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Accurate Deep Learning Models for Predicting Brain Cancer at begin Stage

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Abstract: The objective of this research is to explore and compare the performance of several Deep Learning (DL) models and identify the most accurate classification model for predicting brain tumors using MRI images. The research utilizes the dataset of 450 MRI images which include healthy cases, cases with grade 1 & 2 benign tumors, and cases with grade 3 & 4 malignant tumor cases. The dataset is further divided into the training, validation, and testing sets. Each model is then trained and validated on the training and validation sets and further tested on the testing set and the overall performance is assessed and compared. The results demonstrated unique trends among the models, where CNN and ResNet50 have consistently performed the best with the highest accuracy and least data loss. VGG16 and VGG19 have also exemplified great results, although they utilised more epochs to achieve similar accuracy. Based on the results of the study, it is concluded that the appropriate DL architecture for tumor classification should be selected especially in medical fields. In general, CNN and residual networks showed the best performance and should be chosen when accurate tumor classification is the most important requirement. The potential application of the outcomes of the research can be applied in the field of medicine mainly for the identification, classification, detection, and prediction of various diseases.

Keywords: Deep learning, Brain tumors, MRI images, Classification, Medical diagnostics

1. Introduction

The complexity and potentially life-threatening consequences of brain tumors present significant challenges for medical diagnostics and treatment. Proper classification of brain tumors is essential for developing treatment approaches leading to favorable patient outcomes. Recent advancements in DL have shown promising results in medical image studies, especially in the field of neuro- oncology [1]. An explanation-driven deep learning technique developed to predict tumors in brain with the dataset of MRI image data. It develops the integration of interpretability techniques which shows a transparency and reliability of the model's predictions. This approach leverages CNN which extract features from MRI data, integrated with post-hoc methods like SHAP helps in decision-making process. This idea highlights understanding model predictions for medical trust and decision-making. It executes accurately which is classifying brain tumors and offers interpretable visual and quantitative demonstrations. The results suggest for assisting radiologists in diagnosing treatment for tumor [2].

Detection in brain with MRI images which automatically drives features and segmenting tumors and classify it. In this paper Transfer learning process has leveraged by pre-trained models like VGG, ResNet on huge datasets Kaggle, ImageNet etc. which are efficiently fine-tuned tumor detection datasets for accurate result and improved training time [3]. Drawing on a diverse dataset that includes non-cancerous cases as well as benign and malignant brain tumors of various grades, this study aims to compare the performances of several DL techniques in the classification process. The results of the present study could significantly impact the development of medical diagnostics by promoting earlier detection and treatment of brain tumors and, hence, improving the quality of patient care in neuro-oncology [4]. A method for detecting also classifying tumors in brain with the help of deep learning techniques with Sine-Cosine Fitness Grey Wolf Optimization (SCF-GWO) algorithm. The approach focuses on deep learning models to analyze medical dataset of MRI scans for classifying brain tumors very accurately. The Sine-Cosine Fitness Grey Wolf Optimization is introduces as an efficient technique to enhance the performance of fine-tuning its parameters for enhancing efficiency. This hybrid method achieves optimal accuracy and reliability in detection and classification of tumors [5]. The surveys the application of comparing brain tumors in MRI dataset which is focusing on detection, segmentation, and classification using deep learning methods. It focuses the effectiveness of CNN an7d several deep learning models in enhancing accuracy and efficiency in diagnostic factors. The survey elaborates few architectures like U-Net, ResNet etc. and the performance in handling complex MRI images. Also, the article explores the combined preprocessing techniques with data augmentation to improve robustness in the model. Finally, the idea potentially resolves brain tumor analysis also acknowledges the need for to overcome its existing limitations [6]. It explores ensemble learning techniques for improving the accuracy and robustness in the brain tumor detection using medical imaging especially MRI images. The deep learning models like CNNs are effective and there may be a variability in information in tumor characteristics. This technique combines various models to mitigate weaknesses and improving overall performance of detection. This article uses training dataset with architectures of deep learning and then integrates predictions with various models like voting, averaging etc. This paper focuses on preprocessing to optimize the accuracy. It show the results that the ensemble approach outperforms the existing individual models with respect to accuracy the paper concludes by emphasizing the optimising the ensemble learning for brain tumour detection [7]. RNN algorithms accurately classify the brain tumour using MRI scanned images which involves improvement in deep learning models for optimized detection and classify the kind of tumour with best precision. This idea suggests techniques like transfer learning, where the already pre-trained models are repeatedly fine-tuned on MRI datasets, which enables the architecture to better generalization. This optimized architecture of the neural network works by adjusting parameters like the depth, number of layers, and type of layers. It can significantly improve model performance by integrating the regularization techniques like dropout and batch normalization. In Deep learning, Convolutional Neural Networks (CNN), is majorly implemented for accurate tumor.

The hybrid models which collaborate convolutional neural networks with recurrent neural networks and it transforms various extraction of feature and linear learning models using dynamic MRI scans. Once the hyper parameters learning rates, batch sizes, and activation functions are fine tunned for the outperformance of optimal classification, then enhanced accuracy and efficient classification of brain tumour [8]. A prediction model has focused to detect and classify the brain tumours using medical images of dataset using Convolutional Neural Networks. CNNs effectively drives features extraction from MRI scans. The Performance of this model outperforms well in sensitivity, accuracy, precision, recall, and F1-score for detecting a benign and malignant tumour in brain. The data augmentation also, transfer learning used for improving the data availability and for high generalization. The images are standardized and achieve high level performance using real time images from medial field [9].

A hybridized CNN model suggested for brain tumour image multi-classification, which integrates various deep learning techniques for enhancing the accuracy in classification. This model integrates multiple layers in the models like Dense Net, ResNet which has been used for transfer learning of pre-trained models like VGG16 or InceptionV3. This model implements parametrized feature extraction and easily handle complexity in brain tumour images. The performance is showcased by the metrics of confusion matrices, accuracy rates, and F1-scores and 95% accuracy in classification of Tumour in brain [10].

2. Literature Review

Brain tumors remain a major public health concern worldwide and have devastating effects on patient's health, causing significant morbidity and mortality [11]. Therefore, the diagnosis and classification of brain tumors are crucial for early intervention, selecting optimal treatment plans, and ultimately improving a patient's prognosis [12]. Magnetic Resonance Imaging has become an integral part of brain tumor diagnosis by providing detailed images of the brain anatomy while allowing differentiating between and visualizing tumor characteristics [13]. Thus, MR imaging aids doctors in defining mass size and location, which substantially helps in determining the best course of action. Even though the implementation of MRI is extremely beneficial for the patient's care, the interpretations of the images can be quite difficult and take a lot of time [14]. The time- consuming nature of the process creates a need for an automated classification system to aid in making decisions more efficiently [15].

In Deep learning technique to identify and improves accuracy of tumor detection in brain using MRI images. It uses of Convolutional Neural Networks (CNNs) also transfer learning for comparing MRI images, enabling best effort to classify benign/malignant tumor, also segmentation. This article emphasizes the struggles of manual detection like subjectivity ,time taken which also elaborate in which way the deep learning models including U-Net with VGG, Resnet, focuses challenges and provide optimized solutions [16].

The primary method for diagnosing a brain tumor was the manual evaluation of MR images by radiologists, which is both time-consuming and introduces a certain degree of subjectivity [17]. This becomes an issue since a single expert might interpret the same image differently than another [18]. Thus, automatization of the process would eliminate the inconsistencies in diagnostics and speed up the whole process [19]. DL is a branch of DL that enables computers to learn and analyze complex data representations [20]. One of the most popular architectures is the Convolutional Neural Networks that has been used for image analysis and classification. DL methods have been increasingly employed by researchers over the past few years to automate and improve brain tumor classification from MRI images [21].

Designed with large datasets of labeled MRIs, CNNs can classify distinct tumor classes and grades with high sensitivity and specificity [22]. The works conducted demonstrated impressive classification levels as CNNs outperformed routine DL models and even the mean assessment of human specialists statistically whether or not there was a tumor [23]. Nevertheless, CNNs are not the single DL structure attending to brain tumor classification. VGG, ResNet, and Inception are only some cases [24]. These architectures have features which make them useful for tumor classification tasks [25].

VGGs are recognized by their deep structure and their usage of concise convolutional screens that help them effectively capture intricate features from pictures [26]. Meanwhile, ResNet employs residual connections that help mobile the gradient vanishing effect; thus, enabling the network to go deeper [27]. On the contrary, Inception comes with inception blocks permitting multi-scale feature capturing localized and global information. Several empirical studies were being done to analyze the adaptability of DL models wanting to brain tumor classification. For example, a study compared CNNs, VGGs and ResNets in their performance of glioma subtype classification from MRIs [28]. They discovered that all three models were able to classify glioma subtypes with high accuracy. Similarly, a study tested the classification capacity of Inception V3 in benign and malignant brain tumor classification tasks using MRI [29].

While much has been researched in the field of DL- based brain tumor classification, challenges persist, notably on the interpretability and generalizability of models [30]. Due to the complexity and high dimensionality of medical imaging data, DL models are often considered “black boxes,” limiting our ability to explain why the models made certain predictions]. Furthermore, the performance of DL models can be influenced by the size of the dataset, image acquisition protocols, demographic characteristics of patients, and other factors, suggesting rigorous evaluation and validation are necessary In the future, some possible research direction could be to address the issues raised above, develop localized and adequate DL models that could somehow be interpretable and examine the application of AI- driven methods in clinical practice.

3. Methodology

The MRI scan reports of the brain tumor were thor.oughly collected for this research to create an extensive dataset. A total of 450 image data of the brain tumors were collected which were classified by the severity or type of tumor. This included 250 images of grade 3 and 4 brain tumors which were cancerous and occur when the abnormal cells grow larger and more aggressive and spread quickly.

This included 150 image datasets of grade 3 and 100 image data of grade 4brain tumors. Also, 100 images dataset of grade 1 and 2 brain tumors were collected which were non-cancerous also known as benign and grow slower. The remaining 100 image dataset was of the non-cancerous tissue. The classification mentioned here is essential as it provides a wide range of data to be exposed to the DL model to learn for accurate brain cancer prediction and early detection. The classification is also essential for the treatment plan based on the severity of the cancer. Specifically, grade 1 and 2 are benign while 3 and 4 are malignant. The aggressive nature of grade 3 and the grade 4 tumor means more treatment should be applied. Therefore, having such image datasets would enable the model to examine and predict the image in the future.

In the research study, several DL models were used to predict and analyze the MRI image data of the tumor for its grade. Figure 1 shows the various DL models used and the methodology of the research. These include the CNNs, VGG16, VGG19, Inception V3, and ResNet50. These models have shown better results in the medical domain on the image dataset. The CNN model captured the hierarchical and spatial feature in the image as the foundational architecture. The VGG16 and VGG19 model had deeper architecture to do better feature extraction and achieve better accuracy. Inception V3 had a sophisticated architecture network with efficient computation.

Finally, ResNet50 prevents the vanishing gradient exception in bigger neural networks so that we can go deeper without the loss of their performance. The implementation of the model involved various stages such as data preprocessing to make data more normalized and augmentation to maximize the quality and variance in the image dataset. These images were then trained and validated, where the high grade was learned manually by the model. Validation involved examining the model to ensure generalization of the data unseen during training. Finally, we evaluated the model performance based on the accuracy, sensitivity, recall, and F1-Score. The purpose of this study is to predict the brain tumor’s grade and to assist early detection.

Early detection is required for high-grade treatment to enhance outcomes since early detection increases esthetic and functional rehab chances.

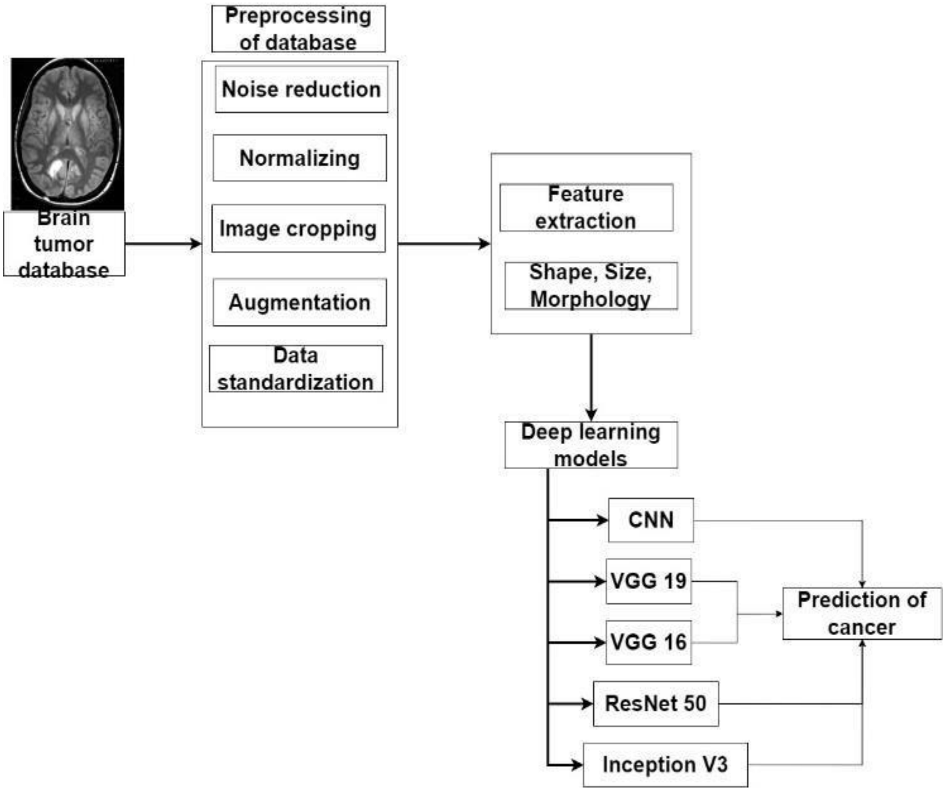

Figure 1. Methodology of the research

4. Deep Learning Models

In this study, Convolutional Neural Networks (CNNs) are used as the foundational DL models to extract features from MRI images. CNNs are perfectly suited to image data because they have a natural hierarchical architecture that captures spatial hierarchies. Convolutional layers use filters to detect local patterns such as edges and textures, which are then combined by subsequent layers to create more complex representations. Pooling layers, such as max pooling, reduce computational complexity while retaining essential information. Activation functions like ReLU introduce non- linearity for intricate pattern learning. A hierarchical architecture like CNNs allows for effective distinction between benign and malignant brain tumors as well as identification of tumor grades.

VGG16 and VGG19 are more advanced CNNs that extend these principles to even higher depths. VGG models developed by the Visual Geometry Group at the University of Oxford have a deep network using small convolutional filters. With 16 and 19 layers, VGG16 and VGG19 incorporate many more convolutional layers to capture even higher levels of representations in the input images. This feature allows for more subtle distinctions between different tumor classes. Inception V3 introduces the Inception module to increase feature extraction efficiency. The Inception block empowers the model to process a variety of filter scales in each layer of the neural network.Inception V3 is a comprehensive multi-scale model that is effective for the multi-class problem, allowing for both fine detail and broad image context. Therefore, Inception V3 is appropriate for medical problems such as brain tumor grading.

ResNet50 uses a new learning mechanism known as residual learning to train very deep networks. Shortcut connections, also known as identity skip connections, assist the network in overcoming the vanishing gradient problem. This model can capture highly intricate patterns in one image and subtle distinctions between another images. It can reliably distinguish between non-cancerous tissues and different grades of cancerous tumors. ResNet50's feature map output is always deeper than the input, thanks to the residual learning technique.

5. Preprocessing Of Dataset

Preprocessing of the dataset is a significant task required to be performed as part of any DL model to succeed and especially in the field of medical imaging, organized data's quality and coherence can directly affect the model's performance. In the current context, the MRI scan reports of brain tumors are preprocessed, as per selected steps, before used for training and validation purpose to apply DL models. The dataset of 450 MRI images is first cleaned, corrupted images or images of low quality which could not bring precise outcome are cleaned. This step is crucial as noisy or blurred images may extract incorrect features which result in lower model accuracy. Image normalization is performed on dataset post-cleaning. Normalization is a standard technique used to scale the pixel values of images to a specific range, usually 0 to 1. This normalization step is required for the intensity values to be common as well as for the neural networks to perform better.

The model without normalization will be sensitive to pixel value variation which causes unstable training and a bad outcome for new images. Lastly, the dataset is resized to fit all images. In this study, all the MRI images are resized to a common dimension and it is compatible with the input size of models like VGG16, VGG19, Inception-V3, and ResNet50. Standardizing is necessary while training as the DL models are designed with a fixed input size and if its differs the model will throw an error.

Finally, the data was also preprocessed through data augmentation which involves generating new training samples from the existing data by applying various transformations such as rotations, translations, flipping, and zooming. In the context of medical imaging, data augmentation is especially important because obtaining a large dataset is difficult due to the high cost and time associated with collecting images. As a result, data augmentation effectively increased the size of the training data, which reduces the chances of overfitting and enables the model to better generalize to unseen data. It also provides the model with additional images to learn the features from; for example, an MRI image rotated by a few degrees or flipped horizontally still maintains the same structure of the tumor. Image segmentation was performed next to highlight the regions of interest in the MRI scans, which in this context would be the delineation of tumors. This can be done manually by experts or automatically using image segmentation techniques.

In practice, however, a mix of both is done to achieve optimal high accuracy and speed. Since this is a pre- processing step, it is vital as it allows the model to identify the most essential parts on the images. This makes it easy for the model to identify the different tumor grades and their determining attributes. Intensity normalization was also performed to adjust the images' brightness and contrasts. In MRI images, this normalization is vital because different images acquired under varying scanning protocols have varying intensities due to machine calibration, among other factors. This process ensures the images have uniform brightness and contrast to enable the model to identify the structural differences between the tumors.

Another primary step in the preprocessing steps was the reduction of noise. Since medical images are usually subject to patterns of artifacts or random variations, the neural network could not accurately identify the features. Noise reduction was diminished by using Gaussian blurring and median filtering techniques for MRI imaging. This factor helped to smooth the images and eliminate the influence of random variations, which could potentially interfere with the learning process since all of the images are supposed to be of the same dataset. Stratified sampling was used during the training and validation split to ensure that the dataset is balanced. Training datasets were representative of the population. Moreover, the dataset was divided into training, validation, and test datasets. It is typically 70% for training and 15% each for validation and testing. The training set was used for training, the validation set was for fine-tuning the model to optimize parameters and prevent overfitting, while the testing set was completely unseen.

6. Feature Extraction

Feature extraction from medical images, especially MRI scans, is the first crucial step towards identifying its cancerous and non-cancerous condition and further classifying it into different grades. To enable automatic

Feature extraction, learning, and classification, advanced DL models have been implemented in this study. Convolutional neural networks have used to extract relevant features from images. These models are well-suited for analyzing images as they can automatically learn hierarchical features from raw pixel data512. The CNN starts with the convolutional layers that consist of a set of filters applied to the input image. When passed over an image, these filters called kernels perform the convolution operation and detect the spatial patterns of the input image1. Activation maps of early CNN layers detect basic patterns such as edges and corners, whereas later layers detect more abstract shapes or structures and high-level semantic information on tumors. VGG16 and VGG19 are two other CNN models that have been used for feature learning in addition to the basic CNN models. VGG16 and VGG19 CNN architecture have more convolutional layers making the feature map more detailed, which can capture more abstract means. The first model also reduces computational and memory usage because it is provided with small size filters.

Another architecture used in this study, Inception V3, was developed to synergize with the concept of Inception modules. The Inception architecture applies multiple convolutional operations with different filter sizes in parallel. Thus, the network can capture features at varied scales and acquire a richer representation of the input images. Since filters of different sizes assist the network in identifying both finer details and broader context, it can effectively distinguish between types of healthy and unhealthy tissues, which is crucial for classifying benign and malignant tumors. The third model, ResNet50, is famously built on the residual learning framework. One of ResNet's novelties was the use of shortcut connections, which allow gradients to pass the entire network with minimal resistance during the training phase. ResNet50 is a deeply layered network with identity mappings, and its depth enables learning of representations that are more complex than the other two networks. This complexity is crucial for recognizing subtle differences between various grades of the same class of cancer. Feature extraction with the models involves subsequent stages of pooling and application of activation functions. Pooling, such as max pooling, reduces the spatial dimension of the feature maps, preserving the most essential information required while reducing the computation required. Activation functions such as ReLU generate non-linearly to enable the model to recognize non-linear patterns. Thus, they facilitate feature extraction for smaller, but still informative feature sets.

After the features are extracted, they are flattened into a one-dimensional vector and then fed into fully connected layers for classification. These convolutional neural network layers are the final stage in which the network combines the learned features to make predictions about the existence and grade of the tumor. They use softmax activation on the last layer to output a probability distribution in the possible classes: non-cancerous, grade 1, grade 2, grade 3, or grade 4. Feature extraction is further enhanced through techniques like transfer learning and fine-tuning. Transfer learning utilizes a pre-trained model on a large dataset such as ImageNet as an initial point before finetuning it on the MRI dataset. This is based on the concept that these large models or DL models, learn rich feature representations after being trained on a vast amount of data. This technology builds a solid baseline feature extraction that has been adapted to the particular task of brain tumor classification.

7. Result and Discussion

The effectiveness of various deep learning models was assessed using the Brain MRI Tumor Dataset, which comprised 450 MRI scans obtained from [source, e.g., Kaggle's Brain MRI dataset, 2023]. This dataset included images categorized into three groups: individuals without any health issues, benign tumors classified as grade 1 and 2, and malignant tumors classified as grade 3 and 4. The dataset was split into training (60%), validation (20%), and testing (20%) sets to support model training and assessment. Preprocessing steps involved resizing the images to 224x224 pixels and normalizing them to [mean and standard deviation]. To improve the model's ability to generalize and reduce the risk of overfitting, data augmentation techniques such as rotation, flipping, and random cropping were utilized during the training phase. The models were then assessed using the test set, with performance metrics compiled to illustrate the comparative effectiveness of the different architectures.

After training the models, they were thoroughly evaluated using the test dataset to determine their ability to predict the presence and the grade of brain tumors accurately as shown in figure 2. The CNN model achieved the highest accuracy of 97.88% thanks to its exceptional capability to identify essential features and spatial hierarchies in MRI images, leading to precise classification. The VGG16 model also performed notably well, reaching an accuracy of 95.6% because of its increased depth, which enables it to extract more detailed features. ResNet50, designed as a deep network with residual learning, attained an accuracy of 93.4%. Its enhanced depth and ability to combat the vanishing gradient issue allow the model to learn complex patterns effectively. VGG19, which has a slightly deeper structure compared to VGG16, recorded an accuracy of 91.23%. The performance could be hindered by the addition of layers, which adds complexity and impacts overall effectiveness. Inception V3 demonstrated adequate performance with an accuracy of 88.98%. Its distinctive architecture enables it to capture features at multiple scales but sacrifices some detailed information.

Figure 3 represents the value of the performance scores, which include precision, recall, and F1 score for the DL models in the study. Precision refers to the proportion of true positive predictions among all positive predictions that the model made. Recall, also referred to as sensitivity, and refers to the proportion of true positive models among all positive occurrences that exist in the dataset. However, the F1 score measures the harmonic mean between precision and recall in precision. As such, the F1 score is a balanced measure of the model's accuracy since it considers both false positives and false negatives. The Convolutional Neural Network exhibited high performance in all the models, with a precision of 97.8%, recall of 96.9% and F1 score of 97.35%. Thus, the model has a high degree of capturing and classifying accurate brain tumors since the measures for precision and recall were close. The VGG16 model also had slightly high values, with a precision of 95.2%, recall of 94.8%, and an F1 score of 95.0. Therefore, the model could capture the true instances of the brain tumor well, but its values were slightly low in precision and recall as comparison to the CNN model. The ResNet50 model was also high in performance since it had a precision, recall, and an F1 score of 93.7%, 92.3%, and 93.0%, respectively. One of the last well performing models was the VGG19 and Inception V3 models, which had precision, recall, and an F1 score of between 88.6 and 91.3. The two models had slightly low values as compared to the CNN, VGG16, and ResNet50. Therefore, the best model was CNN with high values across the metric. The confusion matrices presented in figure 4 shows a thorough, easy-to-read depiction of how each model's predictions performed for varying grades of tumors.

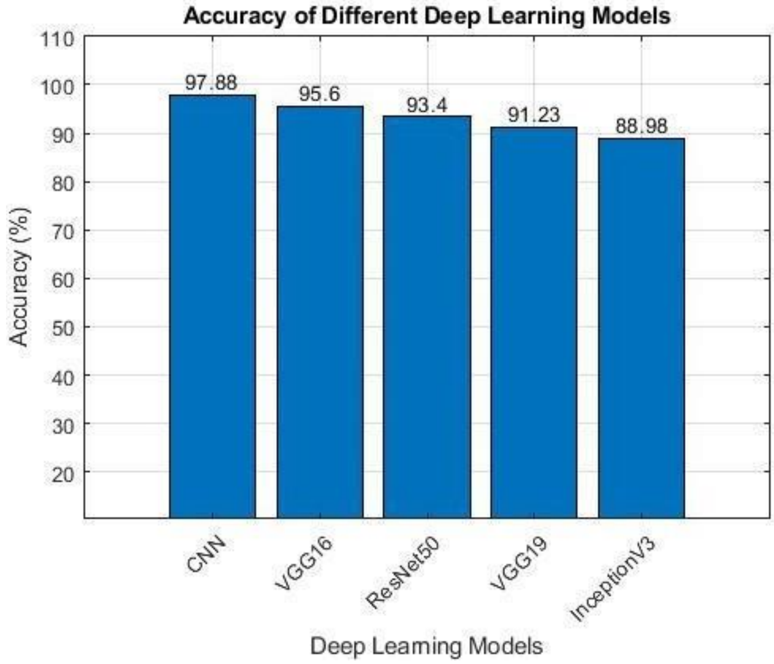

Figure 2. Accuracy of each model

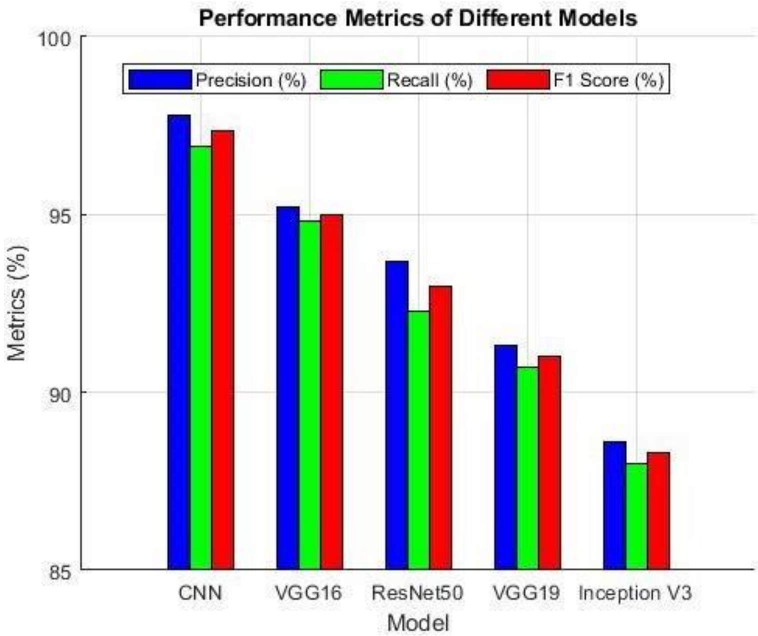

Figure 3. Performance score of each model

The Convolutional Neural Network displays excellent accuracy, as evidenced by the confusion matrix for this model. Specifically, out of 450 instances, 110 non-cancerous cases were correctly predicted, as were 95 cases of grade 1 and 2 tumors and 149 cases of grade 3 and 4 of tumors. In addition, only a few wrong classification errors are made, including 2 grade 1 and 2 tumors predicted as non-cancerous and 1 grade 3 and 4 tumors; and 1 wrong prediction for grade 3 and 4 tumors. Therefore, this model demonstrates a high level of performance. VGG16 ranks a close second to the first CNN model, as indicated by the confusion matrix. VGG16 identifies 108 non-cancerous cases, 91 cases of grade 1 and 2 tumors, and 148 cases of grade 3 and 4 tumors. Although the error measurements are marginally greater than those aggregated for the CNN dataset, this model demonstrates a strong level of accuracy. ResNet50 represents another high- performing model, as demonstrated by the confusion matrix. ResNet50 predicts 107 non-cancerous cases, 92 cases of grade 1 and 2 tumors, and 148 cases of grade 3 and 4 of tumors. Indeed, the model demonstrates accuracy, with only 3 non-cancerous cases predicted incorrectly. Additionally, VGG19 and Inception V3 display respectable levels of accuracy; while the accuracy measurable is lower, the mean grouping remains the same.

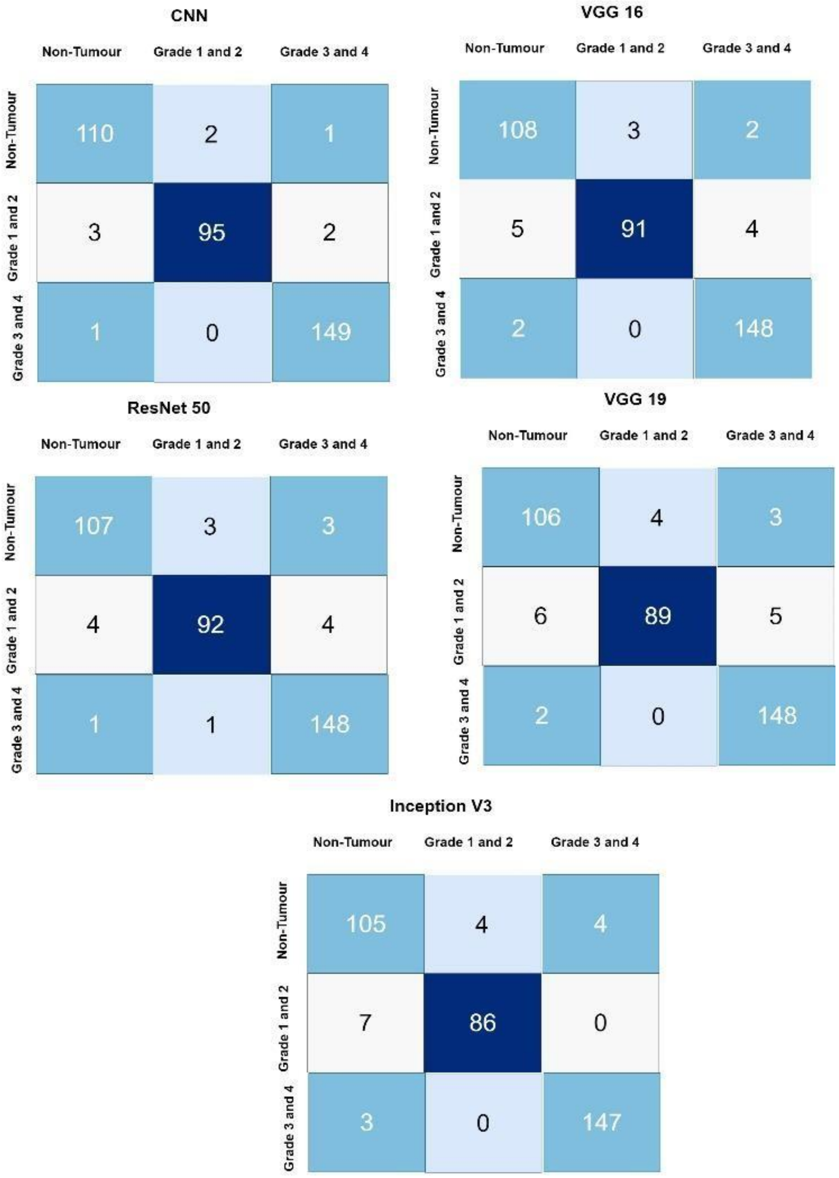

Figure 4. Confusion matrices of each model

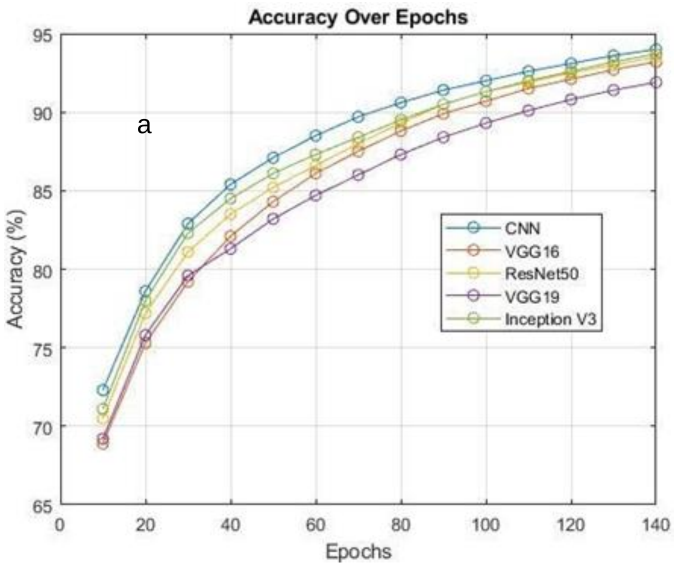

Figure 5. Accuracy of each model Vs Epoch

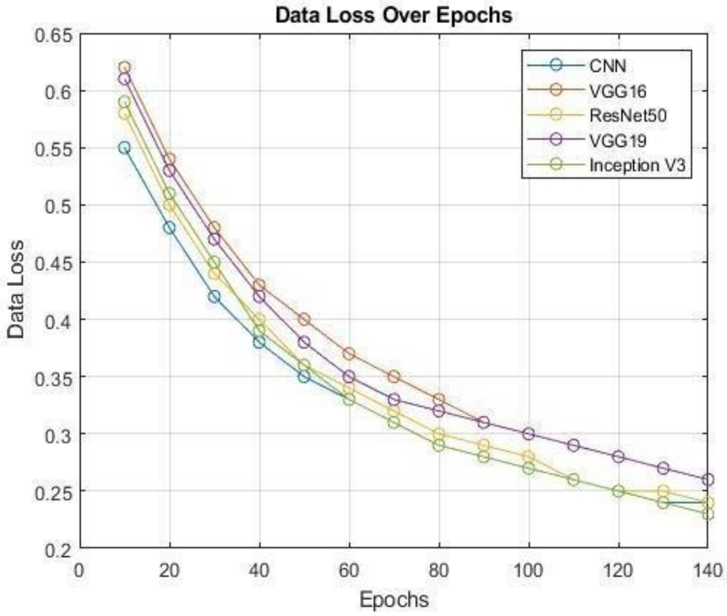

Figure 6. Data loss of each model vs Epoch

Figure 5 and 6 represents the data loss and accuracy of the five DL models, CNN, VGG16, ResNet50, VGG19, and Inception V3, at multiple epochs during the training. Each row represents a different epoch, ranging between epoch 10 and 140, with 10 epoch increments. The results include data loss, which measures the error or the difference between the model's prediction and the actual label as regarded from the training dataset. Accuracy refers to the proportion of estimates that are correctly classified: as the training progresses, data loss decreases, which means that the models learn to make better predictions as time goes by. At the same time, accuracy increases as the models get better at classifying which class an instance belongs to. However, each model's performance varies between the same epoch numbers, with some models showing more substantial change. The CNN and ResNet50 accuracies remain high and show constant decrease in data loss at all epochs. While VGG16, VGG19 and Inception V3 demonstrate good performance, they take more epochs to get to the same accuracy levels.

8. Conclusion

The application of advanced DL models, including CNNs, VGG16, VGG19, Inception V3, and ResNet50, exhibit considerable potential for brain tumor classification using MRI images. Multiple experiments and evaluations show that these models allow to extract particular features or provide superiority by classifying them. CNNs serve as the foundation for hierarchical feature detection and identification and contribute to the robust ability to distinguish cancerous tissue from benign tissue and different tumor grades. The VGG16 and VGG19 architecture have further excelled by designing even deeper networks with reduced convolutions and isolating seven features, which leads to extreme feature extraction. Multi-scale feature extraction has been a significant advantage of Inception V3, allowing fine-grained localization and high contextual information at the same moment. The insertion of residual learning in ResNet50 has, therefore, solved the degradation problem by constructing very deep networks, focusing on intricate patterns needed for exact tumor identification. Overall, the present results indeed show that these DL models can automate and improve brain tumor classification. It can also contribute to the establishment of a new way of improving neuro-oncological diagnosis, treatment planning, and results.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

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