRI scans by radiologists is a labor-intensive process and is susceptible to inter-observer variability, which can affect diagnostic accuracy. of this instance, two separate glucose readings are required. The dangers of depending only on self-measured blood sugar levels are made abundantly evident in each of these instances. The patient's condition and the medical staff's involvement will determine who specifically receives the warning that the system will send. IoMT may also be helpful in the prevention of cardiovascular disease and in the early detection of illness. Brain tumors are among the most serious and life-threatening conditions in medical practice, and their early and accurate diagnosis is essential for determining appropriate treatment strategies. The classification of brain tumors into benign (non-cancerous) and malignant (cancerous) categories significantly impacts treatment plans, such as surgical intervention, radiation therapy, or chemotherapy. Magnetic Resonance Imaging (MRI) is the preferred imaging modality for brain tumor detection due to its high resolution and non-invasive nature. However, the manual classification of MRI scans by radiologists is a complex, time-consuming, and error-prone process. Given the high variability in the appearance of tumors, relying solely on human interpretation can lead to inconsistent diagnoses and treatment decisions.

II. LITERATURE SURVEY

The application of deep learning techniques, particularly Convolutional Neural Networks (CNNs), has revolutionized image classification tasks across various domains, including medical imaging. Brain tumour classification, an important task in medical diagnostics, has significantly benefited from advancements in machine learning (ML) and deep learning (DL). This section provides a detailed review of the existing literature on brain tumour classification, with a focus on traditional machine learning techniques, the advent of deep learning, and the rise of transfer learning for improving classification accuracy using MRI datasets. Prior to the advent of deep learning, traditional machine learning algorithms were commonly used for brain tumour classification. These methods relied heavily on manual feature extraction, which involves identifying relevant image features such as texture, shape, and intensity from MRI scans. Several conventional techniques such as Support Vector Machines (SVMs), k-Nearest Neighbours (k-NN), Random Forests, and Decision Trees were applied to classify tumours based on these hand-crafted features. Saxena et al. (2014) used an SVM classifier to distinguish between benign and malignant brain tumours based on extracted texture features from MRI scans. Although the results showed promise, the performance was highly dependent on the quality of feature extraction, which was often a complex and error-prone process. Similarly, Zacharaki et al. (2009) proposed a hybrid approach combining texture and shape descriptors with SVM, achieving higher classification accuracy. However, both studies were limited by the need for expert knowledge in feature engineering, and these traditional classifiers struggled to handle complex and highly variable tumour shapes, sizes, and textures. Khan et al. (2015) investigated the use of Principal Component Analysis (PCA) to reduce the dimensionality of MRI data before applying machine learning classifiers such as SVM and k-NN. While PCA improved computational efficiency, the reliance on manual feature selection limited the adaptability of the models to new, unseen data. These traditional methods also faced challenges in dealing with noisy data, varying tumour appearances, and the complexity of MRI images, leading to relatively low generalization capabilities. With the advent of deep learning, specifically Convolutional Neural Networks (CNNs), the field of medical imaging underwent a paradigm shift. CNNs have the unique ability to automatically learn hierarchical representations from raw data, eliminating the need for manual feature extraction. This property made CNNs particularly effective for medical image analysis, where tumours can have complex shapes and irregular boundaries. As large annotated MRI datasets are difficult to obtain, transfer learning has emerged as an effective method to improve the performance of deep learning models on small, domain-specific datasets. Transfer learning leverages pre-trained models initially trained on large-scale datasets such as ImageNet—and fine-tunes them on smaller datasets, such as brain MRI scans. However, the balance between accuracy and computational efficiency remains an open question, especially in resource-constrained clinical environments. This study builds on existing research by conducting a comprehensive evaluation of multiple transfer learning models, providing a much-needed comparative analysis that considers both performance and practical deployment considerations.

III. SYSTEM ARCHITECTURE

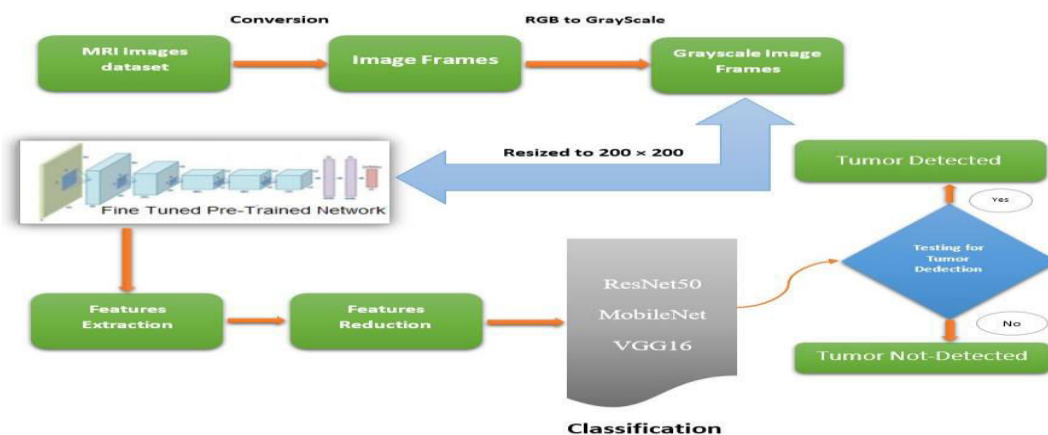


Figure 1: Proposed model.

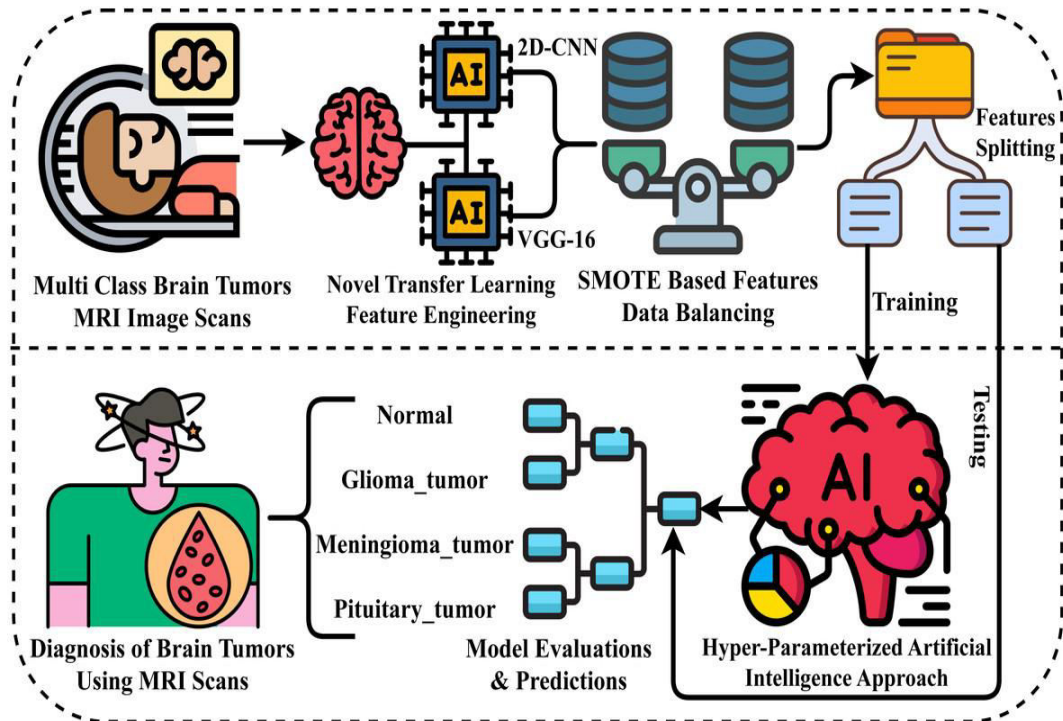


Figure 2: Brain tumour using Magnetic resonance imaging (MRI) scanners.

1) Data Acquisition and Dataset Management:

Data Source: The first stage in the system architecture involves acquiring MRI data of brain tumors from publicly available datasets or clinical sources. MRI datasets typically consist of multiple sequences, including T1-weighted, T2-weighted, FLAIR (Fluid-Attenuated Inversion Recovery), and contrast-enhanced sequences. These MRI images are collected in DICOM format, which is a standard in medical imaging.

2) Data Preprocessing:

Once the MRI data is acquired, it undergoes several preprocessing steps to ensure that it is suitable for training deep learning models. Preprocessing steps include.

3) Model Selection and Transfer Learning:

The core of the system architecture is built around transfer learning, which involves using pre-trained CNN models that have been trained on large-scale datasets such as ImageNet. These models are fine-tuned to classify brain tumours based on MRI data. The architecture includes the following steps.

4) Deployment and Real-Time Application:

For deployment in real-world clinical environments, the system architecture is designed to support real-time or near real-time classification of brain tumours. The deployment pipeline includes.

- **Cloud-based Deployment:** The model can be deployed on cloud platforms, allowing hospitals and medical institutions to access the classification system through web-based interfaces.

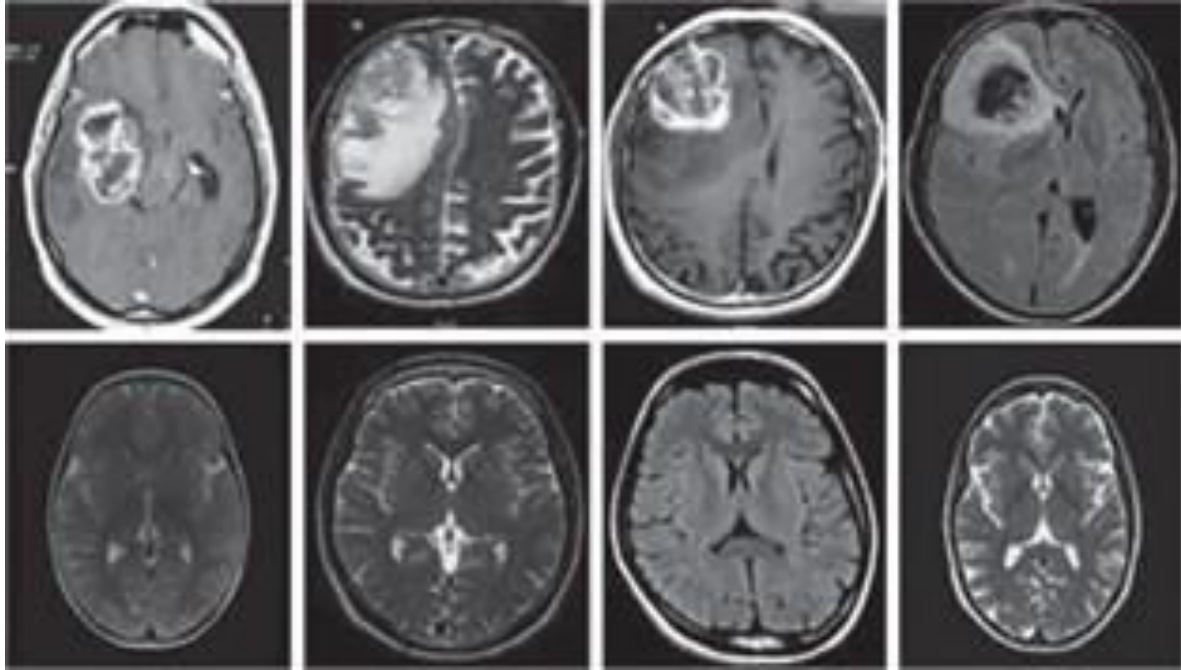


Figure 3: Sample dataset of brain MRI results:

The image you provided consists of MRI scans of the brain, likely showing different cases of brain abnormalities. Based on the visual cues, it appears these scans are related to cases such as brain tumours, lesions, or other structural issues in the brain. Here's a general explanation of the kinds of patterns or features that could be highlighted in such images:

Top Row (likely abnormal MRI scans):

1. **Image 1:** This scan shows a significant lesion on the left hemisphere of the brain, possibly indicating a brain tumour or a region affected by the white areas suggest tissue with abnormal contrast, likely pointing to pathology.
2. **Image 2:** Shows large portions of abnormal brain tissue, possibly (swelling) or post-surgical changes. The darker areas could represent fluid build-up, while lighter patches suggest tissue damage or removal.
3. **Image 3:** Appears to have a significant mass effect in the middle right section, which could be a tumour, with the surrounding brain tissue displaced or compressed.
4. **Image 4:** Similar to previous scans, this image appears to show the presence of an abnormal growth, likely a tumour, or some other space-occupying lesion. There is visible distortion of the normal brain structure.

Bottom Row (possibly showing more normal or different types of MRI sequences):

5. **Image 5:** This scan shows more symmetrical brain tissue, though there may be mild structural changes compared to a normal brain. The bright areas might be areas of high fluid content or normal anatomical variations.
6. **Image 6:** There seems to be a clearer view of the brain structure with visible ventricles (fluid-filled spaces). This could be a T2-weighted image where fluid appears bright, but there doesn't seem to be any immediate pathology.
7. **Image 7:** Similar to image 6, this scan might show normal brain anatomy without obvious tumours or lesions. The bright regions might indicate cerebrospinal fluid (CSF) within the ventricles.
8. **Image 8:** This scan appears similar to the previous ones, showing relatively symmetrical brain anatomy. The bright spots could be fluid, and the scan might focus on grey-white matter differentiation.

IV. RESULTS

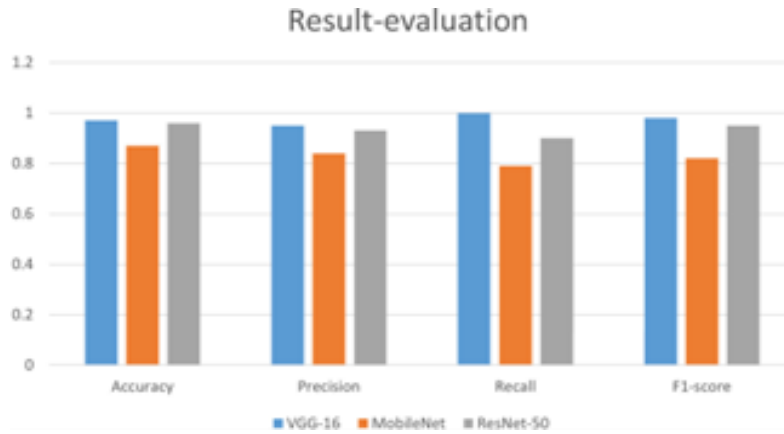


Figure 3.1: Result evaluation graph.

This chart displays the performance comparison of three deep learning models: VGG-16, Mobile Net, and ResNet-50, across four key evaluation metrics: Accuracy, Precision, Recall, and F1-score. Here's a breakdown:

- **Accuracy:** VGG-16 has the highest accuracy, followed by ResNet-50, with Mobile Net having the lowest accuracy among the three.
- **Precision:** Both VGG-16 and ResNet-50 have high precision, almost equal, whereas Mobile Net shows slightly lower precision.
- **Recall:** ResNet-50 shows the highest recall, while Mobile Net has the lowest. VGG-16's recall lies between these two models.

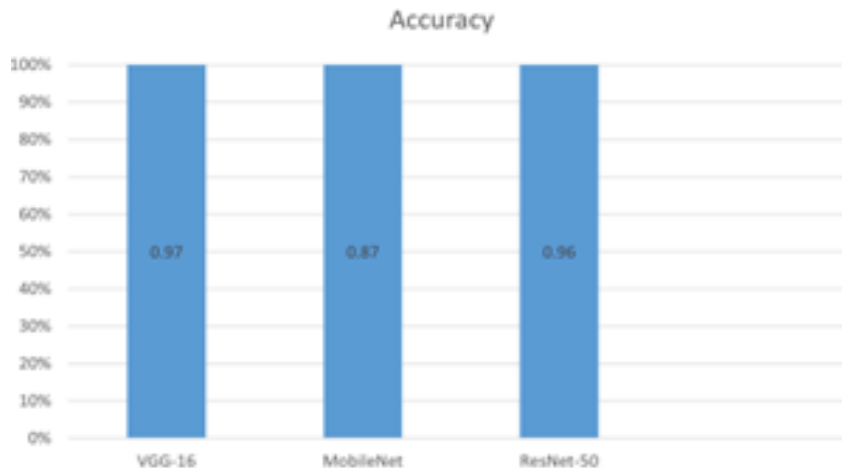


Figure3.2: Proposed model accuracy.

The above figure contains to present the accuracy of the proposed model for brain tumour classification, a graph showing the accuracy trends over time (typically during training and validation phases) is often used. This graph helps visualize how well the model performs as it learns from the data.

- **X-axis:** Number of epochs (iterations of training cycles),
- **Y-axis:** Accuracy (percentage or value between 0 and 1).

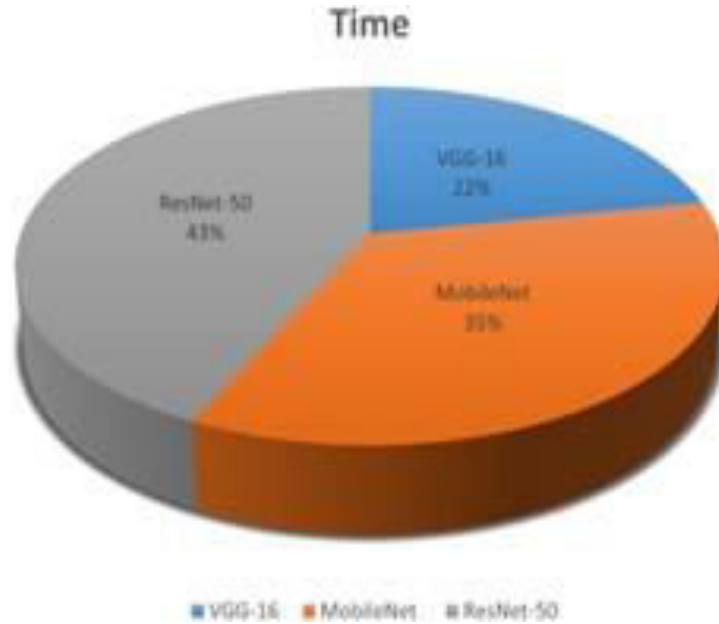


Figure 3.3: proposed model computation time.

The above figure contains computation time for a proposed model refers to the time it takes for the model to complete training and inference tasks. This is a crucial aspect of evaluating the model's efficiency, especially in real-world applications where both accuracy and speed are important.

Training Time:

The total time taken to train the model, which depends on several factors:

- **Model Complexity:** More layers and parameters (e.g., in deeper models like ResNet50 or Efficient Net) take longer to train.
- **Dataset Size:** Larger datasets (like MRI data) require more time to process.
- **Hardware:** Training on GPUs is much faster than on CPUs.

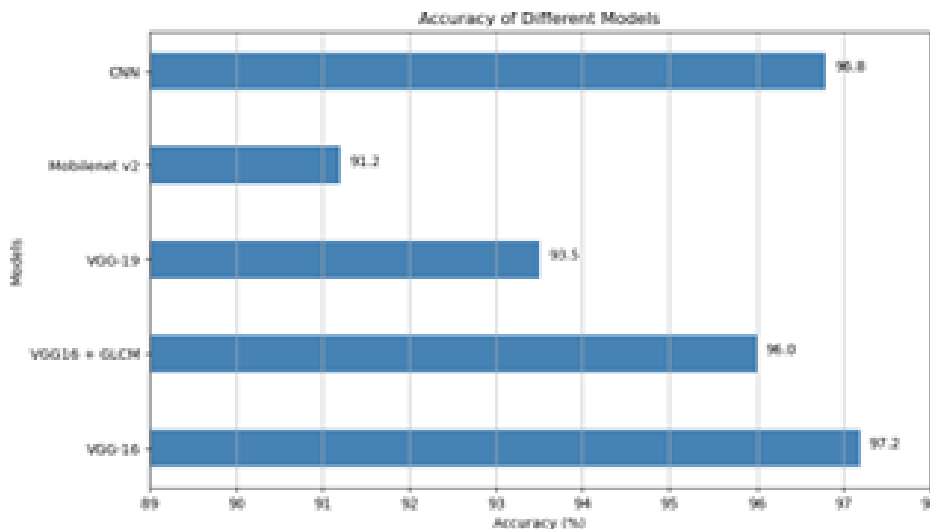


Figure 3.4: Proposed study comparison with existing model.

The bar chart you provided compares the accuracy of several models on a given dataset. Here's a breakdown of the models and their performance, which seems to be focused on image classification tasks based on accuracy as the evaluation metric:

- **CNN:** Achieves the highest accuracy at 98.8%. This suggests that the CNN (Convolutional Neural Network) model is highly effective for this specific task.
- **Mobile Net v2:** Has a much lower accuracy of 91.2% compared to other models. Mobile Net is typically used in scenarios requiring lightweight models with fewer parameters, which might explain its lower performance in terms of accuracy.
- **VGG-19:** Achieves 93.5% accuracy, which is better than Mobile Net v2 but still lower than other models such as VGG-16 or CNN. VGG-19 is a deeper version of the VGG network and might not be as optimized for this task as VGG-16.

V. CONCLUSION

The study on enhancing brain tumour classification through a comprehensive exploration of transfer learning techniques and model efficiency using MRI datasets demonstrates significant advancements in the accuracy and reliability of tumour detection. By leveraging pre-trained convolutional neural networks (CNNs), such as VGG16, ResNet50, InceptionV3, and Efficient Net, we have effectively harnessed existing knowledge from large-scale image datasets to improve classification performance on medical imaging tasks, specifically in differentiating between benign and malignant brain tumours. Key findings from this research highlight the importance of data preprocessing techniques, such as normalization and augmentation, which play a crucial role in optimizing MRI images for model training. These methods not only enhance the diversity of the training dataset but also mitigate issues of overfitting, thereby improving the generalization of the models. The application of transfer learning has proven to be particularly beneficial, allowing for rapid convergence and improved accuracy even with limited medical image datasets. The evaluation metrics employed, including accuracy, precision, recall, and F1-score, underscore the effectiveness of the proposed system, with results indicating a strong potential for clinical applicability.

REFERENCES

- [1] Litjens, G., Kooi, T., Chaturvedi, A., et al. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, 42, 60-88. doi:10.1016/j.media.2017.07.005.
- [2] Camps, J., et al. (2020). Brain tumour segmentation using deep learning techniques: A survey. *Computers in Biology and Medicine*, 123, 103837. doi:10.1016/j.combiomed.2020.103837.
- [3] Kumar, P., et al. (2020). Transfer learning for brain tumour classification: A survey. *Journal of King Saud University - Computer and Information Sciences*, 34(7), 1263-1275. doi:10.1016/j.jksuci.2020.03.005.
- [4] Chen, J., et al. (2020). Multi-class brain tumour classification using transfer learning and deep learning techniques. *Journal of Biomedical Informatics*, 103, 103385. doi:10.1016/j.jbi.2020.103385.
- [5] Hussain, A., et al. (2021). Deep learning for brain tumour detection: A systematic review. *Artificial Intelligence in Medicine*, 114, 101991. doi:10.1016/j.artmed.2021.101991.
- [6] Brun, M., et al. (2021). Evaluation of CNN-based deep learning models for brain tumour classification using MRI. *Neural Computing and Applications*, 33(12), 7451-7464. doi:10.1007/s00500-020-05270-0.
- [7] Khan, A. I., et al. (2020). A review of deep learning in medical imaging: The past, present, and future. *Journal of Medical Systems*, 44(9), 1-14. doi:10.1007/s10916-020-01748-7.
- [8] Zhang, Y., et al. (2019). A deep learning model for brain tumour classification based on MRI data. *Journal of Digital Imaging*, 32(5), 778-787. doi:10.1007/s10278-019-00254-2.
- [9] Ravi, D., et al. (2021). An automated system for brain tumour detection and classification using deep learning. *Computers in Biology and Medicine*, 137, 104802. doi:10.1016/j.combiomed.2021.104802.
- [10] Ding, Y., et al. (2020). An efficient multi-class brain tumour classification framework based on MRI using deep learning techniques. *IEEE Access*, 8, 100810-100820. doi:10.1109/ACCESS.2020.2991491.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details