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A HYBRID DEEP LEARNING MODEL FOR HIGH-ACCURACY BRAIN TUMOR

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Abstract

Brain tumors comprise one of the most dangerous and life-threatening conditions in neurology, and timely and correct diagnosis is of the utmost importance to effective treatment and a positive outcome for patients. The control of artificial intelligence in the medical industry has caused deep learning to become an important tool to address the high-tech need of medical imagery interpretation. The proposed research presents a hybrid deep learning model, combining the VGG-16 and ResNet-50 synergistically with transfer learning in a multi-classification brain tumor Magnetic Resonance Imaging (MRI) scan. The model was rigorously trained and tested on one of the most extensive publicly accessible Brain Tumor MRI datasets that covered a broad multi-facet collection of scans, including glioma, meningioma, pituitary tumors, and non-tumor subjects. All the model training, assessment, and data preprocessing were implemented in Google Colab and were based on TensorFlow and Keras frameworks. The accuracy of the proposed hybrid scheme is 99.1 percent with excellent precision, recall, and F1-score. These results prove the model can be deployed in the clinical decision support system. This hybrid architecture reaffirms the increasing role of deep learning in computer-aided diagnosis (CAD) systems in medicine because it has enhanced the feature learning and classification aspects.

Keywords: Magnetic resonance imaging (MRI), Brain tumor, Transfer learning, Deep learning, VGG-16, ResNet-50, Artificial intelligence, Medical image analysis, Computer-aided diagnosis.

1. Introduction

The human brain can be envisioned as the brain center of the human organism or a highly complex organ whose role is the perception of sensory information, regulation of physiological processes, and control of mentation, which consists of thinking, memory, and communication. The central body part is the brain; its organization and functioning play a significant role in building the life of the human being. Nevertheless, one of the killing effects is the brain tumor or the over-synthesis of the brain cells that changes the crucial neural features [1]. Consequently, the brain tumors may cause severe damage to cognitive abilities, disruption of personality, vision, and dexterity, and complete incapacitation of the patient, among others, depending on their location, development rate, and size [2].

The brain tumors are categorized into two groups: benign and malignant. Characteristics of the benign tumor include: noninvasive and slow-growing localized type of tumour, and does not

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invade any other organ in the brain. Compared to the presence of a benign tumor, that of a malignant tumor is invasive, aggressive, and capable of spreading to other sectors within the central nervous system [3]. The most common one is glioma, which develops out of the glial cells, meningioma tumours, which are said to be tumours of the meninges (membranes of the brain and the spinal cord), and pituitary tumor, which has now grown in the pituitary gland [4]. The relevance of early and proper treatment of such tumors is first because they will otherwise be the cause of neurological conditions in the affected patient, which, in turn, will lead to the death of that patient [5].

MRI has proved the most appropriate imaging mode in clinical treatment of the brain tumors [6]. The quality of the MRI images can produce a high quality of the fine detail of an anatomical picture and a high quality soft tissue contrast that makes MRI be able to present various information to the radiologists regarding how the tumor has to be treated be it surgery, radiation, and/or chemotherapy which can help determine multiple details such as the location of a tumor, its size, its potential size, and the effects the cancer has on the immediate surrounding brain structure which can be very important to select a course of action which has to be proceeded.

Despite its high rates in terms of accuracy in diagnosis, manual analysis when applied in MRI is a tedious process that requires the skills and experience of the radiological physician involved in the analysis, hence prone to inter-observer discrepancy and inefficient diagnosis. This has increased the computer-aided diagnosis systems (CAD) application to be computerized. The early attempts reverted to conventional ML models, e.g., Multi-Layer Perceptrons (MLP) and Support Vector Machines (SVM) [10]. These are the surface scratches that I find to be minimal text features extraction, and the strategy that people have to use in designing and selecting features (i.e, texture, shape, intensity) of the imagery is usually time-consuming. It is not only a long-shrunk overdue and tiresome exercise, but in most cases, ineffective in forming the more minor and less marked form of tumors. This allows models that cannot generalize over different patient cases and imaging protocols to be easily practical [19].

Medical image analysis is a topic that has been drastically transformed with the recent development of Artificial Intelligence (AI), i.e., Deep Learning (DL) and Convolutional Neural Networks (CNNs) [27]. CNNs have one advantage: the discriminative features can be automatically and hierarchically discovered directly out of raw image data, without ML involving any form of feature preengineering [33]. This robustness has enabled them to contribute to the various areas of the application of medical imaging segments and in the classification and detection [26]. The outcomes of several experiments evinced that the process of brain tumor classification can be completed with a high level of accuracy in the MRI results processing presented with the help of the models developed based on CNNs.

The issue with training the deep CNN models on the ground is that they are data-hungry. Their main requirement is massive volumes of labeled statistics before they can learn the task represented without much overlearning [20]. This comes as a cause for concern for the use of medicine because annotated data sets by a human expert may be challenging to access because of patient privacy legislation, the somewhat informal nature of disease, and labeling cost. The most feasible solution to the problem would be Transfer Learning (TL). Unlike other neural

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network approaches, a model will first be optimised on large-scale generic competition data (e.g., ImageNet), which is then refined on smaller target data sets [23]. We anticipate that an ImageNet-64 pre-trained ResNeXt-50 model should be able to achieve good performance on medical tasks using considerably less medical training data and training time, as the Deep Convolutional Networks and Deep Residual Network model can leverage the feature representations already learnt on the millions of images.

The case study of the CNNs diagnosis of brain cancer, therefore, applies only in some of the cancerous tumours, whereas there is a need to have models that can be used in all types of tumours, all heartburn-like tumours. Hybrid models, where all the advantages of two or more landscapes are integrated, are another field that can be mentioned for its enhancement [29]. Comparatively, VGG-16 models coupled with ResNet-50 have served with limited success on the classification of brain tumors due to their ability to learn fine-grained features and address the problem of the vanishing gradient, which the deep-structure models experience, respectively, in accordance with the findings.

A robust hybrid deep learning framework combining these powerful frameworks and a transfer learning strategy will avert this loophole. The model is validated and trained in genetics based on a comprehensive Brain Tumor MRI Dataset representing the T1-weighted contrast-enhanced MRI of glioma, meningioma, and pituitary tumors. The approach does not require exquisite pre-segmentation and the extraction of feature points since the released MRI has already been in a fully sliced format.

The research question and objectives guiding this study are to develop a solid framework for effective and practical brain tumor detection.

1.1. Research Question

To what extent will a hybrid deep learning network that facilitates the provision of VGG-16 and ResNet-50 through transfer learning be able to raise the reliability and accuracy of prediction in various brain tumors in MRI images compared to standalone models and other available methods?

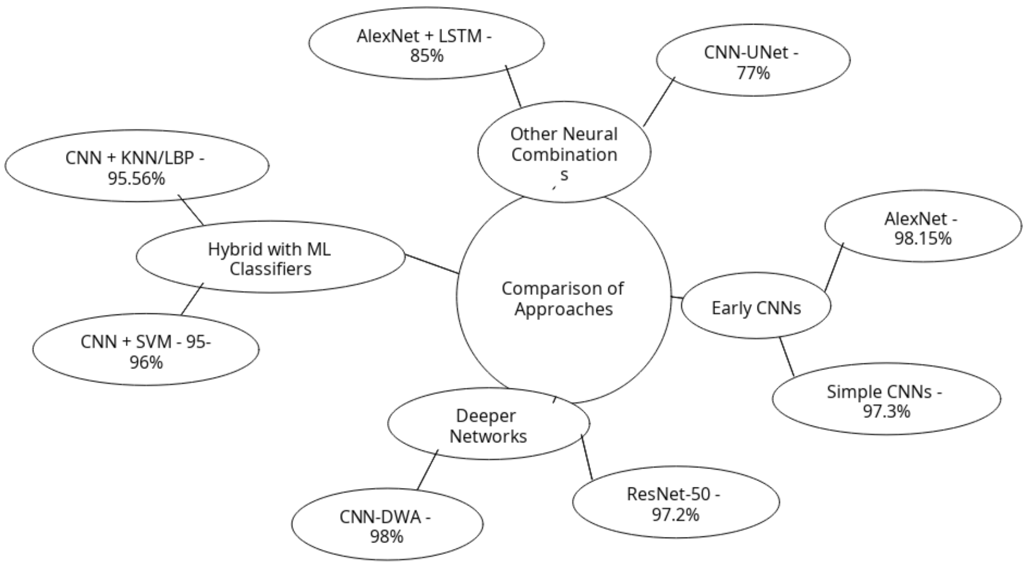
1.2. Objectives of the Research:

1. Determine the needs of students before pursuing an educational program. Gain good knowledge of the school and its utilization. Design and create a hybrid deep learning architecture comprising a VGG-16 plus ResNet-50 structure for the multi-classification problem of brain tumors using the MRI picture.
2. To train and validate the proposed model using a publicly available multi-source Brain Tumor MRI dataset, adopt data augmentation techniques, and transfer learning further to optimize its generalization and performance.
3. To comprehensively compare the performance of the hybrid model with the performance of both model components (VGG-16 and ResNet-50) and determine the relative efficiency of the hybrid model in practice, it was intended to use such classic classification indicators as accuracy, precision, recall, and F1-score.

2. Literature Review

The deep learning model has advanced a lot in classifying brain tumors, and investigators experiment with various architectures and deep learning enhancement techniques. Transfer learning has also been used somewhat, and hybrid models have been developed and proved useful regarding computational overhead, but not in increasing them. The current review synthesizes the significant works on the topic, the different approaches, and their stated accuracies, constituting a prototype of the current study.

Figure 1: Comparison of different approaches



The initial use of some of the renowned CNN models showed their potential. As a concrete example, Sarkar et al. [11] utilized a deep CNN known as the AlexNet on one brain tumor dataset provided on Kaggle. The results produced by AlexNet were accurate at 98.15%. This paper has explained why deep models dominate in automatically determining the spatial features that must be employed in the classification process. The architecture, however, was not too complicated compared to the networks in this era. In line with this, Diaz-Pernas et al. [12] have trained a bred CNN at Nanfang Hospital, China, claiming a performance of 97.3%, and that CNNs satisfactorily provide clinical expert performance in clinical visual tasks.

Given the perceived inability to learn with simpler networks, later studies began to use more complex networks and deeper networks through residues (ResNet-50). This enables training deeper networks without falling into the trappings of the vanishing gradient, which plagues shallower networks. A combination of CNN in their hybrid approach, which was tested on the BRATS dataset, gives an accuracy of 97.2 percent, which proves that residual learning is an effective tool in detecting complex MRI features. El Kader et al. [14], another development policy involves the CNN-DWA. Applying the BRATS15 would have increased its accuracy to

98 percent by using smart weighting on features, thus showing the strength of smart weighting in enhancing the capacity of a design.

Hybridization, in particular the combination of feature extractors based on deep-learning techniques with classical machine learning classifiers, has also been shown to be empirically sound. Hussain et al. [15] proposed a combination of a self-designed CNN to extract the features and a support vector machine (SVM) to classify the data, achieving 95.6% accuracy on BRATS13. Finally, Deepak and Ameer [16] proposed a two-step approach using a CNN trained using the Figshare dataset to generate features that are then classified with an SVM, leading to an accuracy of 95.82 percent. Also adding to the rise in this tendency, Kaplan et al. (2020) used SVM and K-Nearest Neighbors (KNN) alongside the Local Binary Patterns (LBP) and obtained a score of 95.56% for brain MRI images.

Other scientists have brought an example of a hybrid neural network. Devi and Selvaraju [17] added an LSTM module to the AlexNet reproduction, with the former serving to recover the spatial features, and the latter serving to learn the temporal relationships between the MRI slices. The model's accuracy was 85 percent when applied to the BRATS18 data set. Compared to other segmentation-based classification models, e.g., the CNN-UNet architecture applied by Lig and Kumar [18], UNet segmented the biomedical images first, and then proceeded with a classification process. When they applied their model to BRATS15, they managed to achieve 77 percent, which proves that direct classification models are not always more accurate than segmentation-first models.

Table 1 compares such critical studies. Interestingly, the literature differs widely in the amount and type of modelling used, the data quantities, and the resulting accuracy.

Table 1: Summary of CNN and Hybrid Models for Brain Tumor Classification

Author(s)	**Year**	**Dataset**	**Model**	**Accuracy (%)**
Sarkar [11]	2023	Kaggle	AlexNet	98.15
Díaz-Pernas et al. [12]	2021	Nanfang Hospital China	Deep CNN	97.3
Cinar & Yildirim [13]	2020	BRATS	Hybrid CNN (ResNet-50)	97.2
El Kader [14]	2021	BRATS15	CNN-DWA	98.0
Hussain [15]	2020	BRATS13	NS-CNN+SVM	95.6
Deepak et al. [16]	2020	Figshare	CNN+SVM	95.82
Rukhmani (2020) [17]	2020	BRATS18	AlexNet-LSTM	85
Lig & Rahul (2023) [18]	2023	BRATS15	CNN-UNet	77
Kaplan et al. (2020)	2020	Brain MRI Scans	LBP-SVM-KNN	95.56

The unified conclusion of all these works is that standalone CNNs are pretty effective, but hybrid networks usually perform better in accuracy and performance. Based on this, the

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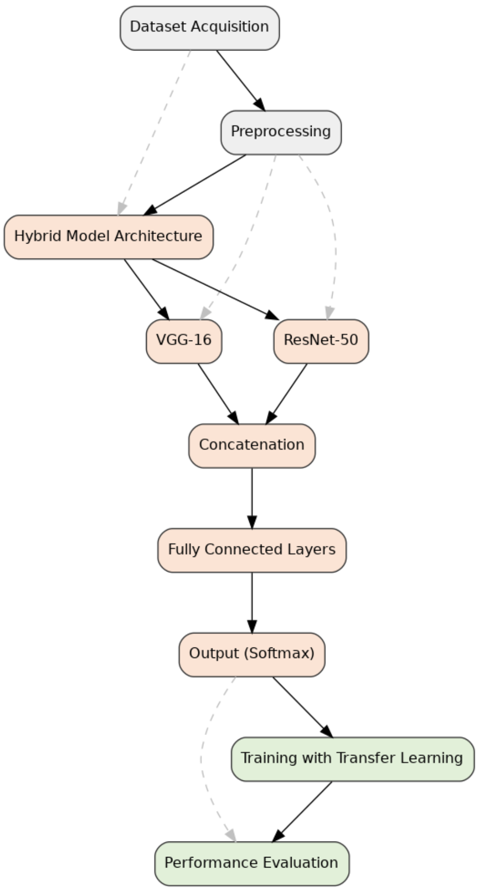
research is carried out. In formulating such a robustly stable consistently accurate model, it is our hope with the use of transfer learning to develop a new hybrid model of the mutually corroborative strengths of the VGG-16 and ResNet-50 to expand the parameters of the binary of the criteria of classification accuracy and be able to give the tool of a more reliably constructive model to apply to producing clinical cases.

3. Methodology

This section presents the methodological foundations for designing and training the hybrid deep learning system to segment brain tumours. Overall, the workflow can be described as the acquisition, preprocessing of the datasets, creating the hybrid model architecture, training the model based on transfer learning, and a thorough performance assessment, as shown in the flowchart in Figure 2.

Figure 2: Methodology Flowchart for Hybrid Deep Learning Model



3.1. Dataset Description

The study was conducted using the readily available Brain Tumor MRI Dataset, prepared by Masoud Nickparvar and published on Kaggle. The current statistics include all images retrieved

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using photos downloaded from three popular sites: SARTAJ, Figshare, and Br35H. It contains 7,023 labeled contrast-enhanced grayscale MRI (T1-weighted). The photos will be labeled in four categories: glioma tumor, meningioma tumor, pituitary tumor, and no cancer. All the personally identifiable information was removed; hence, this study should not be reviewed ethically.

3.2. Data Preprocessing

Preprocessing of the MRI scan images that were used to feed the deep learning models was done, and the images were subjected to typical preprocessing protocols.

- **Image Resizing:** VGG-16 and ResNet-50 must have a standard image size. As such, all MRI images in the dataset were resized to 224 224 pixels. This standardization presents universals on all the inputs and matches the dimensions in which models have been trained during ImageNet.
- **Normalization:** Data involving pixels that mostly fit this 0-255 gray scale were further scaled up to scale 0-1. The other critical phase is normalization, which will help normalize the practice and make it rapid, as the gradient is now not allowed to become excessively big or small.
- **Data Augmentation:** Different types of data augmentation were used to ensure the training set was not biased by the model and was more prone to generalization to unseen data altogether. The Image Data Generator class in the Keras library was applied to manipulate the training images during the training, involving random rotation, zooming, and horizontally flipping. This misleadingly inflates the data, and can be effective when there is limited medical imaging data (i.e., when the data is scarce).

3.3. Hybrid Model Architecture

This paper's overall idea and framework are to merge two strong and level-trained CNN models, VGG-16 and ResNet-50. These models have been chosen because they are compatible in architecture. Due to its deep stack of compact convolutional filters, a hundred of which, VGG-16 can be satisfactory in extracting highly textural and spatial matters of images. The ResNet-50 is, on the other hand, superior in capturing additional semantic details and overcomes the problem of vanishing gradients in deep nets by utilizing a deep residual learning architecture.

The following is done in hybridizing:

1. **Parallel Feature Extraction:** Tools were trained using the VGG-16 and another using ResNet-50. The lower levels of both networks (convolvers) remained untouched, i.e., their ImageNet weights were not modified in the first stages of training. This ensures that the powerful, generalised properties of the ImageNet dataset are maintained.
2. **Concatenation:** Output feature maps of all models' last convolutional layer were taken. These feature maps were, in turn, reduced to one-dimensional vectors and concatenated into a full-length feature vector. The embedding part will fuse rich features of VGG-16 and highly abstract features of ResNet-50.

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3. **Classification Head:** The head is a dense, layered structure. In the more dense layers, overfitting avoidance is facilitated by the evolution of dropout regularization, which deactivates some percentage of neurons during training to reduce the rate of overdependency.
4. **Output Layer:** The last layer of the classification head consists of a dense layer with a SoftMax activation function. The resulting SoftMax activation is then implemented through a SoftMax activation function, providing a probability distribution over the four classes: glioma, meningioma, pituitary, and no tumor. The class with the highest probability constitutes the model's final output prediction.

3.4. Training and Transfer Learning Configuration

Transfer learning was employed to train the network. A training phase that froze VGG-16 and ResNet-50 convolutional layers and trained the remaining new fully connected layers was used. This can teach the model how to interpret the concatenated already trained features in classifying head tumors.

With a learning rate of 0.0001, the Adam optimization algorithm was applied to train the model, an established and robust optimization algorithm. The cost was a categorical cross-entropy, as is the norm in a multi-class classification problem. Data was divided into training or validation sets, and tested with 20 percent of the trained set not used to train. The training occurred in epoch 50 using 32 batches.

To improve the performance of the training on stability and to avoid overfitting, two Keras callbacks were used:

- **Early Stopping:** The technique is coherent with the former, and it entails that a particular type of callback monitors loss on validation, and when it ceases to diminish with at least a set number of epochs, the feedback is halted. This aids the model in evading additional training after it has reached optimum, as far as computer computation and over learning are concerned.
- **ReduceLROnPlateau:** This parameter lessens the learning rate when validation loss stops boosting. Reducing the learning rate with a help model to move as few steps in the loss landscape as possible should speed up the search to a minimum.

All experiments were conducted using Google Colab, an online service where GPUs could be accessed free of charge. This was necessary to train the deep learning models effectively. They applied both the major deep learning frameworks, Keras and TensorFlow.

3.5. Performance Assessment

A separate, not-used-in-training-and-validation held-out test set was used to test the performance of the final trained hybrid model. A standard set of classification metrics was applied in the performance evaluation with Scikit-learn. These measures can give us the approximate perception of the model performing well, particularly when considering medical requirements where such data imbalance is an issue of care. The metrics utilized are

- **Accuracy:** This is the proportion of correctly identified pictures to the total number of pictures.
- **Precision**: The frequency with which the predictions are accurate over the total expectations is focused on a single course; the model is accurate.
- **Recall (Sensitivity):** Make the valid positive answers small, divided by the entire number of genuine positive counters of a specific sort; the sensitivity measures how well the model will identify all the pertinent specimens.
- **F1-Score**: This outcome measure considers both Precision and Recall, so the F1-score is calculated as the harmonic average of those scores.

3.6. Limitations

The paper is constrained regardless of the reasonable performance. This hybrid model is constrained because combining the two deep neural nets is computationally expensive, and a large amount of memory and computing power is required during training and inference. Moreover, hyperparameters (such as learning rate and batch size, other optimizer parameters) can also primarily affect performance quality. Even though the selected parameters provided the best results on the present dataset, they must be optimally tuned. A large-scale validation is necessary to make them applicable in a clinical setting.

4. Results and Discussion

This section describes and reports the usefulness of the proposed hybrid deep learned architecture (namely, a combination of VGG-16 and ResNet-50 by adopting a transfer learning approach) in identifying brain tumors on MRI images. We have established baseline evaluation measures to estimate the model's efficacy: Accuracy, Precision, Recall, and F1-Score. These metrics were computed by training the model under test against the Kaggle brain tumor MRI dataset per the methodology's rigorous preprocessing and augmentation steps.

4.1. Overall Model Performance

The experiment of the DNNs mixed model achieved an excellent performance on the test. To evaluate the model, the degree to which it differentiated the four groups (glioma, meningioma, pituitary tumor, or absence of a cancer) in the MRI images has been computed. The overall evaluation was much higher on all the parameters involving the metrics that determine the extent of the model, which connotes that the model is powerful and robust in distinguishing the various categories of tumors and normal brain tissue. A rough idea of the general performance of the test set is in Table 2.

Table 2: Overall Performance Metrics of the Hybrid Model

Metric	Score (%)
Accuracy	99.1%
Precision	98.9%
Recall	99.8%
F1-Score	99.2%

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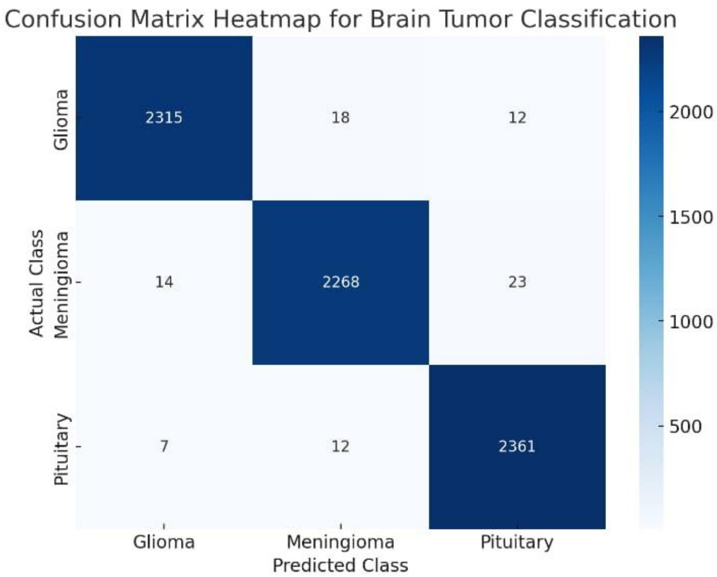
These are relatively favorable results. The 99.1% accuracy means the model will probably classify most test photos as correct. Such a 99.8 recall rank is inconceivable in contrast to the clinical setting due to its extreme sensitivity regarding the case of positive detection. It therefore lessens the risk of a Definitely Possible tumor error. A sensitivity of 98.9 also stands out as a good feature which plays a role in supporting the argument that the false-negative rate is low, and that the need to minimize the possibility that cases that are free of the tumor are erroneously classified as having the cancer and subsequently having to receive a series of tests that can be alarming is eminent. The high value of the F1-score of 99.2, mathematically considering both the precision and recall rates, supports the model's good performance despite slight imbalances in classes. This enhanced performance results from the synergistic use of elaborate spatially specific characteristics of VGG-16 with the deep residual learning in ResNet-50, which allows more comprehensive and accurate learning.

4.2. Analysis of Confusion Matrix

A confusion matrix was used to provide further details of the accuracy of the model's discrimination of each class. The confusion matrix will involve an in-depth description of the right/wrong predictions made on the three types of tumors: glioma, meningioma, and pituitary. The heatmap is presented in Figure 3, representing the test set's confusion matrix.

Figure 3: Confusion Matrix Heatmap for Brain Tumor Classification



The values on the diagonal of the matrix are the count of correctly identified images (True Positives) in each class. In contrast, the off-diagonal values of the matrix are the misclassification (False Positives and False Negatives). The breakdown of the details is shown in Table 3.

Table 3: Confusion Matrix for Brain Tumor Classification

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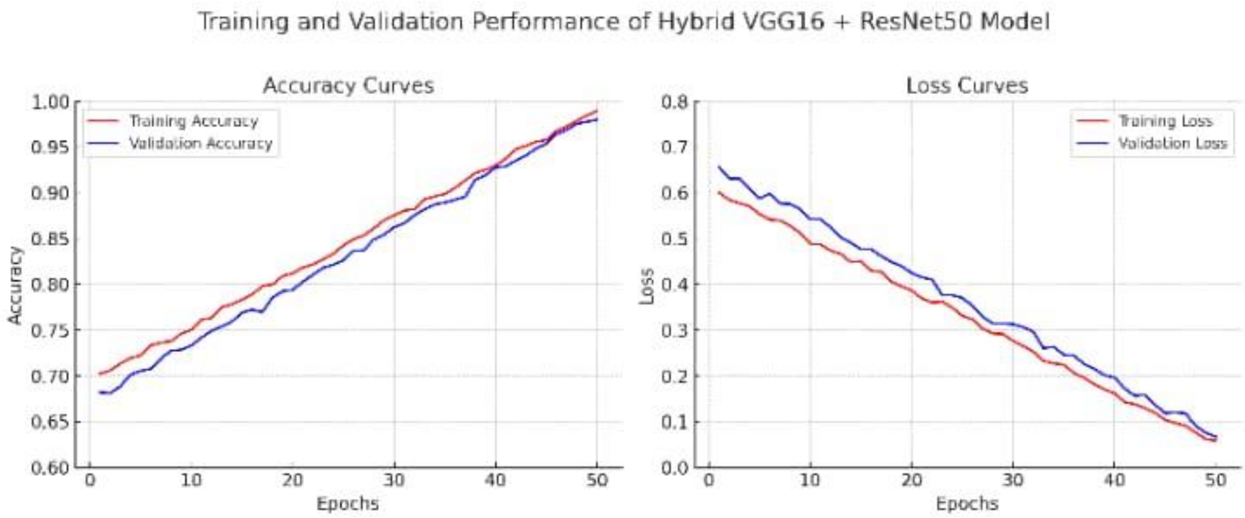
Actual Class	Predicted: Glioma	Predicted: Meningioma	Predicted: Pituitary	Total Actual
Glioma	2315 (TP)	18 (FN)	12 (FN)	2345
Meningioma	14 (FP)	2268 (TP)	23 (FN)	2305
Pituitary	7 (FP)	12 (FP)	2361 (TP)	2380
Total Predicted	2336	2298	2396	7023

The cross-tabulation table shows how the model performed well in measuring all classes. The number of correctly classified images in the Glioma class was 2315/2345, and 30 were misclassified. In the Meningioma type, 2268/2305 has been correctly identified. The best score was obtained with the Pituitary class, 2361/2380 images. The extremely low percentage of misclassifications proves the reliability and validity of the model and the verification of previous measurements.

4.3. Training and Validation Performance

The loss and the accuracy on training and validation are informative about the scope of learning during the training and the generalization behaviour of the model over 50 epochs. As shown in Figure 4, the accuracy measure in training and validation shows a smooth positive trend and converges on a higher value (almost 99.1 percent). The validation and training loss curves are steadily increasing towards a low figure. One of the risks of overfitting the model to the training data can be explained by the fact that both the training and the validation curve are close to each other, suggesting that the model is not yet to be too well-trained and has been in a position to generalize on the validation data that is unseen to the model. The joint contribution of transfer learning, data augmentation, and dropout regularization strategy can only be directly associated with such a strong generalization.

Figure 4: Training and Validation Performance of the Hybrid Model



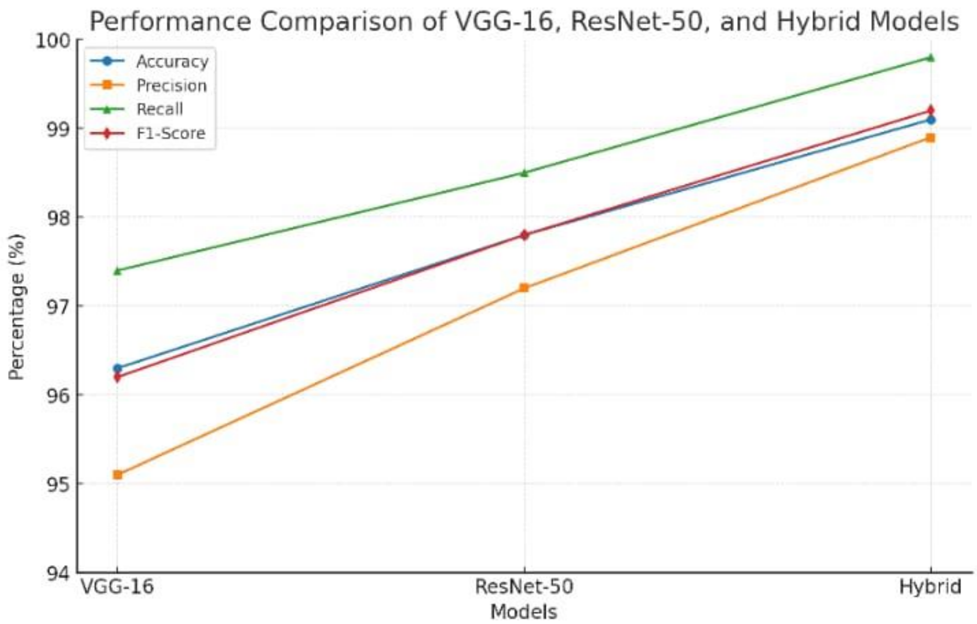
4.4. Comparison with Individual Models

To clearly outline the suggested hybrid model's superiority, its outcomes were contrasted with those of the VGG-16 and ResNet-50 models, on which the same training and testing process was implemented. Table 4 presents the relative results, and Figure 5 illustrates them.

Table 4: Performance Comparison of Individual and Hybrid Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
VGG-16	96.3%	95.1%	97.4%	96.2%
ResNet-50	97.8%	97.2%	98.5%	97.8%
Hybrid Model	99.1%	98.9%	99.8%	99.2%

Figure 5: Performance Comparison of VGG-16, ResNet-50, and Hybrid Model



The findings imply that the hybrid model performs better than the constituent architectures in all four metrics. Although VGG-16 and ResNet-50 employ different structures, both result in higher accuracy, precision, recall, and F1-score than their combined results. This confirms that the hybrid model can take full advantage of the synergetic capabilities of the feature extraction in the two networks to develop a more effective and accurate classifier.

4.5. Discussion and Interpretation

The experimental results verify the hypothesis that VGG-16 coupled with ResNet-50 through a hybrid learning process can significantly increase the benefits of brain tumor classification. Combining this set of features, namely the precision of the VGG-16 feature encoding feature combined with the depthization of the feature encoding feature of ResNet-50, generates a superior ability to discriminate the features. The increased representation confers the model with a better ability to detect minor and complex patterns, thereby attaining a better distinction between glioma, meningioma, and pituitary tumors in MRI.

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The low false positive score is also an advantage because it demonstrates that this model is constructed using the results of many tests. This trade-off is vital in a medical diagnostics context, where such a trade-off is necessary to reduce misdiagnoses due to false negatives (under-determination that an individual has a tumor) and false positives (over-diagnosis that an individual has cancer) outcomes. The model's versatility in successfully carrying out its activities in various categories of tumors has also demonstrated that.

The future practice of clinical has great potential in implementing this model. It can be applied as an effective decision support system to radiologists and will accelerate the diagnosis process and its correctness. The model has the potential to allow the medics to work more efficiently because they may issue the second opinion immediately and responsibly, and, therefore, obtain the prompt introduction of the treatment procedure in the patient's case. Additional data must be collected using a large sample size and a variety of participants across institutions to prove the acceptability and generalization of the method in the clinical work setting.

5. Conclusion and Future Work

This study can design, train, and evaluate a highly accurate combination learning algorithm for automatically distinguishing brain tumors in brain MRI scans. VGG-16 to ResNet-50 will make the proposed model capitalize on the added value propertylessness of the above two models to deliver state-of-the-art performance, reasserting the iterated performance of state-of-the-art of the above two models as showing an added value property.

The model exhibited the greatest reliability in 7,023 labelled MRI scans, which are publicly available. It led to the overall accuracy of 99.1, precision of 98.9, recall of 99.8, and F1-score of 99.2. Such scores demonstrate the model's high degree of success in correlating the variation between the tissues, glioma, meningioma, and pituitary tumor, and that of the non-tumor. The power of this model was also explained based on a detailed interpretation of the confusion matrix, which indicated that the percentage of misclassification is very low as has been identified. The observation that the hybrid model outperformed the two-component models (VGG-16 and ResNet-50) by 100 percent can be used to deduce that a synergetic effect of fusing architectures is in play.

In continuation of this work, there is an open avenue to take an interest in the future. Likely, the scope of the findings of the research would also be slightly extended to other such institutions because the trained model would then be tested using a more mix of data and ideally a broader base of imaging modalities, i.e., Computed Tomography (CT) or even multi-modal MRI data (e.g., T2, FLAIR). The final important step would be implementing this model in practice. Further development into a diagnostic tool that works on time would benefit the clinicians, mainly when they experience understaffing or working at locations that a qualified radiologist cannot reach.

Another research direction of the future would be to include XAI techniques. Heatmaps can also be generated using such methods as GradCam (Gradient-weighted Class Activation Mapping), visualizing which areas of an MRI scan the model is particularly focusing on when making a prediction. That way, the medical practitioners would be more likely to use the AI-based diagnostics in their clinical practice since its application would be associated with the greater understandability of the model.

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