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An Examination Of Various Deep Transfer Learning-Based Models For Brain Tumour Detection

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ABSTRACT

The diagnosis of brain tumours depends on the early detection of these disorders by magnetic resonance imaging (MRI) scans. While there are other imaging modalities used to diagnose brain tumours, magnetic resonance imaging (MRI) is the method of choice because of its higher image quality Finding brain tumours early on in the imaging process is essential for prompt diagnosis and treatment. Tumour diagnosis in medical imaging can now be done more accurately and efficiently because to deep learning, especially transfer learning. This paper offers a thorough examination of the many deep transfer learning models used to detect brain tumours, including an analysis of their architectures, methods, and performance assessments. This survey delves into the development of transfer learning approaches in this field, emphasising the use of pre-trained models, domain adaptation, fine-tuning procedures, and group methodologies. It also clarifies the many datasets that are utilised for testing and training, as well as the difficulties and potential paths for this discipline going forward. This review's comparative analysis attempts to enhance the development of reliable and accurate diagnostic tools in clinical practice by providing insights into the benefits, drawbacks, and future developments of deep transfer learning models for brain tumour diagnosis.

INDEX TERMS Brain tumors, magnetic resonance imaging, deep learning, and transfer learning

I. INTRODUCTION

One of the human body's most intricate organs, the brain regulates every nerve system and functions with billions of cells [1]. The most delicate organ is the brain. The aggressive nature and low survival rate of brain tumours make them among the worst diseases out there. Brain tumours come in two varieties: benign (non-cancerous) and malignant (cancerous). Benign tumours grow slowly and don't contain cancerous cells. It often remains in a single brain region. The rapid spread of malignant tumours to different brain tissues exacerbates the patient's condition. Brain tumours typically cause memory loss, headaches frequently, poor concentration, and coordination issues. In the US, there are over 787,000 patients with brain tumour disorders, according to the National Brain Tumour Association [2]. It is reported that just 36% of patients survive. The anticipated number of patients by 2021 with brain tumours identified in 84,170 cases. Compared to other malignancies like breast and lung cancer, brain tumours are less prevalent. Still, brain tumours rank as the world's tenth most prevalent cause of death. Depending on the size and kind of the tumour, there are various approaches to treating a brain tumour. The size of brain tumours varies, and they are frequently hard to find. A brain tumour may be much more difficult to identify in its early stages if its size and resolution cannot be precisely measured.

It is important to remember that patients' chances of survival might be raised by early brain tumour discovery. When compared to tumours in other areas of the body, brain tumour diagnosis is considerably more challenging. Considering

Tumour cell overactivity cannot be detected by conventional radioactivity markers because the brain is filled with blood brain barriers [3]. In the field of medical imaging, recent imaging techniques have had remarkable success. They can be used to diagnosis serious human diseases such stomach cancer [6], skin cancer [5], and brain tumours [4].

Computer tomography (CT) scans and magnetic resonance imaging (MRI) are thought to be the finest diagnostic tools for finding brain

tumours[44].

MRI scans with tumour texture and shape information, however, are more valuable than CT pictures. Since MRI is the only non-invasive medical imaging method that can produce high-resolution images of brain tissue, it is recommended. Radiologists can benefit from computer-aided diagnostic (CAD) devices in the clinic for early identification of brain tumours. Many automated systems, including supervised and unsupervised machine learning techniques [7], transfer learning [8], [41], [42], and deep neural models [9], have currently been created by researchers for the purpose of detecting brain tumours. Deep learning (DL) and artificial intelligence (AI) have made significant strides in the medical field. This enables an early diagnosis of the illness by the physician. Many different CAD systems make extensive use of convolutional neural networks (CNNs) [10], [11]. The CNN is composed of three fundamental layers: a pooling layer that reduces the feature map's dimensions, a fully connected (FC) layer that performs classification, and each convolution layer that extracts features.

Deep learning techniques have the potential to significantly increase performance by automatically extracting features. But these techniques necessitate a lot of data to increase accuracy, yet getting such information in tissue is a challenging undertaking. Systems for computer-aided diagnosis (CAD) can assist radiologists in the clinic with early data mounts.

II.LITERATURE REVIEW

The proliferation of deep learning techniques has revolutionized the field of medical image analysis, particularly in the classification and detection of brain tumors using Magnetic Resonance Imaging (MRI). A comprehensive analysis of multiple studies reveals significant advancements and varied methodologies employed in this domain

[1] D. N. Louis This paper provides a summary of the 2016 World Health Organization (WHO) classification of central nervous system tumors. It outlines the updated classification and criteria for diagnosing various types of brain tumors.

[2] M. I. Sharif This research paper discusses the use of active deep neural network features selection for the segmentation and recognition of brain tumors in MRI images. The authors propose a method for selecting relevant features to improve the accuracy of brain tumor segmentation and recognition using deep learning techniques

[3] J. J. Graber This paper presents a systematic review and evidence-based guidelines for the use of stereotactic radiosurgery in the treatment of adults with metastatic brain tumors. It offers recommendations and insights based on a comprehensive review of the available literature.

[4] A. Rahman This paper focuses on the detection and classification of microscopic brain tumors using a 3D Convolutional Neural Network (CNN) and feature selection Architecture. It describes a method for enhancing the accuracy of brain tumor detection and classification in microscopic images

[5] M. A. Khan This paper presents a Newton-Raphson Based deep feature selection framework for recognizing skin

Lesion .It offers a method for improving the accuracy of skin Lesion recognition using deep learning techniques.

[6] M. A. Khan This paper explores optimal fusion techniques for deep learning features to classify stomach abnormalities. Stomach Net employs fusion strategies, integrating multiple deep features for improved classification accuracy, demonstrating advancements in stomach abnormality detection.

[7] P. M. S. Raja The authors propose a hybrid approach involving a deep autoencoder and Bayesian fuzzy clustering-based segmentation for brain tumor classification. This method showcases a unique combination of techniques to enhance the accuracy of brain tumor classification using MRI data

[8] Z. N. K. Swati This study employs transfer learning and fine-tuning techniques for brain tumor classification from MR images. By leveraging pre-trained models and adapting them to the specific task of tumor classification, this approach demonstrates promising results in accurately identifying brain tumors.

[9] K. Muhammad Focused on smart healthcare systems, this survey paper delves into the application of deep learning for multigrade brain tumor classification. It provides an overview of the prospects and challenges of implementing deep learning models in healthcare settings for accurate and efficient tumor classification.

[10] S. Deepak Utilizing deep Convolutional Neural Network (CNN) features via transfer learning, this paper focuses on brain tumor classification. Transfer learning techniques are leveraged to extract meaningful features from MRI images, showcasing the effectiveness of deep CNNs in accurately classifying brain tumors.

III Approach

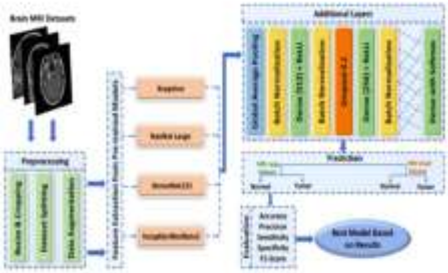
Preprocessing the MRI images, identifying the brain tumors, and extracting deep features using trained models are the steps in the research methodology.
To improve the training process, the study makes use of different regularization techniques, normalization, and data augmentation. Various assessment measures, including F1-score, accuracy, sensitivity, precision, and specificity, are employed to evaluate the efficiency of the suggested models.

IV Model Architecture

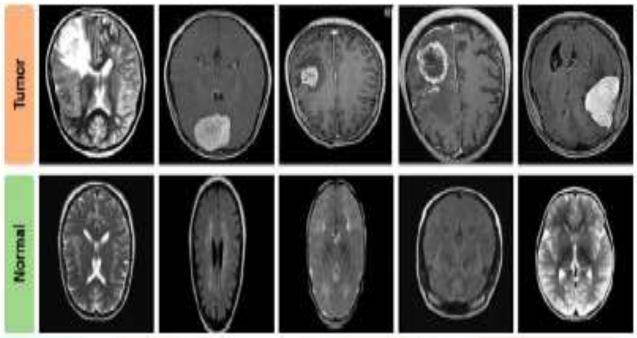
Step 1: The architecture of the proposed solution involves utilizing pre-trained deep learning models to extract deep features from brain MRI images

Step 2: classification using dense or fully connected layers with global average pooling.

Step 3: Various optimization algorithms such as ADAM, SGD, and RMS prop are used to train the models and evaluate their perform an



V Data Sets



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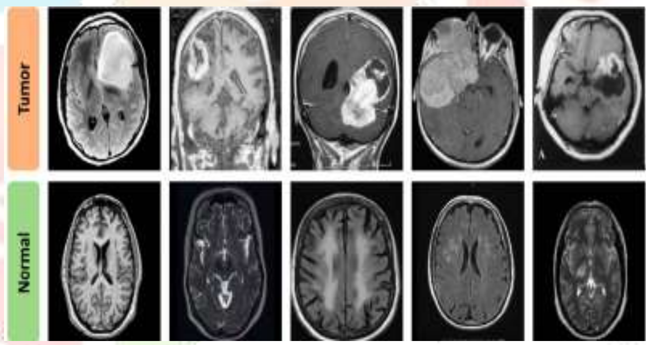
BR35H: Brain Tumor Identification in 2020: 1500 of the dataset's photos show the tumor, whereas the other 1500 show normal images



MRI-small: Dataset contains 253 images from 253 patients. The dataset includes 155 tumor images and 98 normal images.

VI EXPERIMENTS

1) **Deep learning models used:**
a) **Xception**
b) **NasNet Large**
c) **DenseNet121**
d) **InceptionResNetV2**
2) **Optimizers used in model training:**
a) **Adam**
b) **SGD**
c) **RMSprop**

VII Solution

The work proposes the development of robust and efficient methods based on transfer learning techniques using popular deep learning architectures such as Xception, NasNet Large, DenseNet121, and InceptionResNetV2 for classifying brain tumors from MRI images.

The models are trained and tested using multiple benchmark datasets and optimization algorithms to evaluate their performance.

VIII RESULTS AND DISCUSSION

Performance Measure	Xception	NasNet Large	DenseNet 121	InceptionRes NetV2
No. of epochs	50	50	50	50
Batch Size	64	64	64	64
Image Size	224×224	224×224	224×224	224×224
Optimizers	Adam, SGD, RMSprop	Adam, SGD, RMSprop	Adam, SGD, RMSprop	Adam, SGD, RMSprop
Activation Function	Softmax	Softmax	Softmax	Softmax
Learning Rate	1e-4	1e-4	1e-4	1e-4
Decay Rate	1e-5	1e-5	1e-5	1e-5
Dropout Rate	0.2	0.2	0.2	0.2
Regularizer	1e-4	1e-4	1e-4	1e-4

Summary of Hyperparameters used for training the models

Optimizers	ACC	SEN	PRE	SPE	F1-Score	NPV	MCC	FPR	FNR
ADAM	**99.67**	**99.68**	**99.68**	**99.66**	**99.68**	**99.65**	**99.33**	**0.0034**	**0.0032**
SGD	96.35	98.39	94.74	94.16	96.53	98.21	92.75	0.581	0.161
RMSprop	99.34	99.04	99.68	99.66	99.35	98.98	98.67	0.0034	0.0096

Xception model of each optimizer in terms of different evaluation metrics.

IX CHALLENGES AND FUTURE DIRECTIONS:

Optimizers	ACC	SEN	PRE	SPE	F1-Score	NPV	MCC	FPR	FNR
ADAM	99.34	99.36	99.36	99.31	99.36	99.31	98.67	0.0069	0.0064
SGD	98.34	98.71	98.08	97.94	98.40	98.62	96.68	0.0206	0.0129
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

NasNet Large models of each optimizer in terms of different evaluation metrics.

Optimizers	ACC	SEN	PRE	SPE	F1-Score	NPV	MCC	FPR	FNR
ADAM	99.00	99.36	98.72	98.63	99.04	99.31	98.01	0.0137	0.0064
SGD	94.68	95.82	94.01	93.47	94.90	95.44	89.37	0.0653	0.0413
RMSprop	98.84	99.68	98.10	97.94	98.88	99.65	97.68	0.0206	0.0032

Despite the successes, challenges persist. Limited availability of annotated datasets remains a bottleneck, hindering the development of highly accurate models. Model interpretability and explain ability also stand as critical areas for improvement, especially in the medical domain where decisions impact patient care. The exploration of hybrid models, incorporating different neural network architectures, and the integration of domain-specific knowledge could potentially mitigate these challenges.

X Research void

Gap1: The method relies on transfer learning. If not properly executed, transfer learning algorithms might result in negative transfer, which impairs rather than improves learning ability. So it's best to employ distillation, assembling, or voting approaches.

Gap 2: The augmentation method is easy. It may provide a similar contrast across all regions. As a result, it may be improved by incorporating additional augmentation approaches that contrast the local significant region of interest.

Gap3: CNN should create a full picture of the internal structures and their relationships to one another, which can be done via 3D CNN or by evaluating many slices at once.

Gap 4: The usage of temporal information does not exist. Multiple slices with ISTM can be considered.

XI **CONCLUSION**

The key findings indicate that the Xception and InceptionResNetV2 models demonstrate superior performance in classifying brain tumors, achieving high accuracy, sensitivity, specificity, precision, and F1-scores. The study highlights the potential of deep transfer learning-based models for improving the effectiveness of brain tumor detection from MRI images and significantly impacting patient outcomes.

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