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A Comprehensive Review of Machine Learning Techniques for Brain Tumour Classification and Detection

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ABSTRACT

Because brain tumours vary widely in size, location, and form, diagnosing them can be extremely difficult. Although manual evaluation and conventional imaging techniques are still widely used, deep learning has become a game-changing technology for automated diagnosis. The study discussed in the thesis is summarised in this review, which also places it in the larger context of brain tumour detection methods. It addresses classical machine learning algorithms, the advent of convolutional neural networks (CNNs), and hybrid procedures. The report offers a thorough reference for audiences in academia and medicine by highlighting present strengths, enduring constraints, and prospects for further research.

1. Introduction

The brain, which is made up of billions of neurons and other supporting cells, is one of the most important biological organs. Unusual and unchecked cell development in the brain can cause damage and even death. This is known as a brain tumour. Cancerous (malignant) and non-cancerous (benign) brain tumours are among the different types of brain tumours. Primary brain tumours start inside the brain, whereas secondary (metastatic) brain tumours start in other organs and spread to the brain, including the lungs, breast, colon, kidneys, or skin (melanoma). Classifications such as low-grade and high-grade are used to characterize the growth behaviour of initial tumours. Although a low-grade tumour usually grows slowly, it might develop into a more aggressive type. High-grade tumours, on the other hand, usually grow more quickly and are more deadly. Unlike malignant tumours, benign tumours can not spread to other regions of the body, yet they can still cause serious problems because they put pressure on brain structures.

1.1. The Work's Scope

The prevalence of brain tumours has increased dramatically worldwide in recent years, and many people are still ignorant of or have not been diagnosed with this illness [2]. In order to diagnose brain tumours, a number of studies have used machine learning algorithms in conjunction with statistical and textural data. The goal of the current study is to demonstrate how artificial intelligence may be used to detect and predict brain tumours. Automatic brain tumors diagnosis is necessary because of the complex and closely packed structure of the brain. The primary goal of the research project is to use customized CNN models to classify different kinds of cancers from brain MR images. In the area of medical diagnosis and prognosis, artificial intelligence (AI) has become a leading method [3].

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Deep learning has become a state-of-the-art method that has attracted a lot of interest and been widely used in many fields, most notably medical picture analysis. Deep learning models produce descriptive data, including texture characteristics, shape features, and hidden patterns, that accurately represent and differentiate brain cancers in DNN-based brain tumour classification [5]. Two novel deep neural architectures, BT-GPM and LS net, have been created and trained for the classification of brain tumours.The new Lightweight Sequential net was developed with the intention of cutting down on calculation time and model parameters. To cut down on computation time and improve performance, three different optimizers have been investigated. Additionally insignificant is the development of the computer-aided diagnostic (CAD) paradigm for brain tumour diagnosis and prognosis. As a result, a smartphone app for brain tumour diagnosis was developed using the Lightweight Sequential Network. The suggested application can be used for preliminary brain tumour screening by neurosurgeons and other medical specialists.An ensemble method based on deep learning has been used to segment the area of the brain tumour. Additionally, the prognosis of survival for individuals with brain tumours has been predicted using ML algorithms and 3D radiomics features [4].

2. Literature Survey

Clinical diagnosis is costly and time-consuming. The best subjective and economical methods for identifying brain tumours have been the topic of numerous studies. MRI is a cutting-edge medical imaging technique that produces finely detailed pictures of the body's internal organs. It has multi-planar capability, the greatest soft tissue resolution, and no ionizing radiation. One of the most important steps is determining the best course of action for a person with a tumour at the right moment. Numerous techniques, such as deep learning-based algorithms, artificial neural networks (ANN) [1, 2], and machine learning methods, have been developed for the classification of brain tumours in MR images. The review focusses on using machine learning and deep learning methods to effectively diagnose brain tumours. Deep neural networks and ensemble methods can improve the prediction model's performance.

ROI detection and acquiring picture characteristics through traditional feature extraction approaches are the hurdles in machine learning methodologies. Few studies have been conducted that concentrate on identifying brain tumours and creating a Additionally, the Computer Aided Diagnostic (CAD) model for brain tumour diagnosis and prognosis is noticeably insufficient [6].

2.1. The Status of Country

Using the AlexNet CNN architecture, Alok Sarkar et al. (2023) present a novel and effective method for categorizing brain tumours. Brain pictures are classified as glioma, meningioma, pituitary cancer, and no-tumor using Bayes Net, Sequential Minimal Optimisation (SMO), Naïve Bayes (NB), and Random Forest (RF).The AlexNet CNN + RF model yielded an accuracy rate of 100%, the AlexNet CNN + SMO model 98.15%, the AlexNet CNN + Bayes Net model 88.75%, and the AlexNet CNN + NB model 86.25%.

Javeria Amin et al. (2022) demonstrated a method that uses softmax to build a score vector after extracting deep features from the InceptionV3 model. QVR, or the Quantum Variational Classifier, is used to differentiate between meningioma and Glioma, pituitary tumour, and no tumour. The model achieved over 90% detection accuracy.

In order to classify brain cancers, Ayadi et al. (2021) proposed a customized Convolutional Neural Network (CNN). Three distinct datasets were subjected to an 18-layered CNN model. The findings revealed a remarkable categorization accuracy of 90.74% accuracy in differentiating between brain cancer types and 90.35% accuracy in assessing tumour severity.

Tazin et al. (2021) implemented several advanced DL methods for brain tumour detection. X-ray images were used to identify malignant and benign images. InceptionV3, MobileNetV2, and VGG19 models achieved accuracy of 91%, 92%, and 88%, respectively.

In 2020, Raja et al. introduced a deep auto encoder that uses the Bayesian Fuzzy Clustering (BFC) approach to classify brain tumours. To remove the image's artefacts, a mean filter was used. Furthermore, several strong characteristics were recovered, and a hybrid Deep Brain tumours are categorized using the Auto Encoder (DAE) approach. The suggested model's complexity, which necessitates a substantial amount of processing effort, is the main drawback of this strategy.

Berkeley Wavelet Transformation (BWT) and Support Vector Machine (SVM) algorithms were created by Bahadure et al. (2017) for the diagnosis and classification of brain tumours. In order to eliminate the impact of

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unwanted noise and raise the SNR, pre-processing is used. SVM classifier is used to classify brain tumours based on texture and histogram characteristics and yielded a 95% of accuracy. With a remarkable accuracy rate of 96.1%, Selva Pandian et al. (2018) proposed a categorisation method for brain cancer diagnosis based on an Adaptive Neuro Fuzzy Inference System (ANFIS) algorithm.

For the purpose of classifying brain CT (Computerised Tomography) pictures, Cheng Da et al. created a DNN algorithm. A DNN was utilised for classification in their investigation after Gray-Level Co-occurrence Matrix (GLCM) attributes were extracted, with an average accuracy of 83% was successful. Using a DNN classifier, Heba Mohsen et al. achieved 96.9% accuracy in their investigation.

Roy et al. classified brain tumours using intensity-based and texture-based characteristics using an Adaptive Neuro Fuzzy Inference System (ANFIS) classifier. Furthermore, their approach was evaluated against ANN and KNN approaches, and a 95% accuracy rate was obtained.

2.2. A Global Situation

A deep learning method for identifying MRI pictures of patients with and without brain tumours was presented by Mujeeb et al. in 2023. To identify tumour locations in MRI scans, this method uses a morphology-based segmentation technique. The diagnosing performance of a number of convolutional neural networks, including LeNET, MobileNetV2, Densenet, and ResNet, was assessed, and the most effective technique was found. 98.7%, 93.6%, 92.8%, 91.6%, and 91.9% were the respective accuracy rates for LeNET, MobileNetV2, Densenet, ResNet, and EfficientNet.

Ullah et al. presented a novel hybrid technique in 2020 that used histogram equalisation, artificial neural networks, and the discrete wavelet transform to distinguish between normal and pathological states. Features were retrieved from an improved MR brain image using a discrete wavelet transform. A complex deep neural network (DNN) was trained to identify whether MRI pictures were tumorous or not. The accuracy of the approach was 95.8%.

A modified version of the ResNet-50, designed especially for the diagnosis of brain tumours, was used by Cinar and Yildirim (2020). The last five levels underwent changes, and eight distinct layers were used in their place. This improved CNN model achieved a remarkable 97.2% accuracy rate. The current CNN models, AlexNet, GoogleNet, and VGG-16, were used in a different study by Rehman et al. (2020) to classify brain tumours into three categories. VGG-16 showed the best classification accuracy of 98.69% among these models.

A dataset of 3064 brain MRI pictures from 233 participants was used in the study [3]. In their research, Ali Arı et al. (2020) recommended pre-processing brain MR images using a Gaussian filter. Deep feature extraction (CNN) was carried out A deep learning method for identifying MRI pictures of patients with and without brain tumours was presented by Mujeeb et al. in 2023. To identify tumour locations in MRI scans, this method uses a morphology-based segmentation technique. The diagnosing performance of a number of convolutional neural networks, including LeNET, MobileNetV2, Densenet, and ResNet, was assessed, and the most effective technique was found. 98.7%, 93.6%, 92.8%, 91.6%, and 91.9% were the respective accuracy rates for LeNET, MobileNetV2, Densenet, ResNet, and EfficientNet.

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Hassan Ali Khan presented a DNN method in 2020 to differentiate between benign and malignant brain tumours. The approach achieved an 89% classification accuracy rate by using edge detection to identify the precise cancer location in MRI images before extracting features using a CNN model.

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A CNN design was presented by Khan et al. (2020) to differentiate between brain tumours that are malignant and those that are not. 253 real brain MRI pictures were used as the dataset. The edge detection technique was used to locate the pertinent area in the MRI pictures. A CNN model was then used to classify the tumours and extract features. Eighty-nine percent categorization accuracy was attained [4].

The possibility of using radiomic characteristics to enhance the diagnosis of patients suffering from glioblastoma multiforme was examined in the study by Bae et al. (2018). A collection of 217 MRI pictures of patients with glioblastoma was used to extract radiomic characteristics. Clinical data was combined with a set of 18 radiomics characteristics to enhance patient classification [5]. An improved AlexNet model was created by Khawaldeh et al. (2017) to classify brain MRI images into three groups: normal, LGG, and HGG. Researchers were able to attain an overall accuracy of 91.16% using 4069 brain MRI scans [6].

Navid Razmjooy et al. (2015) presented a unique method for melanoma diagnosis in their study by combining neural networks with a meta-heuristic algorithm called the World Cup Optimisation (WCO) algorithm. Filtering and segmentation procedures were performed before the images were divided into lesion and healthy groups. The accuracy of the suggested MLP-WCO method was 92% [7].

3. Existing Pre-Trained

RESNET: This architecture introduces a revolutionary concept called Residual Blocks to solve the vanishing or growing gradient problem. This is because the network is so deep that the gradients calculated for the loss function become significantly smaller after several chain rule runs. ResNets solve this problem by allowing gradients to flow in reverse from deeper layers to earlier filters, propagating straight through the skip connections. By basically bypassing some intermediate layers, the skip connections establish a link between the activation of a particular layer and the layers that follow. A residual block is represented by this arrangement. These residual blocks are stacked one after the other to create Residual Networks, or ResNets [7–10]. There is a clear advantage to having such skip connections. Regularization can be used to get around any layers that have a detrimental effect on the architecture's performance. Consequently, this reduces the difficulties related to the disappearing or exploding gradient problem while also making it easier to train deep neural networks.

A customized Convolutional Neural Network designed especially for mobile devices with little processing power is called Shuffle Net. Two innovative methods are used in this architecture: channel shuffle and pointwise group convolution. These cutting-edge processes are used to maintain accuracy while reducing processing needs.

Grouped Pointwise Convolution: This technique divides the filter banks and associated feature maps into discrete processing groups in an effort to increase the effectiveness of convolutional operations. This method makes it possible to process each group in parallel on different GPU units, which speeds up training and improves the model's comprehension of more accurate input data representations.

By separating spatial and cross-channel correlations, it also introduced the idea of depthwise separable convolutions, which significantly decreased the number of learnable parameters. Depth-wise convolution and point-wise convolution are the two operations used to accomplish this. The former produces intermediate outputs by performing a spatial convolution independently for every channel.

Shuffle operation: One crucial realization about the arrangement of grouped point-wise convolutions is that, when several group convolutions are placed one after the other, some channel outputs are only affected by particular channels. For example, if there are four groups with three channels each, the result of the first group's pointwise convolution will only include representations from each group, leaving out the contributions from the other groups. This feature reduces the representation capacity by blocking the information flow between channel groups. In order to get around this, a Shuffle operation was created, which mixes channels from several groups.

4. Conclusions

Given the wide variety of tumor sizes and shapes, diagnosing brain tumors is a complex undertaking for medical professionals. As a result, research on brain tumors is crucial in an effort to reduce medical stress and improve diagnostic accuracy. Many computer-aided methods for detecting brain tumors have been created throughout the years, and they all use transfer learning techniques and conventional machine learning classifiers.

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But current methods frequently fail to recognize the important characteristics needed for precise brain tumor identification. Furthermore, it is crucial to choose the right feature acquisition strategy. Regretfully, there is a chance that important characteristics may be missed while, in some cases, unimportant ones will be mentioned. These techniques are therefore frequently intricate and time-consuming. An automated method for multiclass brain tumor detection based on MRI was presented in this paper. Automated feature learning from brain MRI images is made possible by the suggested deep CNN model.

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