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Automated Brain Tumor Detection via Transfer Learning Techniques

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Abstract: Brain tumors disrupt the regular operation of the brain, and if left untreated, these malignant cells can impact the adjacent tissues, blood vessels, and nerves. Moreover, it affects a large number of individuals worldwide and can result in substantial damage. Thus, it is crucial to understand that brain tumors are a severe medical disease that demands appropriate medical attention. Tumors are the primary cause of a significant number of deaths in modern times. They damage the brain, leading to severe mental as well as physical problems. Detecting brain tumors manually is a difficult task because of variations in their appearance, such as differences in shape, size, and nucleus. Consequently, there is a need for an automated approach to detect brain tumors at an early stage. This paper presents a study on detecting brain tumors utilizing a "Convolutional Neural Network (CNN)" with the "Adaptive Moment Estimation (ADAM): optimization algorithm. Using transfer learning, the researchers built a base model in CNN and combined it with "RESNET-152", MobileNet, and Densenet-121. The classification of brain tumors as either tumors or non-tumors was performed and evaluated on a public Kaggle brain-tumor dataset. The results showed that the proposed model achieved 98.7% accuracy and 99.8% AUC for Resnet, 96.5% accuracy and 98.6% AUC for Dense Net, and 87.2% accuracy and 98.7% AUC for MobileNet, respectively. The data indicate that using the RESNET-152 model produced better results than other baseline approaches. This suggests applying the model to additional disorders and its clinical utility in routine practice.

Keywords: Brain Tumor; Deep Learning; Transfer Learning; CNN; Medical Imaging.

1. Introduction

The brain is one of the most complex and vital parts of the human body, which controls all the actions and the main nervous system of the body. When cells in the brain grow uncontrolled and irregularly, it causes brain tumors [1]. It causes pressure in the skull, which initiates disruption of the brain's normal operation. Brain tumors are divided into two categories: benign (non-cancerous) and malignant (cancerous). When compared to benign tumors, malignant ones grow in the brain far more quickly, damaging normal tissues in the process. Additionally, they have the potential to spread to other parts of the body, which is how cancer spreads [2]. In cancers, it has the world's highest mortality rates in both adults and children [3].

The brain tumor's creation or origin, as well as its rate of growth, are unknown. While secondary brain tumors start elsewhere in the body and move through blood flow to the brain, primary brain tumors form in the tissues of the brain. Glioma, pituitary, and meningioma are the most dangerous types of primary brain tumors [4]. Glioma is one of the main brain tumors (only Grade I, out of Grades I to IV, is benign; 80% of brain tumors are malignant) [5]. For early detection and treatment, one of the most difficult types to identify by the physician is Meningioma and pituitary. Among the various types, glioma is the most common, beginning in the brain's glial cells. Meningioma is generally benign [5]and begins inside the membrane of the skull, which envelops the brain and spinal cord. The pituitary gland, which is primarily responsible for regulating the body's hormone levels, is primarily linked to pituitary tumors. It can cause both benign and malignant conditions, and among other issues, its disruption may cause visual disturbances. Four distinct grade categories are used to categorize brain tumors:

A) These take time to develop and disseminate. These can be virtually completely removed surgically and are associated with an increased likelihood of enhanced order. The pilocytic astrocytoma is one instance of this type of tumor. B) These tumors grow over time and can spread to higher grades and migrate surrounding tissues. One type of tumor that grows over time is an oligodendroglioma. C) Compared to Grade II malignant tumors, these tumors have a far faster growth rate and the capacity to spread to nearby tissues. Surgery alone is not enough to treat these tumors; post-operative chemotherapy or radiation therapy is necessary. Adenosquamous astrocytoma is one such tumor. D) These are among the most harmful and prone to proliferate. This category includes malignant tumors. They may even accelerate their growth by using blood vessels. Glioblastoma multiforme is one of these tumors, for instance [6], [7].

One of the most critical steps in saving a patient's life lies in the early detection of the tumor and further classification of the tumor with high diagnosis detection. The most laborious task for doctors and radiologists is to analyze the MRI image manually to detect and localize the tumors from the normal ones and to identify their type [1]. One of the most common techniques of identifying brain tumors, which is non-invasive and also preferred by radiologists for scanning, is MRI, while a CT scan makes it difficult to identify the structural changes happening [5].

Among the leading cause of deaths, the number of brain tumors related deaths is far too high and thus, better diagnosis and treatment cannot be stressed enough [3]. Yet manual interpretation of MRI images as a rule is the main way used in the clinical decision on brain tumors, however this meticulous process is replete with mistakes, so the best cost-effective solution would be to include the computer-aided support to the analyst. Machine learning algorithms, especially, those based on convolutional neural networks (CNNs), appears profitable for improvements in the diagnoses results and make not only the classifications faster but more accurate.[8]

Brain tumors are a major global health problem, with an estimated 308,000 new primary brain and central nervous system (CNS) tumors diagnosed each year. Incidence rates vary by region, age group, and sex, with developed countries generally reporting higher rates due to better diagnostic facilities and greater access to health care. In the United States, for example, the annual incidence is about 6.4 per 100,000 population. Europe also sees slightly higher rates, while areas in Africa and Asia report lower rates, possibly due to under-reporting and lack of diagnostic systems.

The most common types of brain tumors in adults are gliomas, including glioblastomas, which are highly aggressive and account for a large proportion of brain tumors.

The prevalence of brain tumors reflects the number of people living with the disease at any given time. Advances in medical technology and treatment have improved survival rates, contributing to population growth. In children, brain tumors are the second most common cancer, after leukemia, and represent the leading cause of cancer-related death in the pediatric population. Worldwide, brain tumors account for approximately 2% of all cancers, but because of their complexity and location, they have a disproportionate impact on health and quality of life. Ongoing research and improved treatment strategies are needed to address this important health challenge, as early detection and effective treatment are critical to improving outcomes for those with brain affected by the ulcers

Machine learning is the process of extracting knowledge from data that is available. It is an intersection of statistics, artificial intelligence, and computer science and is also a research field. The applications of machine learning have become very vast in recent years, with applications ranging from the recommendation of movies to categorizing pictures, and much more [8]. The main aim of ML is to construct a software program that can learn and adapt accordingly without the hassle of pre-programming a system and how it will behave according to different scenarios. These can automatically learn from any mistake they may have made [9]. Neural networks are widespread across many industries and encompass wide areas of study, which include healthcare, NLP (Natural Language Processing), cybersecurity, and much more. In ANN (Artificial Neural Network), small neurons (processing units) that are connected together make up the backbone of a neural network. These neurons produce activated values which make it possible for us to achieve our desired result [10]. CNNs (convolution neural networks) are multiple-layered neural networks that are connected together. Little bits of the image are fed into the lowest layer of the CNN structure as input. Information is derived from several layers, each of which carries out a specific task to produce the notable characteristics of the data that are seen. This technique gives the neuron or processing unit access to fundamental elements like corners, edges, and lines [11]. To make tasks easier transfer learning is adopted. It's a method that applies the knowledge of a trained model to learn on a different data set. Different transfer learning environments are used based on the issue at hand and the available data [12].

Formulating and programming of the convolutional neural network (CNN) model which would be optimal for brain tumor diagnostics. Application of transfer learning strategies while training the neural networks, so as to speed up the learning process. Performing in-depth performance evaluation researches for the error ratios and reliability determining between proposed model and the manual diagnosis of the professionals. Assessing the possible indications for clinical use and bringing the model into practical settings for enhancing patient management and ultimate outcomes.

2. Related work

This section will highlight different algorithms for detecting brain tumors using algorithms for both machine learning and deep learning, which is a field of continuing research. Many studies have already been completed in this area, and researchers are still working to advance the field's progress.

Almadhoun et al [13] proposed a deep model for detecting brain tumors utilizing an MRI dataset. Additionally, they also implemented four different transfer learning models, namely VGG (Visual Geometry Group)16, MobileNet, ResNet-50, and Inception V3.10,000 MR images with a 200 × 200-pixel resolution were used as the dataset. With 5000 photos of brain tumors and 5000 images of non-brain tumors, the dataset was split into two categories. The deep educational model that they suggested performed better; it had a 100% training accuracy and a 98% test accuracy.

Garg et al. [14] proposed detecting brain tumors using various machine learning models, including naive Bayes, "Random Forest (RF)", "Neural Network (NN)", "KNN", and "Decision Tree (DT)" algorithms. They also utilized a hybrid ensemble classifier combining KNN, random forest, and decision tree "(KNN-RF-DT)". To evaluate their models, they split a dataset of 2556 brain tumor images into 85% for training and 15% for testing. Feature extraction techniques like GLCM, PCA, and SWT identified thirteen features for the classification process. The proposed method achieved an accuracy of 97.305%, a precision of 97.73%, and a reliability score of 97.41% in detecting and classifying brain tumors.

Sajid et al [15] developed a hybrid CNN model that used the "BRATS MR images" to identify brain tumors. Two phases—the training method and advanced regularization techniques—were subjected to analysis and validation. In addition to combining two- and three-path networks, their proposed hybrid model improved its performance. The analysis of the CNNs suggests that it can be useful for various segmentation tasks and that further training could lead to much better performance. Examining further revealed that their specificity was 91%, their sensitivity was 86%, and their Dice score was 86%.

Lotlikar et al. [16] proposed a classifier utilizing KNN with additional classifiers like RF, NB, and RBF, which were also considered for their research. After the evaluation of the models that they selected, 95.6% accuracy was achieved, and 99% AUC was achieved for their KNN classifier. They would require many brain images to improve the results of their ongoing research.

Irfan et al [16] utilized super-resolution (SR) to locate the brain tumors, a problem that had proven difficult for many years. The super-resolution technique improves the quality of the images. Tumors in the images will show up more through the borders, and after the algorithm processed the tumors, it was much easier to identify them. They suggested combining machine learning algorithms with fuzzy c-means clustering and super-resolution. When DICOT format MRI images were used, the model achieved an accuracy of 98.33%, which was significantly higher than expected.

"Musallam et al [17] suggested using CNN-SVM, VGG16, VGG19, and Deep Convolutional Neural Network (DCNN) to identify brain tumors. 3394 MRI images were utilized in which their proposed Deep convolutional neural network achieved 97.72% accuracy. Wozniak et al [18] suggested using CNN as a correlation learning mechanism (CLM). Using 3064 CT scan images, their suggested CLM model produced an accuracy of 96%, 95% precision, and 95% recall."

"Aamir et al [19] suggested an automated technique that uses MR images to identify brain tumors. After testing, the ML model they suggested outperformed the previous methods regarding classification performance, exhibiting a 98.95% accuracy rate."

"Mittal et al [20] employed a GCNN (Growing CNN) in conjunction with the SWT (Stationary Wavelet Transform) to automate the segmentation process. These techniques worked well for them in identifying brain tumors. The outcomes demonstrated that, compared to other algorithms such as K-NN, SVM, and CNN, the accuracy was the highest."

"Kermi et al. [22] provided an automatic technique of tumor segmentation using the DNNS (Deep Convolutional Neural Networks). The network design was upgraded using the Generalized Dice Loss function to improve the efficiency of the brain tumor segmentation process."

"Mahmud et al. [23] proposed a CNN model while discussing other available models like Resnet-50, VGG-16, and Inception-V6 for the early detection of brain tumors using MRI images. Different models' performance was analyzed using different metrics like accuracy, recall, and loss. A dataset of 3264 MRI images was used and their proposed CNN model performed better than other models with an accuracy of 93.3% and a loss of 0.25."

"Soheila et al. [24] proposed a 2D CNN and an Auto-encoder network to identify brain tumors. A dataset of 3264 MRI images was utilized. With a kernel size 2*2, the 2D CNN employed multiple layers, including four pooling layers, eight convolution layers, and batch normalization after each convolution layer. The suggested auto-encoder achieved an accuracy of 95.6%, while the suggested 2D CNN achieved an accuracy of 96.4%."

"Obeidavi et al [21] proposed a CNN model based on residual Networks for early detection. A dataset of 2000 MRI images from BRATS 2015 was utilized. The result of their algorithm showed an accuracy of 97.05%. Other metrics also achieved exceptional results of 97.05% mean accuracy and a global accuracy of 94.4%. To achieve this improved performance, 100 epochs were utilized.

"Amin et al [22] proposed a method using ensemble transfer learning and QVR (Quantum Variational Classifiers) to detect brain tumors. For feature extraction, Inception v3 which used SoftMax was used. The new model was applied to different datasets such as BRATS-2020, a local image, and data from Kaggle. Their proposed model achieved an accuracy of 90%."

"Qureshi et al [5] proposed the "UL-BTD (Ultra-light brain tumor detection)" system for brain tumor detection. Its foundation is the more recent light curriculum. Features are extracted from the grey-level matrix. It developed a hybrid feature space using SVM for brain tumor detection. The proposed algorithm was applied on "T1-weighted MRI". it achieved a detection accuracy of 99.23% and a 99% F1 score."

"Senan et al [23] proposed a system for brain tumor detection. It blended deep learning and machine learning techniques. Tumor detection and classification are performed through RESNET-18, Alexnet, and SVM (assisted vector machines). After this extraction, the features are classified using SoftMax and SVM. When applied to an MRI dataset of 3060 images, both SVM and Alexnet demonstrated an accuracy of 95.10 percent."

"Alsaif and colleagues [24] proposed a model that incorporates features from other models, such as VGG, ResNet, and AlexNet. This was based on MRI dataset and methods for data augmentation using CNN. According to the results, the VGG model achieved a high accuracy of 93%.

Khan et al [25] [38]proposed a model to classify brain tumors MRI images using VGG16 and K-Means clustering. First, the MRI images were sliced, and then statistical normalization was used for preprocessing. This model achieved 94% accuracy."

"Grampurohit et al [26] proposed a model to classify tumor MRI using CNN and VGGNET. The dataset contained 253 MRI images. The overfitting problem was tackled using data augmentation and preprocessing techniques. The proposed CNN model showed a validation accuracy of 86% and VGGNet showed 97% accuracy."

Majib et al [27] proposed a method combining "VGGNET" with a stacked classifier. It facilitated faster and more effective training to automatically identify brain tumors from MRI images. The Vgg-16 fine-tuned model was used with additional layers. Imbalances in the MRI images were removed using different augmentation techniques. The tumor detection was achieved by using a layered classifier.99.2% precision was achieved using this method.

3. Materials and Methods

In our proposed study, CNN (Convolutional Neural Network), a supervised machine learning algorithm, was used for model training in combination with other transfer learning techniques to conduct this proposed research work. 4600 images were first used to train our base CNN model, which was then joined with other available models consisting of ResNet152, DenseNet121, and MobileNet.

3.1. Dataset

The brain tumor dataset used in this Research was taken from the Kaggle library [28] [34]. It was divided into two classes: tumor and healthy. A total of 4,600 images were taken, of which 55% were images of brains with tumors and 45% were images of healthy brains. The dataset was divided into three parts: 70% data for training, 15% data for validation process, and 15% data for testing. Before using the images, they were first preprocessed [35]. Performed preprocessing methods such as zoom range, shear range, horizontal flip, and resize. For each model, the preprocessing remained the same except for the transfer learning part, where preprocessing functions appropriate to the requirements of the model were used.

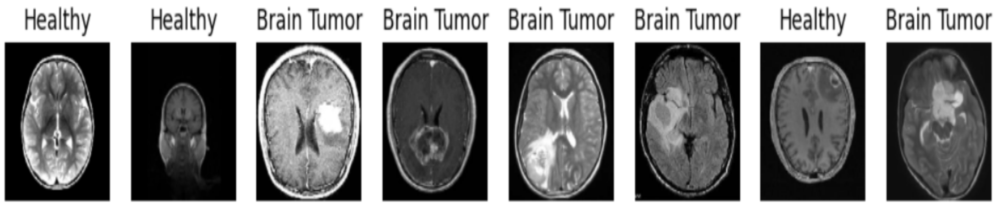

Figure 1. Dataset Labeling

3.2. Transfer Learning

However, along with the base CNN model, we also implement ResNet152, DenseNet121, and MobileNet through transfer learning. Transfer learning is a process by which knowledge gained from a pre-trained model can be used and applied to a specific task: brain tumor detection. We continuously adjusted the model architecture of each transfer learning model, kept certain layers fixed, and experimented with different approaches to removing and adding different layers to determine the most appropriate model settings. The output layer of the untrained model was concatenated with the peak CNN, and subsequent convolutional and dense layers were added for feature extraction and detection.

3.3 Proposed Architecture

We developed a basic CNN model tailored to process input images of 256x256 pixels. The architecture featured several convolutional blocks, each followed by a MaxPool2D layer to reduce dimensionality. Dropout regularization with a factor of 0.6 was applied after each convolutional layer to mitigate overfitting. The top layer comprised a fully connected dense layer with an appropriate number of units and an activation function, culminating in a sigmoid function for binary classification.

Initially, the input image of 256x256 pixels was fed into the first CNN layer, which had 256 filters with a 3x3 kernel size, followed by MaxPool2D for size reduction. Subsequently, it was passed through another convolutional layer with 128 filters and a 3x3 kernel size, then again to a MaxPool2D layer for further size reduction. This process continued with another convolutional layer with 64 filters and a 3x3 kernel size, followed by MaxPool2D. After these layers, a dropout of 0.6 was applied before smoothing the output. The output was then passed to a fully connected dense layer with 64 units, with another dropout of 0.6. The final dense layer contained one unit and used a sigmoid activation function.

We then ran several tests using different filter sizes while keeping the layer density the same, using ADAM as the default optimizer. Various filter sizes included 16,16+32,16+32+64,16+32+64+128 and 16+32+64+128+256. Hyper-parameter tuning was then performed to obtain the required results. The best results were obtained using the Adam optimizer, learning rate 0.001, and batch size 32, and 100 epochs.

Binary cross-entropy was used to calculate the loss values. After successfully training and evaluating the base model, we moved on to the next step. That is, using transfer learning to integrate the base model with a Pretrained model. We experimented with fine-tuning the transfer learning model by freezing and thawing different layers to choose the best layer for the task. Each model was trained for 100 epochs using the same optimizer, learning rate, and loss function.

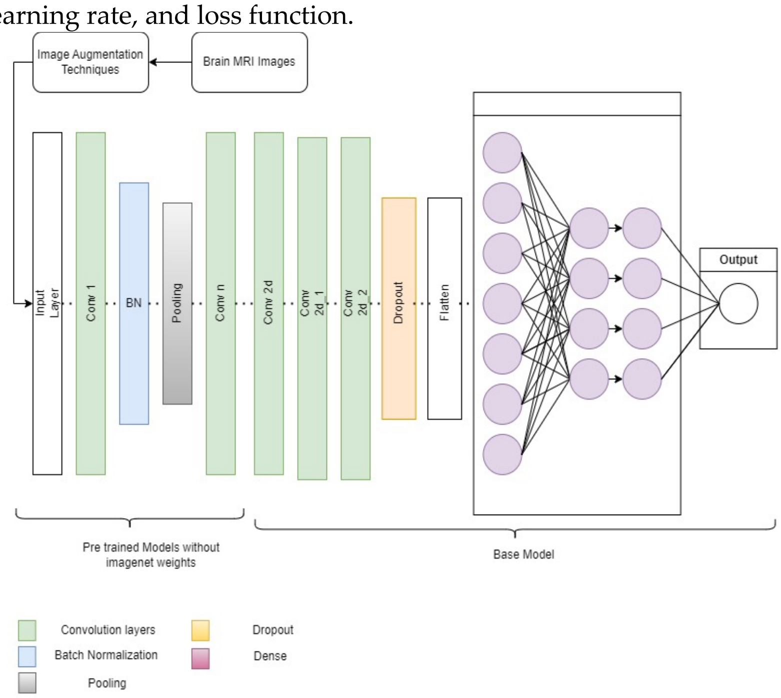

Figure 2. Proposed Architecture

The first transfer learning model utilized the ResNet152 CNN model while freezing its layers until conv5_block1_1_conv and unfreezing all the layers till conv5_block3_out. The default image net weights were not used, the top was not included, and the image input size was 256x256x3. As an output layer, we used our CNN with three convolutional layers, each with 256, 128, and 64 filters. Then we utilized a dropout layer with a rate of 0.6 and added a dense layer with 64 units and RELU activation. A dropout layer with a rate of 0.6 was again utilized, and a last dense layer with 1 unit utilized the sigmoid activation function.

The second transfer learning model utilized the DenseNet121 CNN architecture while freezing its layers until conv5_block1_0_bn and unfreezing them until RELU. The default ImageNet weights, top was discarded and similarly the image input size was confined to 256x256x3. A CNN with three layers containing 256,128, and 64 filters were used respectively as an output layer. Similarly, a dropout layer with a rate of 0.6 was included before a dense layer containing 64 units and ReLU activation. Another dropout with a similar rate of 0.6 was again utilized before adding the last dense layer with 1 unit utilizing the sigmoid activation function.

MobileNet CNN architecture was utilized as the third transfer learning model. The initial layers were frozen till conv_dw_10 and the others were unfrozen. The default ImageNet weights, top was discarded and similarly the image input size was confined to 256x256x3. A CNN with three layers containing 256,128, and 64 filters were used respectively as an output layer. Similarly, a dropout layer with a rate of 0.6 was included before a dense layer containing 64 units and ReLU activation. Another dropout with a similar rate of 0.6 was again utilized before adding the last dense layer with 1 unit utilizing the sigmoid activation function.

3.4. Experimental Settings

Table 1. Hyperparameters

Hyperparameters	**Configuration**
Optimizer	ADAM
Number of epochs	100
Learning rate	0.001
Input size	256*256*3
Batch size	32
Dropout	0.6
Activation function	Sigmoid

For our base model, a series of multiple tests were performed using multiple optimizers, which included SGD, ADADELTA, ADAGRAD, ADAM, and RMSPROP. We used the same experimental settings in all models, which included the ADAM optimizer, a learning rate of 0.001, and a dropout rate of 0.6. The size of the input remained identical, i.e., 256x256x3, and the batch size was 32. The sigmoid activation function in the last layer is poised to classify binary classifications.

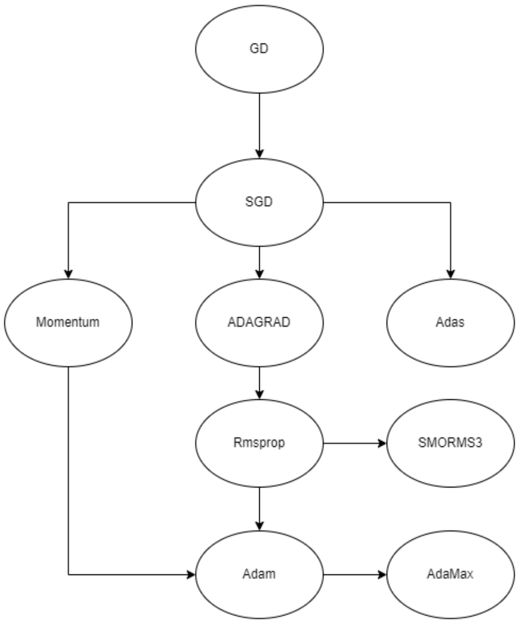

Figure 3. Optimizer Chart

3.5. Environment

We utilized Google Collab's base-free variant, which provided us with 13 GB of RAM, 80 GB of disk space, and 15 GB of T4 GPU.

3.6. Supervised Learning

In supervised learning, both labels and results are provided to the machine-trained model. Training data is provided for training, and a validation set is provided to test what has been learned. Training data consists of a dataset with accurate labels. In other words, we can say that it is an input data set with accurate output results. Using previous training, the model optimizes performance accordingly. Supervised learning is divided into two sub-algorithms, namely classification and regression. Classification is the process of choosing or predicting labels from a list of predefined possibilities. Classification is separated into two parts: binary classification and multiclass classification. In binary classification, there are only two classes to choose from, and in multiclass classification, there are multiple classes from which to choose the outcome. Regression is the process of predicting continuous or floating-point numbers, such as predicting the value of a house using characteristics such as the number of rooms, the age of the house, and the size of the house.

3.7. Convolutional Neural Network (CNN)

CNN is one of the most common types of ANN. It is a feed-forward neural network that consists of the following parts:

- Convolutional Layer
- Relu Layer
- Pooling Layer
- Fully Connected Layer

3.8. Convolutional Layer

Convolutional layers are the most important part of CNN architecture. When an image is passed as input to a convolutional layer, a filter is passed to the image and iterates over the image. This is a mathematical function that executes or slides another function and then performs a point-by-point multiplication. This architecture allows the network to focus on low-level functions starting at the first layer, and then transition those functions to high-level functions at the second layer. This cycle continues until the network is analyzed.

3.9. Pooling Layer

A pooling layer is used to compress the provided input image. The main objectives are to reduce the risk of overfitting, reduce memory usage, and reduce computational load on the system. The input is connected to the output of the neuron of the previous layer. There are no weights, but you need to define pitch, size, and padding size. A two-dimensional filter is applied to the features of each channel and the features included in the filter area are summed.

3.10. Relu Layer

The "Rectified Linear Unit (ReLU)" is an activation function commonly used in neural networks (NN). It operates by setting all input values below 0 to 0 and leaving all input values above 0 unchanged. Mathematically, this can be expressed as:

$$f(x) = max(0, x) = \frac{(x + |x|)}{2}$$

ReLU introduces non-linearity into the neural network, which is essential for learning complex patterns. It helps to mitigate the vanishing gradient problem, allowing for more efficient training of deep networks. While ReLU can transform negative pixel values to zero, its primary function is to aid in the training process of the neural network, rather than directly affecting the color of images in a meaningful way.

3.11. Transfer Learning Models Overview

3.11.1. ResNet152

ResNet, short for Residual Networks, is a Convolutional Neural Network (CNN) architecture introduced in 2015. Previously, deep neural networks (DNNs) were difficult to learn due to their large number of parameters and low accuracy. ResNet introduces a framework that is much easier to train, optimize, and achieve accuracy than any other model. Instead of learning unused features, we redesigned the layers from scratch based on the input layer. ResNet152 contained 152 layers, used 11.3 billion flops, and had much lower complexity than VGG-16 and 19. ResNe50, ResNet101, and ResNet152 were more accurate than 34 layers in terms of accuracy and did not suffer from performance degradation issues, further improving accuracy. Each residual block can be described mathematically as [28].

$$X_{n+1}X_n + \Delta t f(x_n, \theta_n).$$

3.11.2. MobileNet

MobileNet is a CNN based Pretrained architecture which presented by "Google" in 2017. They focused on creating efficient and lightweight model classes for mobile and embedded vision applications. They created a lightweight deep neural network (DNN) using depth-separating convolutions. It targets machines with limited resources, such as mobile phones and older car models. "Depth-separable convolution" consists of two layers: depth convolution and point-wise convolution. Depth convolution is used to apply one filter to each input channel [29].

3.11.3. DenseNet121

DenseNet is a CNN (Convolutional Neural Network) architecture introduced in 2018. CNNs can be significantly deeper, more accurate, and easier to train when the connections between the layers are made shorter, which are close to the input side and the output side. In DenseNet, each player is connected with another layer in a Feed-Forward manner. In standard CNN, if there are X layers, they are connected with X connections, one for each layer. But in DenseNet there are:[35]

$$X\frac{(X + 1)}{2}$$

It greatly diminished the problem of vanishing gradient, reduced parameters, and vitalized feature reuse. All the layers were directly connected with each other, and each layer could access the gradients from the loss function and the input layer, which led to deep supervision and improvement in the flow of information and gradient. A Dense Connectivity pattern was introduced in which any layer could connect to any other subsequent layers. The Lth layer will then receive the feature maps of every preceding layer which is [30] [37].

$$"X_0, \ldots, X_{L-1} \text{ As Input } X_L = H_L([X_0, X_{1,\ldots\ldots,}X_{L-1}])"$$

4. Results Analysis

The findings of our research illustrate the capability of different models to detect and classify brain tumors by using convolutional neural networks (CNNs) and transfer learning. Regarding different network architectures, ranging from our base CNN model to pre-trained models such as ResNet152, DenseNet121, and MobileNet, we achieved notable results considering the accuracy, area under the curve (AUC), and loss metrics. Furthermore, ResNet152 had the greatest AUC of 0.988, which means that it has better performance as compared to DenseNet121 and MobileNet, equipped with AUCs of 0.986 and 0.987, respectively. These models demonstrated significant accuracy scores anomalously on validation and test datasets, suggesting their robustness to generalized data. The models' classification performance was once again clarified by the confusion matrices provided, revealing their capability to recognize tumor and normal brain images accurately. Our findings show the power of using convolutional neural networks and transfer learning for a successful brain tumor detection algorithm. It seems that this approach could play an important role in contemporary medicine by improving diagnostics and treatment procedures.

The use of graphic illustrations and interpretations was important to reflect the effectiveness of our proposed model. Researchers can demonstrate the performance of their models using visual tools such as ROC curves, accuracy versus validation precision, loss versus validation loss, and confusion matrices. By performing graphical analysis, we were able to see what our model was capable of in terms of performance.

4.1. Area Under the Curve (AUC)

Figure 4 (a), (b), (c) and (d) shows the AUC (area under the curve) of the models, which came out to be 0.95 for the base model, 0.986 for DenseNet, 0.987 for MobileNet, and 0.998 for ResNet. It provides an overall measure of performance that includes every possible categorization level. Its value ranges from 0 to 1; a model with a 100% wrong prediction will have an AUC of 0, and a model with a 100% correct prediction will have an AUC of 1.

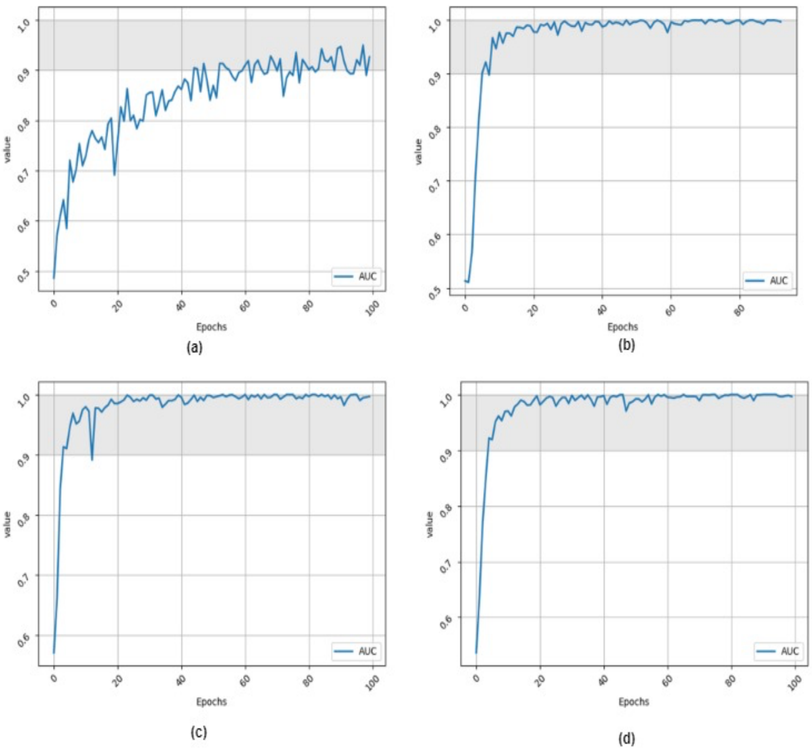

Figure 4. Shows the AUC (Area Under the Curve) of the models, (a) Base Model, (b)DenseNet, (c)MobileNet, (d)ResNet

4.2. Accuracy vs Validation Accuracy

Figure 5 (a), (b), (c) and (d) shows the models' accuracy and validation accuracy. The red line represents validation accuracy, and the blue line represents the accuracy of the models. Accuracy is a metric that evaluates the performance of a model on the training data by determining the percentage of instances that are categorized correctly. Validation accuracy, however, measures the model's performance on new and unknown data (the validation set), which aids in assessing its ability to generalize. Test accuracy refers to the level of accuracy that a model achieves when it is assessed on a separate dataset known as the test set. The test set is utilized to impartially evaluate the final model after all decisions regarding model tweaking and selection have been made [36]. It predicts the model's performance on new, unknown data in a production environment. The test accuracy of the models came out to be 0.8710 for the base model, 0.965 for DenseNet, 0.872 for MobileNet, and 0.987 for ResNet.

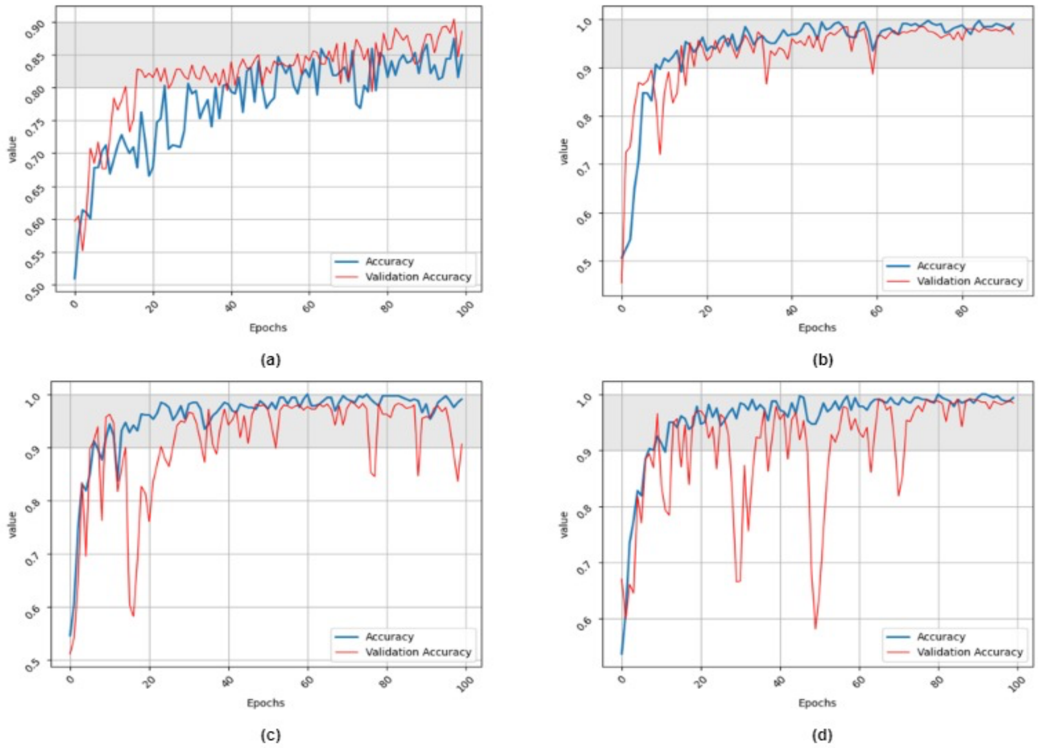

Figure 5. Shows the Accuracy and Validation Acuuracy of the models, (a) Base Model, (b)DenseNet, (c)MobileNet, (d)ResNet

4.3 Loss vs Validation Loss

In Figure 6 (a), (b), (c), and (d), the model's loss and validation loss are illustrated. The red line denotes the validation loss, while the blue line represents the loss. The loss metric serves as a quantitative measure that evaluates the variance between the expected output of a model and the actual target values in the training data. Its primary objective is to minimize this variance during the training process. Validation loss is a metric utilized to assess the performance of a model on a distinct validation dataset during training. It plays a crucial role in combating overfitting by monitoring the model's ability to generalize to unfamiliar data. Furthermore, the test loss is utilized to evaluate the model's performance on a separate test dataset, providing an unbiased assessment of its ability to apply knowledge to new data. The test loss values for the models were 0.26 for the base model, 0.17 for DenseNet, 0.33 for MobileNet, and 0.041 for ResNet.

4.4 Confusion Matrix

In Figure 7 (a), (b), (c), and (d), the confusion matrices of the model are illustrated, showing the values of true positives, true negatives, false positives, and false negatives. A confusion matrix is a tabular representation used to assess the performance of a classification model. This involves comparing the model's predictions for a classification task with the actual labels in the test dataset. The matrix is organized so that the rows represent the actual classes and the columns represent the predicted classes. The cells in the matrix display the frequency or proportion of cases belonging to each combination of actual and predicted classes. The confusion matrix is useful for evaluating a model's performance across different classes by calculating performance metrics such as precision, recall, and F1 score.

4.5. Comparision with State-of-art Models

The performance with the Adam optimizer was found to be precise and on point. In the future, CNN, with other techniques like Gradient boosting, SGD can be used to enhance the model in terms of its performance measures. A larger dataset could be used for a more refined system. Additionally, this research can advance by creating methods for precisely categorizing tumors according to their features or disease type, such as benign or malignant.

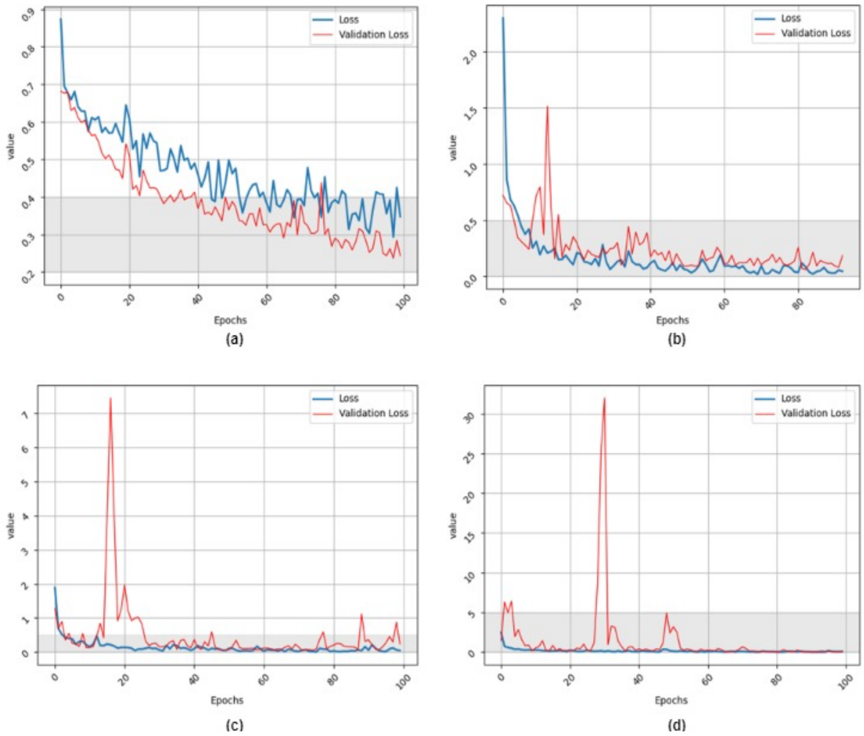

Figure 6. Shows the Loss and Validation Loss of the models, (a) Base Model, (b) DenseNet, (c) MobileNet, (d) ResNet

Figure 7. Shows the Confusion Matrix of the models, (a) Base Model, (b) DenseNet, (c) MobileNet, (d) ResNet

Table 2. Comparison of Different Models

Method	F1 Score	Precision	Recall	Accuracy
VGG-16 [31]	93.27%	93.28%	93.27%	93%
Resnet-50 [32]	96.10%	96.50%	95.62%	99%
CNN-KNN [33]	96.25%	96.67%	95.83%	96.25%
Proposed Method	**98.6%**	**97.6%**	**99.6%**	**98.7%**

5. Conclusion

The primary objective of this study was to develop a more generalized model that helped us to validate the presence of the tumor more precisely at an early stage as a tumor or no tumor while keeping in mind the complexity of the model and the resource availability of the systems it will be implemented on. The initial stage of diagnosis of the patient's condition is a crucial step as it paves the way for the future prognosis. The dataset was procured from Kaggle, which contained 4600 total images, of which 55% were of a brain with a tumor and 45% were of a healthy brain. Deep learning using CNN was used to train four different models, each utilizing the ADAM optimizer and running for 100 epochs. Out of all the models, ResNet-152 was observed to be much more accurate than the other models, all in terms of accuracy (98.7%), AUC (0.998), precision (97.6%), recall (99.6%), and F1 score (98.6%). Several ML and DL models were utilized, with variations tested to check which achieved better performance, as represented in the table.

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