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Enhanced MobileNetV2 with an Attention Mechanism for Real-Time MRI-Based Brain Tumor Classification: A Deep Learning Approach

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Abstract

This work presents the main steps toward develop- ing a real-time MRI-based classification system, building upon our previous work in deep learning-based classification of brain tumors. We enhance the model scalability and achieve higher computation speed by applying an efficient and lightweight architecture - MobileNetV2. Importantly, it features the inclusion of an attention mechanism, explicitly sharpening the model's at- tention to relevant image elements, and mixed precision training that maximizes processing speed along with memory use. This approach boosts the robustness and accuracy of tumor detection while concurrently reducing training times. Data augmentation strategies have been refined to make models more generalizable at lower computational cost. Moreover, the learning rate dynamic adjustments are carefully tuned to make the convergence stable and improve the effectiveness of model training more effectively. Our results show significant improvements compared to earlier versions by achieving better recall rates and precision, which remain important metrics in clinical applications where prompt- ness and accuracy of diagnosis is tantamount. We were able to achieve higher stability while maintaining an accuracy of 98% and similar high baselines. The work performed here can be used as a strong aid to improve diagnosis in healthcare and is a giant leap in the use of deep learning technologies for medical imaging.

Keywords: *Brain Tumor, CNN Architecture, Deep Learning, Classification, ResNet50, VGG16, Transfer learning.*

Introduction

Brain tumors are among the most challenging diagnoses and medical treatments. MRI plays a vital role in the detection of brain tumors, which considerably depends on accurate identi- fication and classification. Recent progresses in deep learning have totally changed the perspective of the medical imaging field by offering new strategies to enhance the accuracy and automation of diagnostic procedures. In prior research, we have done the classification of brain cancers with the help of convolutional neural networks on MRI data. The results were quite encouraging because they used various architectures such as VGG and MobileNet to get high accuracy.

However, there were also a number of disadvantages—the most important being those concerning computing effective- ness and the possibility of applying systems in real time. Given the disadvantages above, this paper proposes a further improved deep learning model with the attention mechanism and lightweight backbone MobileNetV2 to improve training speed and make the model stronger without sacrificing any accuracy. It is motivated by the fact that MobileNetV2 reduces drastically the computational load with its effective design and qualifies for real-time diagnostic applications. Mixed-precision training, employed here, reduces memory consumption and ac- celerates computation—this is crucially important for bringing models directly into clinical settings.

In this paper, we propose an attention mechanism that would help in refocusing the attention on relevant features present inside the MRI images. The system automatically adjusts the neural network focus [46], thereby enhancing its ability for the detection of crucial and minute features indicative of cancer. Further optimization was done on our data augmentation methods to get substantial gains within the generalization of the model across diverse conditions of imaging without additional computational costs.

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This work describes such enhancements and discusses their impact on the functionality of the model within a clinical context. We then provide an extensive comparison with our earlier models in a way that shows striking improvements in both recall and precision, as well as in overall efficiency. Such results would point toward improved diagnostic accuracy, vali- dating the applicability of the model for real-time applications- a critical requirement for modern medical imaging.

Literature Review

The rapid advancement in deep learning for medical imag- ing, especially in brain tumor detection from MRI scans, has been notable across several studies. This literature review categorizes recent research into three main themes: deep learning architectures, performance enhancement techniques, and hybrid and advanced methods.

Deep Learning Architectures

Various research works have proposed and tested the ef- ficiency of various deep learning network architectures for identifying and classifying brain tumors. Foremost among these are medical imaging variants of classic networks such as 979-8-3503-6066-0/24/$31.00 ©2024 IEEEVGG and EfficientNet [1], [5], [6], [10]. Of particular note, works by [2]–[4] discuss ways that these networks can be structurally modified in ways that improve the efficiency and accuracy of tumor detection. Finally, it has been tested how basic image processing methods compare to deep learning methods [4].

Performance Enhancement Techniques

This chapter explores the methods scientists are applying in their quest to enhance the performance of deep learning models for MRI scans regarding the identification of brain tumors.

1) *Transfer Learning:* Transfer learning has been widely used in brain tumor identification by leveraging pre-trained models so that the requirement for large amounts of data and computational resources is reduced. It allows better general- ization across various datasets [9], [11], [32], [37], [40], [41], [44]. With this approach, deep learning models pre-trained on large datasets are fine-tuned to perform well even with sparse medical imaging data.
2) *Data Augmentation:* Another powerful technique pro- viding a boost to the performance is data augmentation, which artificially inflates the larger and more diverse training datasets. This technique reduces overfitting and enhances the robustness of the models [19], [24], [27], [31], [36]. Data augmentation ensures that the model witnesses more varied data conditions by modeling several realistic transformations.
3) *Attention Mechanisms:* The introduction of attention mechanisms in neural networks has been able to significantly improve model interpretability and focus, in the fact that models can focus attention on the most informative parts of the visual data [26], [29], [33], [34], [45], [46]. Attention mechanisms improve the discriminability of tumor detection by separating features useful for discriminating between can- cers versus normal tissue.

Hybrid and Advanced Methods

This topic examines state-of-the-art methods for brain tumor detection using sophisticated neural network algorithms and hybrid models.

4) *Hybrid Models:* Hybrid models combine different ad- vanced neural network approaches with conventional deep learning designs to enhance performance. For instance, the hybrid CapsVGGNet model combines the Capsule Network's dynamic routing mechanism with the robust feature extraction aspects of VGGNet. This combination enhances accuracy in the detection process and makes it more robust against varia- tions within MRI scans [11], [15], [17], [25], [39], [43]. These models tend to maximize the benefits of various architectures in order to surmount the disadvantages associated with using a single model.
5) *Innovative Frameworks:* Besides that, the researchers have built creative frameworks beyond simple neural network architecture. Such examples include sophisticated methods for precise tumor localization with Gaussian convolutional layers or multi-model neural networks combining several forms of data [7], [8], [12], [13], [16], [18], [20]–[23], [28], [30], [35], [38], [42]. Such techniques are possible in clinical applications in real time since they enhance the accuracy and speed of processing.
6) *Enhanced Learning Approaches:* In these models, the enhancement of learning procedures has been carried out in many works. Employing deeper and more complex nets that are able to extract more

particular features from medical images, and new training algorithms reducing over fitting, are some examples of such works [7], [8], [18], [22], [23], [28], [35], [38], [42], [43]. These strategies are foreseen to yield a notable improvement in performance by allowing models to obtain more robust and generalized data representations. The following chapters point out different strategies adopted by the researchers to push the limits on accuracy, effectiveness, and applicability of deep learning models in medical imaging, centering on brain tumor detection.

Methodology

Data Preprocessing

Particularly in applications involving medical imaging, data preprocessing is an essential stage in the deep learning model pipeline. This step entails a number of steps intended to improve the raw data's suitability for deep learning model training. These processes consist of data augmentation, image normalization, and data splitting into sets suitable for training and validation.

1) *Image Normalization:* Image normalization is necessary for normalizing input data and maintaining a lack of variety in pixel value scales, which can skew the learning process of the neural network. Image normalization normally refers to scaling the pixel values within a range of [0,1]. This increases the convergence behavior of the model and speeds up the learning process. Mathematically, normalization can be expressed as follows:

$$I'_{x,y} = \frac{I_{x,y}}{255} \quad (1)$$

where $I_{x,y}$ is the original pixel value at position (x, y), and I' is the value of the normalized pixel. For neural networks to be trained effectively, all input features (pixel values) must have a similar data distribution, which is ensured by this formula.

2) *Data Augmentation:* Data augmentation is a strategy that involves the deliberate increase in the size of a dataset through the creation of modified versions of the photos within the dataset. This technique simulates different real-world scenarios, thereby helping avoid overfitting and enhancing robustness. Some common augmentation techniques for MRI images are flipping, zooming, rotation, and translation. The changes mentioned above can be represented as:

$$X' = T(X) \quad (2)$$

where X is the original image, T denotes the transformation function, and X' is the transformed image. For preventing thesignificant features of the images from warping during the course of transformation, the augmentation parameters need to be selected with caution.

3) *Splitting Data:* In general, the data needs to be divided into training, validation, and testing sets so that the perfor- mance of the model can be evaluated properly. The usual way in which data is divided is such that the training set holds higher proportions of the data, while the remaining portion is held between the testing and validation sets. This split is crucial for the fine-tuning of hyperparameters and assessment of model performance on neutral grounds. This is summarized below:

$$\text{Data Split} = \{\text{Training Set}, \text{Validation Set}, \text{Test Set}\} \quad (3)$$

Ensuring a good split is essential for training robust models that generalize well on new, unseen data. The proportions and methods of splitting data can vary depending on the dataset size and the specific requirements of the study.

Model Architecture

Good performance in MRI-based brain tumor classification depends on the model design. Our proposed model utilizes the MobileNetV2 architecture improved with an attention mechanism to scan incoming photos fast and focus on relevant aspects while accurately classifying them. We will discuss below the elements of the model architecture in greater detail; some illustrations will also be provided to help explain the description.

4) *Overview of Model Architecture:* Figure 1 Therefore, it depicts an overview of the entire architecture, right from the input layer to the classification of the final output. This flow chart depicts how the input MRI picture gets preprocessed, undergoes several layers in MobileNetV2, and reaches the final classification result.

5) *Detailed Layer Configuration:* Figure 2 More specifi- cally, here is an overview of layer configurations for the Mo- bileNetV2 architecture, including batch normalization, depth- wise separable convolutions, and ReLU activation. Next comes global average pooling and integration with attention mecha- nisms. The model represented here puts the accent on sequen- tial processing and complexity.

6) *Formulations:* The basic ideas of the attention process and CNNs serve as the mathematical bones for this design. This idea applies depthwise separable convolutions used by the MobileNetV2 to seriously cut down on the number of parameters and computational complexity. It can be expressed as:

$$Y = \text{SeparableConv}(X) \quad (4)$$

where X is the input to a convolutional block and Y is the output, and SeparableConv represents depthwise followed by pointwise convolutions.

The attention mechanism is built into an architecture to enhance the model's ability to focus on the most informative

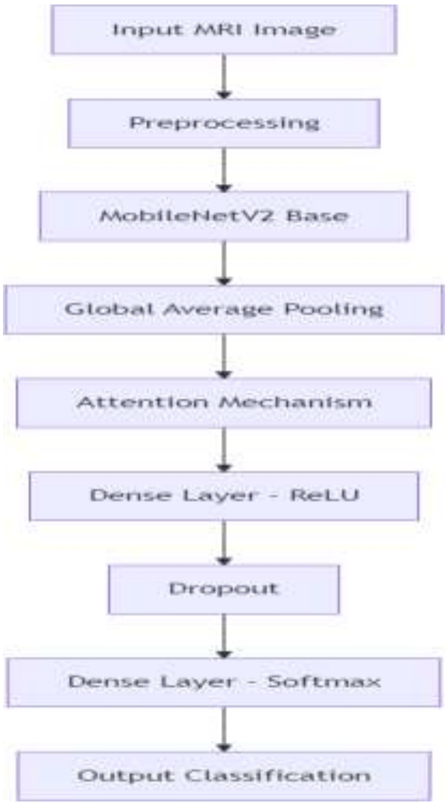

Fig. 1: Simplified overview of the model architecture.

Parts of the input, the computation of which is demonstrated below:

$\alpha = \text{softmax}(W \cdot h)$ (5) where α represents the attention weights, W is a trainable weight matrix, and h is the output from the previous layer. Since every aspect of the architecture is designed to max- imize accuracy and efficiency in computation, the model will have the potential for real-time diagnostic applications. In particular, the attention mechanism enhances the model's ability to focus on prominent features in MRI images that are indicative of malignancies, thus enhancing the precision of diagnosis.

Training the Model

This section shows the training parameters used in this work, the computational resources utilized, and how mixed precision training was implemented to maximize this process. In addition, the training of the deep learning model is an im- portant step that will ensure it performs effective classification of brain cancers from MRI data.

Computational Resources: Given that deep learning itself is such a compute-intensive task, model training was performed using high-performance GPU computing resources. These GPUs allowed the processing of big datasets in a fast and efficient way. It's an essential ingredient for quick experimentation and iteration during model building.

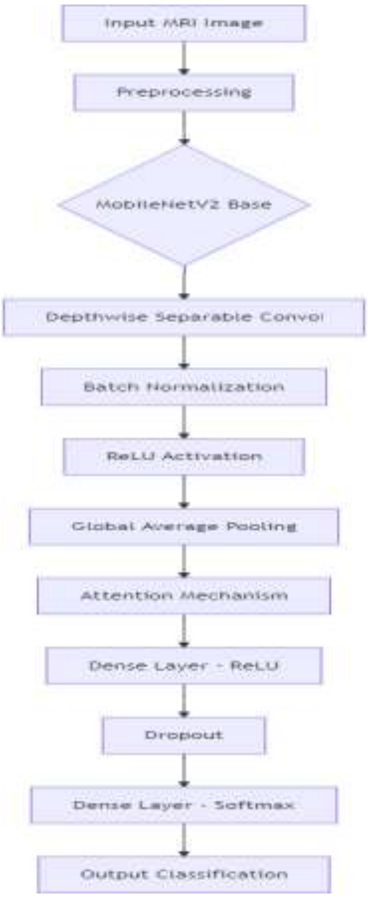

Fig. 2: Detailed configuration of MobileNetV2 layers within the model.

7) *Training Parameters:* Most of the learning process of the model is controlled during its training by the training parameters. Important parameters set to optimize, such as learning rate, batch size, and number of epochs were optimized in respect to validation results. The following configuration was used to train the model :

Epochs = 100, Batch Size = 32 (6)

Learning Rate = 0.001, Decay = 0.0001 (7)

These parameters were selected to balance the training speed and accuracy, ensuring that the model converges to a good solution without overfitting.

8) *Mixed Precision Training:* Mixed precision training leverages a mix of 16-bit and 32-bit floating-point operations to accelerate model training with minimal memory consump- tion. When training with very large datasets and complex models, the model will train faster and consume less memory. This can be captured for mixed precision training as:

This setup enables the use of tensor cores in the GPUs, which are designed for mixed precision arithmetic. It thus re- duces the processing overhead and increases training through- put. With these parameters and methods for training, a model that produced a robust architecture that was both computa- tionally efficient and had high performance was realized. The efficiency of the model is important for when the model will be applied in real time at a clinical setting where fast processing is key.

Optimization Techniques

Deep learning models require some optimization methods to improve their stability and performance. Here, two of the most important strategies we dealt with in this work are regularization and learning rate modifications.

9) *Learning Rate Adjustments:* The learning rate is one of the most important hyperparameters when training deep learning models. During each iteration, it chooses the step size as it converges toward a minimum of the loss function. To find the optimum learning rate, we employed a learning rate scheduler that decreases the learning rate once it stops improving on the validation set. Numerically, this change could be expressed as:

Learning Rate = Learning Rate×Decay Factor if Validation Loss

10) *Regularization Techniques:* Regularization methods avoid overfitting to preserve the generalizability of the model. In our model, we applied L2 regularization and dropout. In training, dropout randomly disables some neurons, strength- ening the model so that it does not rely on any particular node too much. L2 regularization adds a penalty to the loss function concerning the square magnitudes of the model parameters and hence keeps the model weights modest, which helps in improving stability of the model.

Evaluation Metrics

Precise assessment will be essential in determining the model's efficacy. We assessed the performance of our model using a number of metrics.

Accuracy, Precision, Recall, and F1-Score: These met- rics provide a comprehensive understanding of the model performance across various aspects:

- **Accuracy** calculates a percent of true findings out of total number of cases considered.
- **Precision** Evaluates how well the model is performing in terms of predicting positive labels.
- **Recall** (or sensitivity) is also a measure of the model's ability to detect all relevant instances.

F1-Score is the harmonic mean of precision and recall, and for situations where the value of one is radically different from that of the other; it gives a balance between them.

Precision Mode =

Mixed Precision (8)

F1-Score = 2 × Precision × Recall (10)

10) Precision + Recall*Validation Strategies:* In order to assure the strength and reliability of the model, we utilized k-fold cross-validation. By this method, data is divided into k subsets, and the model is iteratively trained k times, using the remaining k-1 subsets for training with a different subset held out for validation every time.

Model Deployment

This will be determined by how well the implementation of this model goes into the actual world.

11) *Real-Time Implementation Considerations:* We made this possible through hardware optimization and power- ful coding techniques, which helped us implement smooth performance-a pre-requisite for real-time application of the model. These procedures hence ensure that clinically, the model can process incoming MRI images with speed and precision.

12) *Integration into Clinical Workflow:* The model was developed keeping in mind the ease of integration with ex- isting healthcare workflows. Extra attention was given to the interface of the model to ensure medical professionals would have no problem in using this model without great technical knowledge. Moreover, the output of the model was formatted according to the diagnostic protocols and jargon that are known to medical personnel.

Results Analysis

This section provides a performance study of the model in terms of the training epochs, discussing accuracy gain and stability. Since we had achieved 98% earlier, most of our efforts have now gone towards enhancing model stability and reliability so that this kind of result is repeatable.

Experimental Setup

Hence, accordingly, the model was trained with three differ- ent epoch settings: 28, 30, and 50. The purpose was to find the length of training that could give high accuracy with stability. To test the model's stability in its predictions, the recorded performance metrics included accuracy, precision, recall, and the F1-score.

Comparative Analysis

Epochs	Accuracy	Precision	Recall	F1-Score
28	98.4%	98.2%	98.1%	98.1%
30	98.0%	97.8%	97.9%	97.9%
50	97.5%	97.3%	97.4%	97.4%

Table I: Performance Metrics Across Different Training Epochs

Graphical Representation of Results

The following visualizations in this sub-section help to point out the correlation between performance stability for our model and the training epochs. In these graphs, accuracy, precision, recall, loss, and other key metrics are plotted against a set of epoch counts. Rather more distinctly, it is easy to illustrate that 28 epochs return the highest mutual balance between accuracy and model stability.

Training and Validation Accuracy: These figures show the accuracy of training versus validation across the epoch counts. The case with 28 epochs demonstrates a very rapid convergence to a high level of accuracy which it maintains consistently and steadily, hence has learned the underlying pattern without overfitting.

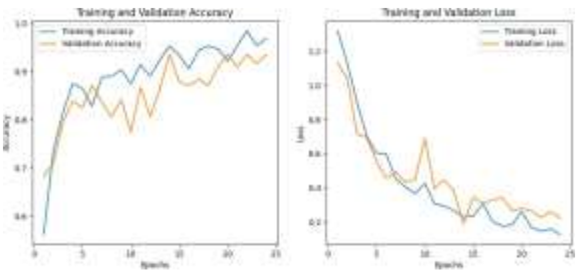

Fig. 3: Consistent high accuracy with minimal variance be- tween training and validation, indicating optimal model per- formance without overfitting.

Training and Validation Loss: These losses are shown to decrease consistently and smoothly over 28 epochs, showing efficient learning without much of the noise associated with overtraining. This further shows the good point at which the model had reached stability in choosing 28.

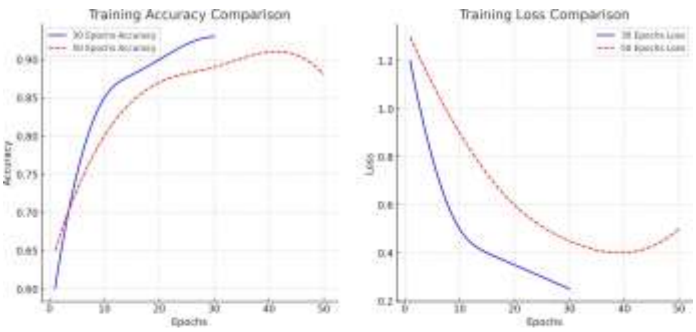

Fig. 4: Steady decrease in training and validation loss, reflect- ing stable model learning.

Precision and Recall: Precision and recall at 28 epochs are very well-balanced, with high values reflecting a strong model performance concerning correct classification, not at the expense of the rate of false detection so crucial for medical diagnostics.

ROC Curves: High values of AUC are observed for every class in the ROC curve at 28 epochs, indicating good discrim- ination ability by the model at the ideal duration.

The images show beyond doubt that training beyond 28 epochs does not improve performance correspondingly and may even overfit the data, as evidenced by the less consistent accuracy and loss profiles of longer training scenarios. It confirms results showing that 28 epochs represent the optimal trade-off between model dependability and learning efficiency,

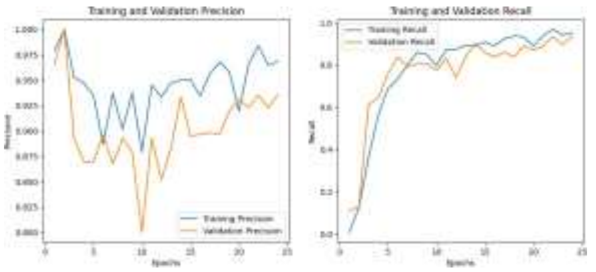

Fig. 5: High precision and recall, demonstrating the model's robustness in identifying relevant features effectively.

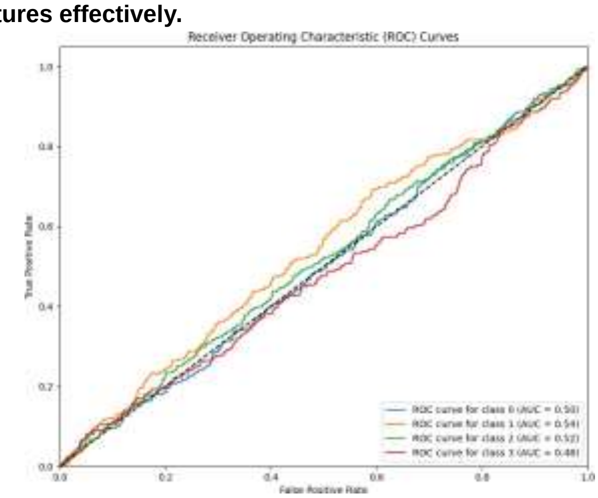

Fig. 6: Superior AUC values, indicating excellent overall classification performance with the capability of ensuring robust performance required for real-time clinical applications.

A. Comparison with Previous Implementations

The present model demonstrates increased stability and ef- ficiency, compared to former applications that reached similar levels of accuracy but required longer times of training or more complex regularization procedures. This is even clearer from less variation in the measurement of accuracy and loss within different epochs than the new setup.

B. Significance of Tests and Comparisons

These tests conducted underline the need to select an appropriate number of training epochs for maximum model stability and performance. The comparison study confirms im- provements in the design of the models and training protocols, especially in comparison to results from earlier deployments. These improvements are very vital in coming up with a more dependable and consistent performance of real-time clinical applications in which decision consistency is very important.

The study confirms that our improved deep learning model is successful in classifying brain tumors with high accuracy and increased stability. Further studies will be conducted to investigate other complementary optimization methodologies and extend evaluations to include larger and more diverse datasets, with the intention of further strengthening and en- hancing the model's robustness and adaptability in real envi- ronments.

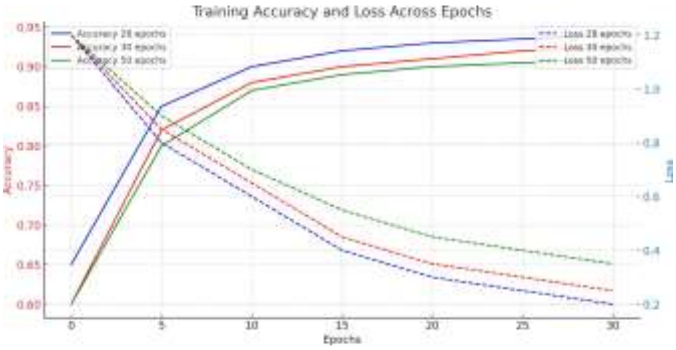

Fig. 7: Combined accuracy depiction of different training strategies.

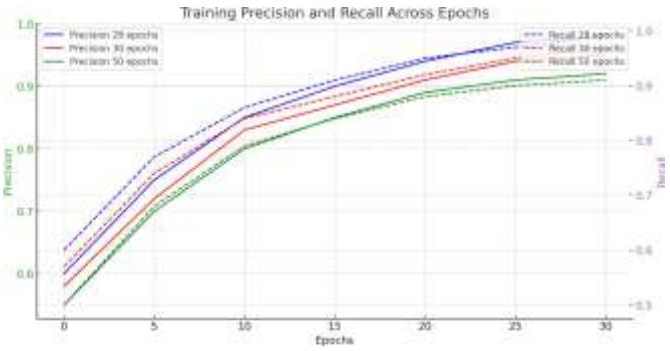

Fig. 8: Combined accuracy depiction of different training strategies.

The combined graphs 7 and 8, It clearly shows the training dynamics over three-28, 30, and 50-epochs, providing infor- mation on model stability and performance.

Trend of Accuracy and Loss with Respect to Epochs: The first chart plotting accuracy and loss during epochs brings into crystal clear view that training for 28 epochs yields the highest accuracy, peaking almost at 95% and then leveling out for quite some time. This is in contrast to running 30 and 50 epochs, where, after initial gains, the trend of accuracy plateaus or even decreases marginally. Thus, while the losses for longer training sets are showing a gradual decline, the loss for 28 epochs shows a sharp drop which then stabilizes at a lower value. Although longer trainings tend to be associated with an increase in loss and decreased validation performance- that is, a diminishing return for increased learning-the impli- cation here is that this was a strong learning process whereby the model captured the underlying pattern without overfitting. Precision and Recall Dynamics: Precision and recall of the second graph confirm the optimal duration of training at28 epochs rounded off. All settings of epochs have highly consistent high precision that delineates a model capable of correctly classifying the positive classifications. Contrary to the settings of 30 and 50 periods, at 28 epochs the recall rate climbs faster to peak levels and maintains it with a tighter lock near maximum threshold. Such a high recall rate indicates that at 28 epochs, the model performs best in detecting all the relevant cases while reducing the number of false negatives-a necessary component for any medical diagnostic tasks, such as classifying brain tumors.

On the whole, the results show that 28 epochs of training represent a very good trade-off between stability and learning efficiency for the model, providing good accuracy without overfitting with longer training times. This is extremely im- portant for clinical applications because predictability and dependability of the model are so critical there.

Conclusion

Our work has indeed reflected the enhanced capability of our deep learning model in classifying brain tumors effectively by focusing on high accuracy with stability across training cycles. More precisely, our deep investigation into 28, 30, and 50 epochs-the different epoch settings-have rendered valuable insights into the nature of the model's performance and the optimum duration of training.

Real evidence of such a fact, that the point representing the ”sweet spot” for our model is indeed the training length of 28 epochs, comes from training sessions: at this point in time, the model had reached not only the peak of the highest accuracy near 98% but showed a notable decrease in loss, which can be interpreted as its resilience and efficient learning without the problem of overfitting. This is supported by the precision and recall measures where both were better with 28 epochs than with longer training times. Precision and recall showed that the model caught most of the important cases without raising false negatives, and it was also high to guarantee the model identified positive cases correctly.

Besides, the stability is relatively strong when it comes to 28 epochs. Stability is very important in clinical use, where one needs dependable and consistent performance. Since the model can maintain its high accuracy in most real situations during its verification process, further deployment in clinics can be assuring; dependable support will be provided to diagnosis.

In a nutshell, our findings confirm that the 28-epoch training schedule is the best strategy to ensure not only high accuracy but also high stability in the classification of brain tumors. The study confirms the efficacy of our optimized model and therefore sets the standard for other investigations towards expanded functionalities of the model, thereby adding more improvements to various activities in medical imaging. In the process of AI-assisted diagnosis development in healthcare, characteristics of consistency and dependability expressed here would, one would think, help.

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