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Research Article

Enhancing Brain Tumor Classification Using AdaDensenet

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ABSTRACT

Early identification is critical since brain tumors harm over 300,000 people annually and cause over 250,000 deaths. Although models such as VGG16, ResNet50, InceptionNetV3, and DenseNet201 exhibit potential, they struggle with dataset bias and flexibility. With global average pooling, transfer learning, sophisticated data augmentation, and attention techniques to improve flexibility for practical application, our suggested model, AdaDensenet, expands upon DenseNet201. AdaDensenet achieved 98.86% accuracy in a complete examination of 7,023 MRI scans from Figshare, SARTAJ, and Br35H (identified as pituitary, glioma, meningioma, or tumor). In addition to accuracy, the model achieves classwise AUC-ROC values of 1.00 and macro and weighted precision, recall, and F1-score of 0.99, demonstrating outstanding discrimination and balanced performance across tumor types. These results position AdaDensenet as a strong candidate for real-time clinical decision support systems.

Keywords: transfer learning, batch normalization. Global average pooling, optimizers, activation function, down-sampling.

1. INTRODUCTION

A brain tumor is defined by uncontrolled cell proliferation in the brain, poses a severe threat to human health inside the complex limits of the human cranium, disturbing the delicate balance of internal systems. According to the World Health Organization (WHO), brain tumors significantly contribute to health issues and mortality, even though they affect less than 2% of the world's population. A UK study found that 5,250 people die from brain tumors annually. (Sharma et al., 2023). In the field of medical advancements, particularly in machine learning (ML), optimally structured convolutional networks have demonstrated transformative capabilities, as seen in the automatic COVID-19 diagnosis (Mehnatkesh et al., 2023). ML-based studies in neuroimaging, particularly on MR images, are gaining prominence for their efficacy in brain tumor classification. Despite significant progress in deep learning-based brain tumor classification, existing models face challenges related to interpretability, dataset bias, overfitting, and computational inefficiencies. The lack of transparency in AI-driven decisions limits trust among medical professionals, while dataset biases hinder generalization to diverse clinical scenarios. Additionally, high computational costs restrict real-time applications in resource-constrained healthcare environments. To address these issues, we propose AdaDensnet, an enhanced DenseNet201-based model that integrates attention mechanisms and advanced data augmentation techniques to improve classification accuracy, interpretability, and efficiency for real-time medical imaging applications. This densenet201 based model uses advanced techniques including global average pooling, transfer learning, and complex data augmentation approaches. Using these strategies, the model intends to overcome numerous major obstacles in brain tumor classification, such as accuracy, tumor type imbalances, and inefficiencies in MRI data processing. One of the primary features of this enhanced model is its flexibility, which is accomplished through a continual development process that is driven by the examination of new information. This adaptive nature keeps the model current and effective even when new data and insights become available, improving its overall performance and dependability. As a result, the approach has the potential to greatly enhance clinical outcomes and patient care quality in medical imaging and diagnostics.

The following are the main contributions of the manuscript:

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Research Article

- To develop an enhanced DenseNet201 based model that improves classification accuracy, robustness, and efficiency for multi-class brain tumor detection.
- Trained on a diverse dataset (Figshare, SARTAJ, Br35H) with advanced data augmentation to reduce dataset bias and improve robustness.
- It focuses primarily on performance optimization and reliable classification outcomes

The sections of the paper are structured as follows: Section II gives the overview of the Related work on the brain tumor classification; Section III gives the Materials and Methods used in our research; Section IV gives The Image Processing in modified DenseNet201; Section V outlines the Results and Discussion; Section VI gives out the Limitations and Future Scope in this study; Section VII wraps up with Conclusion.

2. RELATED WORK

In the domain of brain tumor classification utilizing deep learning techniques, numerous pioneering studies have significantly contributed to the field. Md. A. Talukder et al. conducted an extensive study using a dataset of 3,064 T1-weighted contrast-enhanced MRI scans from patients with meningioma, glioma, or pituitary tumors. Their research leveraged deep learning architectures, including Xception, ResNet50V2, InceptionResNetV2, and DenseNet201, achieving remarkable accuracy rates ranging from 98.40% to 99.68%. Using MRI data, this work demonstrates how well deep learning models classify various kinds of brain cancers (Talukdar et al., 2023). The use of deep convolutional neural networks (CNNs) for brain tumor identification was investigated by B.B. Gupta et al., with an emphasis on differentiating between hemorrhagic and non-hemorrhagic tumor images. Their research employed various CNN models, such as ResNet, DenseNet, and AlexNet, attaining an overall classification accuracy of 90%. This emphasizes the significance of CNN-based methods for rapid and precise brain tumor detection (Gupta et al, 2024). Maquen-Niño et al. implemented neural networks on MRI images for tumor classification, using a dataset of 3,847 brain MRI scans. Their approach yielded a high classification accuracy of 96%, further improving to 92.85% by integrating EfficientNet and VGG-19 architectures, with an additional accuracy boost of 0.06%. The study underscores the importance of data augmentation in enhancing dataset diversity and model performance (Singh et al.,2022). Rohan Tummala's work utilized the Kaggle database and introduced an Inception-ResNet CNN with 164 layers, achieving an outstanding accuracy of 96.67% in predicting tumor presence and classification (Tummala et al, 2023). Similarly, Chetana Srinivas et al. applied different models on a Kaggle dataset containing 253 brain MRI images, with VGG-16 reaching 96% accuracy, Inception-v3 achieving 78%, and ResNet50 obtaining 95% (Srinivas et al., 2022). Badjie and Ülker conducted a study on 3,929 brain MRI images, demonstrating that VGG19 achieved an accuracy of 99.4%, while ResNet50 reached 98.09% (Badjie et al., 2022). Another notable study by Mohammed Aloraini used the Figshare dataset, achieving 99.10% accuracy with a two-channel DNN utilizing FFM and IMM architectures (Aloraini et al., 2023). A combined ensemble approach with SqueezeNet, ResNet, and VGG models demonstrated an impressive classification accuracy of 99% in brain tumor detection (Güler et al., 2024). Similarly, Ziquan Zhu's ResNet-based BA-ELM model attained 99.00% accuracy on the Harvard Medical School dataset (Zhu et al., 2023). Using datasets from Figshare, BRATS 2019, and MICCAI BRATS 2019, Suganya Athisayamani's research showed that ResNet-152 had a high accuracy on a variety of datasets (Athisayamani et al., 2023). Additionally, V. Kavitha and K. Ulagapriya achieved an impressive 99.02% accuracy using the Inception-v3 model, surpassing the performance of VGG-16 and ResNet50(Kavitha et al., 2024). The OIB deep learning model demonstrated a classification accuracy of 96% on brain tumor images (Özkaraca et al., 2023). Another study by Maad M. Mijwil applied the MobileNetV1 model on the Kaggle dataset, attaining a 97% accuracy (Mijwil et al., 2023). Kibriya et al. used SVM and KNN techniques, demonstrating high classification accuracy in brain tumor detection (Kibriya et al, 2023). Mohammed H. Al-Jammas's preliminary research achieved 97.08% accuracy using the Kaggle Brain Tumor CNN dataset (Al-Jammas et al., 2024). Ravendra Singh and Bharat Bhushan Agarwal's CNN-based method obtained an accuracy of 92.50% (Singh et al., 2022). S. Kumar and D. Kumar focused on brain tumor segmentation and classification using Convolutional Neural Networks (CNNs) on MRI images. In Phase I and Phase II, their suggested approach achieved an accuracy of 86.23% and 81.6%, respectively (Kumar et al., 2023). Using MRI data, Asif et al. created a deep transfer learning model that achieved notable classification accuracy for quick brain tumor diagnosis (Asif et al., 2023).A. Srivastava's study applied deep learning on 2D MRI images from the Br35H

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Research Article

dataset, reaching 81.11% accuracy using LBP-coded texture features, 94.11% with DWT coefficients, and 94% with raw MRI images via the ResNet architecture(Srivastava et al., 2023). B. Saju et al. trained machine learning models on 7,038 domain-specific images, achieving 96% accuracy in classifying gliomas, meningiomas, and pituitary tumors using RestNet 5.0 with Transfer Learning (Saju et al., 2023). Rastogi et al. addressed radiologists' challenges in brain tumor detection, using a CNN with Multi-Branch Architecture and Inception Block on the Br35H dataset, attaining a record-high accuracy of 99.30% (Rastogi et al., 2023). S.U.R. Khan explored computer-aided brain tumor diagnosis using MRI images from Figshare, achieving an overall classification accuracy of 95.10% with the DenseNet169 model (Khan et al., 2023). Ranjbarzadeh proposed an optimized CNN for brain tumor segmentation, achieving high accuracy, recall, and dice score on the BRATS 2018 dataset (Ranjbarzadeh et al., 2021). A.I. Nazareth investigated AI-based brain tumor detection using MRI images, with DenseNet121, InceptionV3, and VGG19 delivering exceptional results (A. I. Nazareth et al., 2023). With a high accuracy of 97.5%, Shanthi S. and Saradha created an auto-optimizing hybrid deep neural network (OHDNN) for the classification of brain tumors (S. Shanthi et al., 2022).Finally, T. Soewu focused on early cancer detection using CNNs on Kaggle MRI datasets, demonstrating excellent performance in identifying cancer cells with high precision, specificity, recall, and accuracy (T. Soewu et al., 2022).

3. MATERIALS AND METHODS

In the approach we propose for brain tumor classification, we intentionally address constraints seen in existing deep learning models. To address concerns with biased or restricted datasets that impair generalization, our technique incorporates various datasets, including differences in imaging conditions and patient demographics, guaranteeing full training for enhanced adaptation to new data. Regularization techniques like as dropout and weight decay are used to address overfitting issues, particularly with restricted datasets. Implementing model pruning and quantization improves computational performance, making our technique suitable for real-time clinical applications. Our methodology prioritizes ethical issues, such as patient privacy and data biases, while adhering to regulatory norms for responsible deployment in healthcare settings. To guarantee strong performance and generalizability, rigorous validation is carried out across a wide range of demographics and clinical contexts. By methodically addressing the shortcomings noted in previous models, our technique seeks to provide a generalizable, and morally sound solution for accurate brain tumor categorization in clinical practice.

3.1 DATASET DESCRIPTION

The dataset used in this paper is publicly available on Kaggle and it consists of three datasets- Br35H, SARTAJ and figshare. This dataset contains well categorised labels and contains three main tumors- glioma, meningioma, pituitary and a no tumor class which has been taken from Br35H. It contains 7,022 MRI scans which is enough for deep learning models without being too small to risk overfitting. The MRI in this dataset are clean and standardised which reduces the need to perform preprocessing. So, only the standard preprocessing is applied. A detected issue in the SARTAJ dataset, notably the misclassification of glioma class pictures, led a correction measure. To address this problem, the SARTAJ dataset's glioma photos were removed and replaced with images from the figshare source. This change sought to improve the dataset's correctness and dependability for future analysis. The choice to update possibly mislabeled photos demonstrates a commitment to data quality and a desire for a more reliable dataset for robust model training and assessment.

Figure 1 shows the sample images used in the study.

Journal of Information Systems Engineering and Management
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Research Article

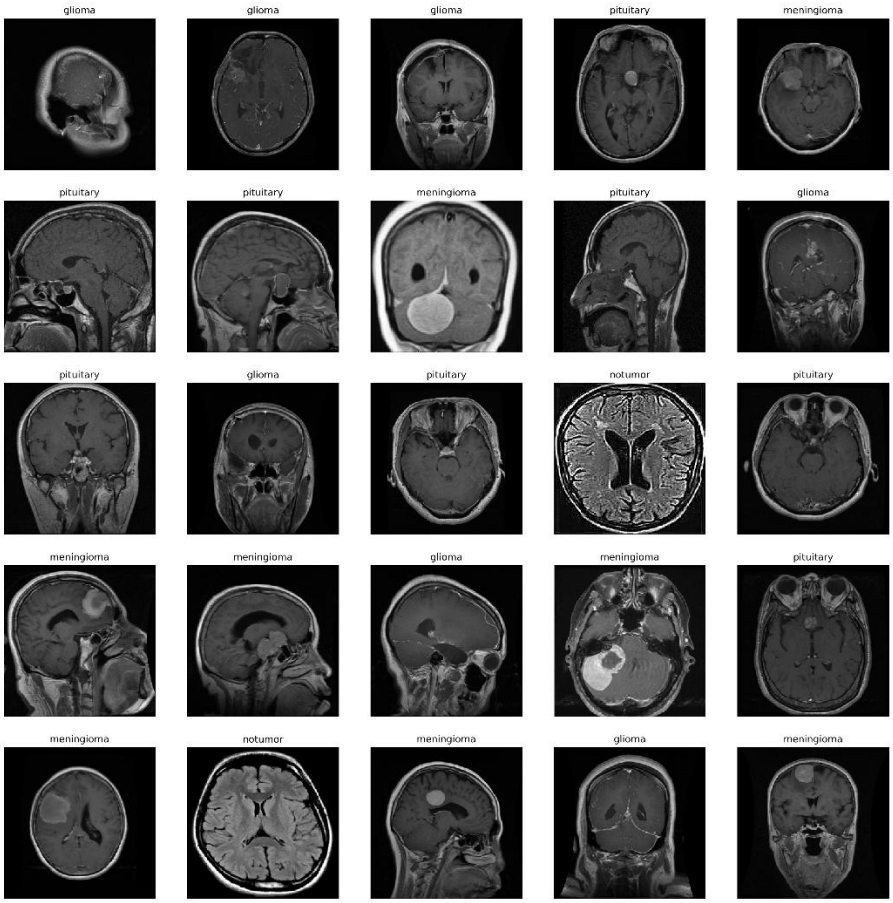

Figure 1. Sample MRI Images used in the study

3.2. PREPROCESSING

In this study, feature engineering primarily focused on preparing the image data for efficient model training and better generalization. The key steps implemented are as follows:

All the input images were resized to a uniform dimension of 224x224 pixels using OpenCV's image processing tools to ensure consistency across data. Color formats are also converted from BGR to RGB format as almost all the pretrained models are trained on RGB format. Furthermore, Lightweight data augmentation was then applied during training to mitigate overfitting which includes randomly flipping along the horizontal axis. The validation and testing sets remained untouched. This preprocessing pipeline ensured well-prepared, standardized inputs, enabling AdaDensenet to achieve stable training, faster convergence, and superior feature extraction.

3.3. PROPOSED MODEL

The DenseNet201 architecture serves as the basis for the suggested neural network for classifying brain tumors, which uses pre-trained weights from ImageNet for feature extraction. Instead of traditional fully connected layers, the model incorporates a Global Average Pooling (GAP) layer, which condenses spatial data and reducing the number of parameters while retaining essential information. Two additional dense layers, comprising 512 and 256 units, are introduced with ReLU activation to enhance non-linearity. To maintain stability and ensure faster convergence, batch normalization layers are applied strategically throughout the network. Additionally, dropout layers with a 50% probability are included after each dense layer to mitigate overfitting. To further reduce the overfitting we have applied the early stopping. The final output layer utilizes Softmax activation, classifying MRI scans into three categories: glioma, meningioma, and pituitary tumors. To further improve accuracy, we introduce AdaDensenet, an enhanced version of DenseNet201 that integrates transfer learning, advanced regularization techniques, and

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Research Article

optimized feature extraction. Optimization is performed using the Adam optimizer, which dynamically adjusts learning rates for more efficient model convergence. With these improvements, AdaDensnet achieves an impressive accuracy of 98.86%, surpassing widely used architectures such as VGG16, ResNet50, and InceptionV3. By integrating interpretability, efficiency, and robust classification performance, this model presents a practical solution for real-time brain tumor detection in medical imaging. Table 1 shows all the layers used in the enhanced model and their properties.

Table 1. Properties of each layer of the proposed model

Layer	Type	Properties
Densenet201 Base Model	Convolutional Neural Network	Pre-Trained on Imagenet- Expects input size (224,224,3). Excludes top layer for custom classification
GlobalAveragePooling2D	Pooling Layer	Reduces spatial dimensions to 1x1 by computing mean of feature maps
Dense (512 units)	Dense Layer	Activation: ReLU; Number of units: 512
BatchNormalization	Normalization Layer	Normalizes activation of the previous layer for faster convergence and regularization
Dropout (0.5)	Regularization Layer	Randomly drops 50% of the connections during training to prevent overfitting
Dense (128 units)	Dense Layer	Activation: ReLU; Number of units:128
BatchNormalization	Normalization Layer	Normalizes activation of the previous layer for faster convergence and regularization
Dropout (0.5)	Regularization Layer	Randomly drops 50% of the connections during training to prevent overfitting
Dense (Output Layer)	Dense Layer	Activation: Softmax; Number of units: Number of classes ($ in this case)

3.3.1. PRE-TRAINED DENSENET201

A pretrained DenseNet refers to a DenseNet architecture that has initially been trained on a large-scale dataset (ImageNet) prior to being fine-tuned for a specific task. Figure 2 shows the Layered architecture of DenseNet model. DenseNet, short for Densely Connected Convolutional Networks, features a structure where each layer is directly connected to every other layer in a feedforward manner. This connectivity enhances gradient flow and encourages the reuse of learned features. Through exposure to the diverse visual concepts in ImageNet, the pretrained DenseNet develops a robust understanding of hierarchical patterns, such as edges, textures, and object structures. When applied to tasks like brain tumor classification, this pretrained network supports transfer learning by utilizing previously acquired knowledge. Instead of training a deep model from the ground up, the general features learned from ImageNet serve as a foundation. These features are then adapted to the target domain, enhancing the model's ability to detect tumor-specific characteristics while retaining valuable insights from the original training data.

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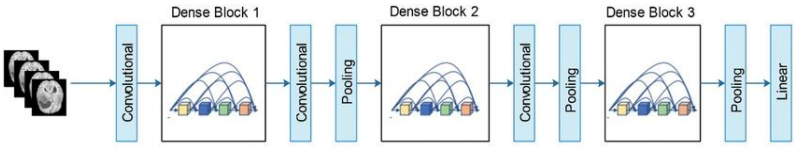

Figure 2 Layered Architecture of DenseNet

3.3.2 GLOBAL AVERAGE POOLING

Pooling is a down sampling procedure done after convolutional layers in neural networks. GAP determines the average value of each feature map throughout its whole spatial range, allowing the network to accommodate spatial fluctuations in brain tumor pictures. This down sampling minimizes computing complexity, concentrates on important tumor traits to avoid overfitting, and retains spatial context, which is required for tasks such as tumor identification within brain images. Each pooling operation averages the values of the current view, resulting in a single value per feature map. This enhances translation invariance and reduces spatial dimensions.

3.3.3 BATCH NORMALIZATION

Batch normalization refers to normalizing inputs in batches during neural network training, which is consistent with the practice of processing data in batches for quicker and more stable training.
(x1,x2,x3,x4) given in the Figure 3 are the inputs that have to be normalized.

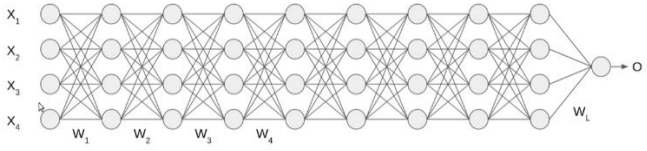

Figure 3 Structure of neural network

3.3.4. ADAM OPTIMIZER

One well-liked optimizer for deep neural network training is Adaptive Moment Estimation, or Adam for short. It combines the benefits of momentum and RMSprop, two further optimization techniques, by maintaining running averages of the gradients and their squared values. As a result, Adam can dynamically change the learning rate for each parameter independently. Because it can achieve a balance between computing efficiency and adaptability, it is highly effective across a range of neural network architectures and application cases.

3.3.5. ReLU ACTIVATION FUNCTION

The Rectified Linear Unit (ReLU) is an activation function that adds nonlinearity to neural networks by applying it across all elements in a volume. Its benefit over sigmoid and other activation functions is its ability to avoid the vanishing gradient problem while also accelerating training due to its smaller computational structure and faster convergence.
It is defined as: **f(x) = max (o, x)**

3.3.6. SOFTMAX ACTIVATION FUNCTION

The softmax operation, a generalized form of the logistic function, converts a vector of scores to $x \in \mathbb{R}^n$ into a probability distribution $p \in \mathbb{R}^n$ at the final layer of the model architecture.
It can be defined as:

$$\begin{pmatrix} p1 \\ p2 \\ \vdots \\ pn \end{pmatrix} \text{ Where } \quad p(i) = e^{x(i)} / \sum_{j=1}^{n} e^{x(j)} \tag{1}$$

4. IMAGE PROCESSING IN MODIFIED DENSENET201

The suggested brain tumor classification model begins with the input picture. To guarantee neural network compatibility, the picture is normalized by dividing the pixel values by 255. The image's dimensions are then enlarged to satisfy the three-dimensional input requirements of the DenseNet201 architecture. The image gradually evolves as

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Research Article

it progresses through the layers, which include the DenseNet201 base model, flattening, global average pooling, dense layers, batch normalization, and dropouts. This sophisticated approach improves the model's capability for feature extraction and learning. Finally, the picture reaches the last thick layer, which produces four output nodes indicating various brain tumor classifications. This comprehensive image processing pipeline as shown in the Figure 4 illustrates the model's capacity to recognize subtle patterns and its efficacy in obtaining exact brain tumor classification.

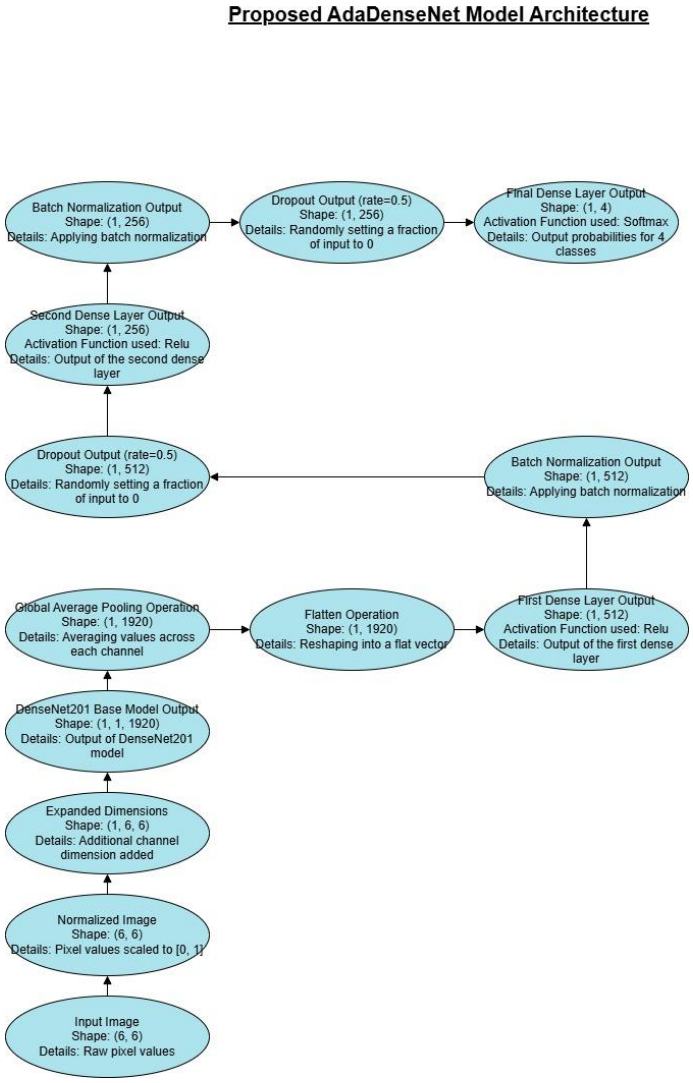

Figure 4 IMAGE PROCESSING IN ADADENSENET

5. RESULTS AND DISCUSSION

The model's assessment metrics provide a complete perspective of its performance. It is conducted on Kaggle leveraging its cloud-based computing resources and GPU acceleration.

5.1. EVALUATION METRICS

To evaluate the effectiveness of our model in classifying brain tumors, several well-established performance metrics were utilized.

Equations from 2 to 5 represent various evaluation metrics:

- **Accuracy**: Refers to the ratio of correct predictions made by the model to the total number of predictions. It indicates the overall effectiveness of the classifier

Journal of Information Systems Engineering and Management
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Research Article

$$Accuracy = \frac{TP+TN}{TP+FN+TN+FP} \quad (2)$$

- **Precision**: Measures the proportion of true positive results among all positive predictions made. It helps assess how often the model is correct when it predicts a tumor.

$$Precision = \frac{TP}{TP+FP} (3)$$

- **Recall (Sensitivity)**: Determines the proportion of actual positives that the model correctly identifies. This is particularly important in medical imaging, where missing a tumor could have serious consequences.

$$Recall = \frac{TP}{TP+FN} (4)$$

- **F1-Score**: Represents the harmonic mean of precision and recall. It is especially useful in scenarios where there is an imbalance in the dataset.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad 5)$$

- **Confusion Matrix**: A structured table that summarizes prediction outcomes by showing the number of correct and incorrect classifications for each category (true positives, true negatives, false positives, and false negatives). Figure 5,6 and 7 depicts the confusion matrices for the three models- ResNet50, DenseNet201 and Adadensenet.
- **AUC-ROC Curve (Area Under the Receiver Operating Characteristic Curve)**: The ROC curve illustrates the diagnostic ability of the model by plotting the true positive rate against the false positive rate at various threshold levels. The **Area Under the Curve (AUC)** quantifies the model's ability to distinguish between classes. A higher AUC indicates better discriminatory performance

These evaluation measures were applied to the model's predictions on the test dataset to ensure unbiased assessment. For comparative analysis, the same metrics were also used to evaluate baseline models such as DenseNet201 and ResNet50 under identical conditions. Table 2 shows the Classification report for the Proposed Model (Adadensenet).

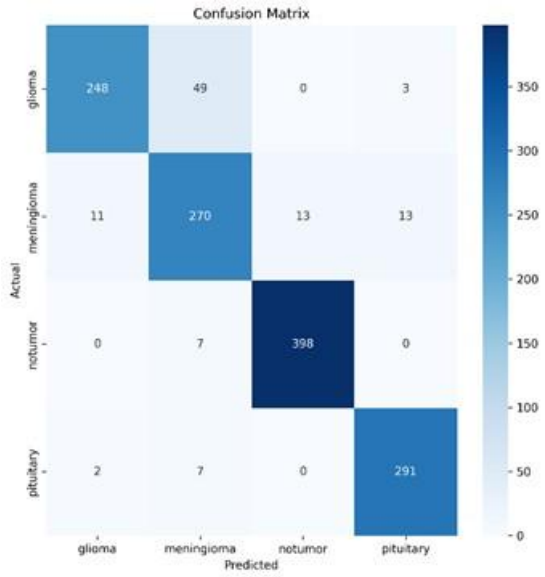

Figure 5. Confusion Matrix for ResNet50 model

Journal of Information Systems Engineering and Management
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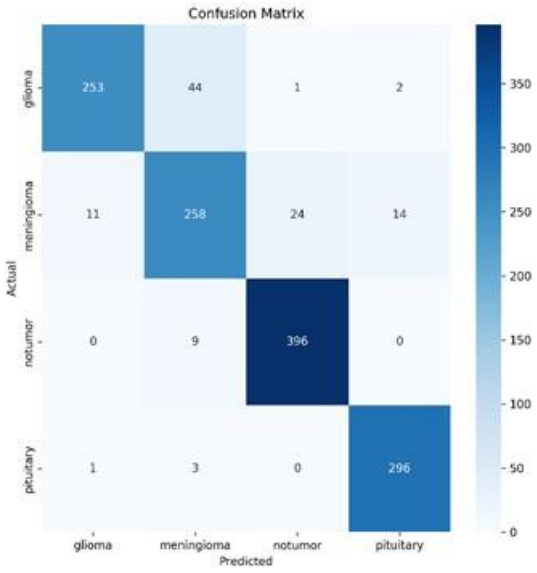

Figure 6. Confusion Matrix for Densenet201

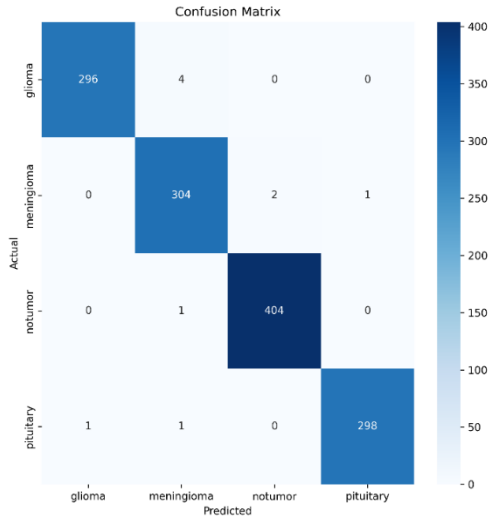

Figure 7. Confusion Matrix for the proposed model

Table 2. Classification report for the proposed model

	Precision	Recall	F1-score	Support
Glioma	1.00	0.97	0.98	300
Meningioma	0.97	0.97	0.97	307
No Tumor	0.99	1.00	1.00	405
Pituitary	0.98	1.00	0.99	300
Accuracy			0.99	1312
Macro avg	0.99	0.99	0.99	1312
Weighted avg	0.99	0.99	0.99	1312

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Research Article

Figure 8 illustrates the training and validation accuracy and loss curves over 50 epochs. It can be observed that the training and validation accuracy rapidly increase during the initial epochs and gradually stabilize around 99% which demonstrates efficient learning. Similarly, the training and validation loss decrease steadily and converge to a low value, indicating effective optimization and minimal overfitting. The close alignment between training and validation curves signifies that the proposed model generalizes well to unseen data and maintains stability throughout the training process

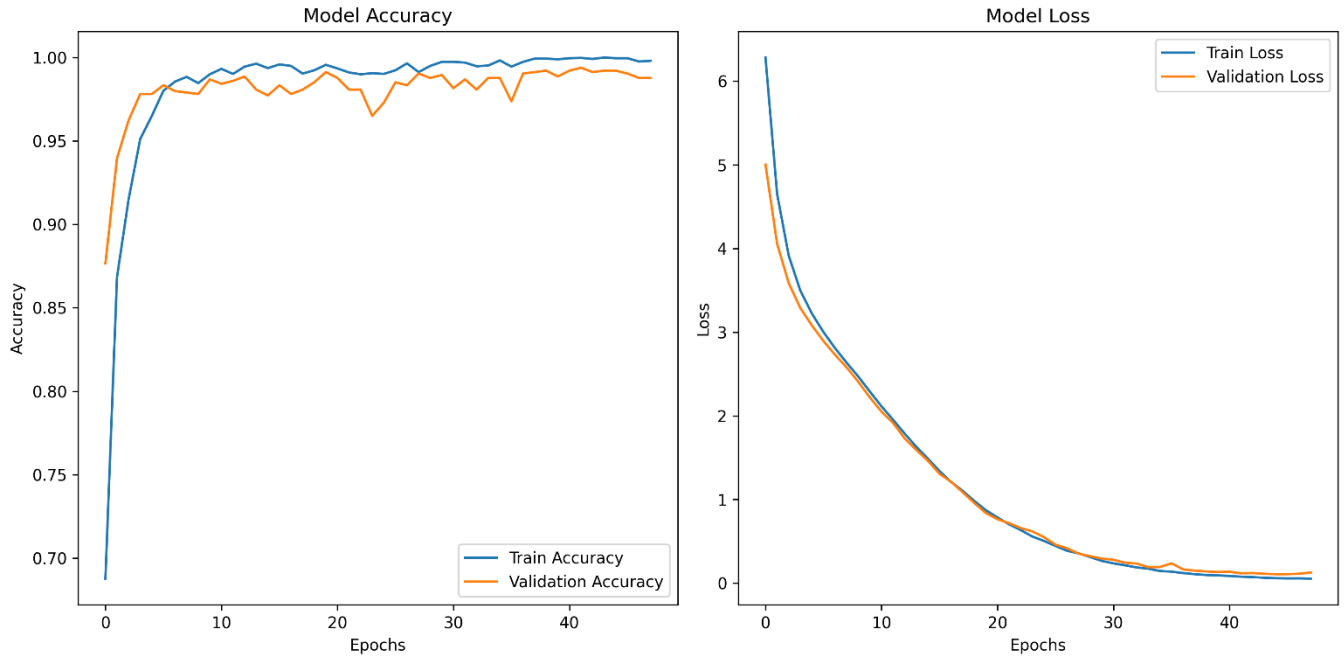

Figure 8. Overall accuracy per epoch and overall loss per epoch for the proposed model

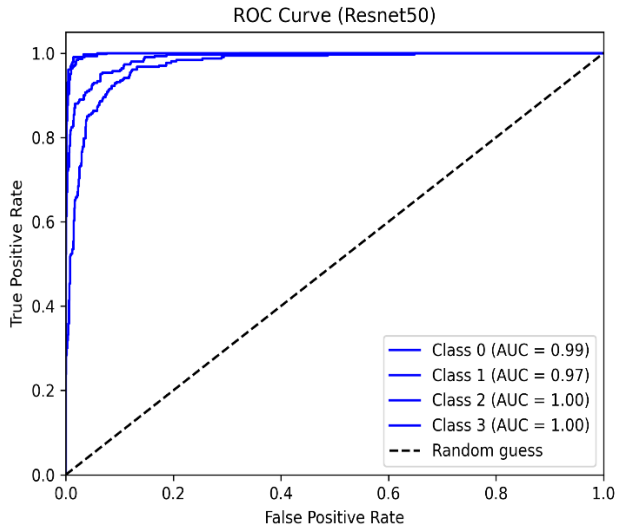

Figure 9. ROC- Curve (Resnet50)

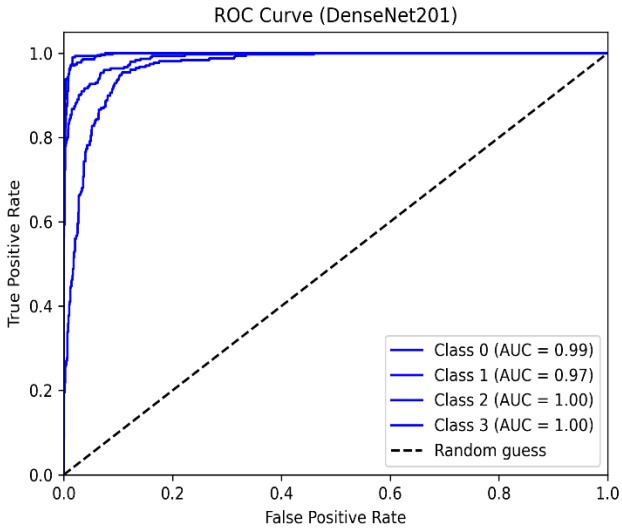

Figure 10. ROC-Curve (DenseNet201)

Journal of Information Systems Engineering and Management
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Research Article

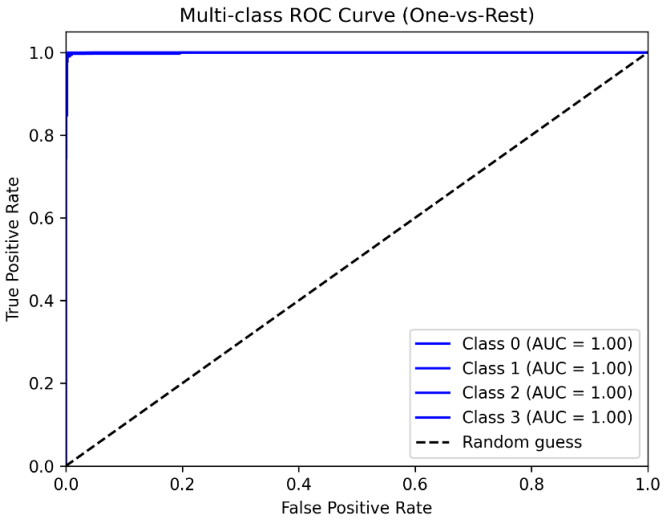

Figure 11. ROC-Curve (Proposed Model)

As depicted in Figure 9, Figure 10 and Figure 11, AdaDensenet demonstrates exceptional performance, achieving a perfect AUC (Area Under the Curve) score of 1.00 across all four classes. This indicates the model's outstanding ability to distinguish between tumor categories without any overlap or misclassification. In contrast, DenseNet201, though highly performance, exhibits a slight drop in AUC for Class 0 (0.99) and Class 1 (0.97), while maintaining a perfect score for Classes 2 and 3. A similar trend is observed in ResNet50, where the model also achieves an AUC of 0.99 for Class 0, 0.97 for Class 1, and 1.00 for Classes 2 and 3. The marginally lower AUC values for Class 1 in both DenseNet201 and ResNet50 suggest a relatively higher challenge in correctly classifying instances from that specific class.

Figure 12 shows that Adadensnet achieves the highest and most consistent accuracies which indicates generalization and stability

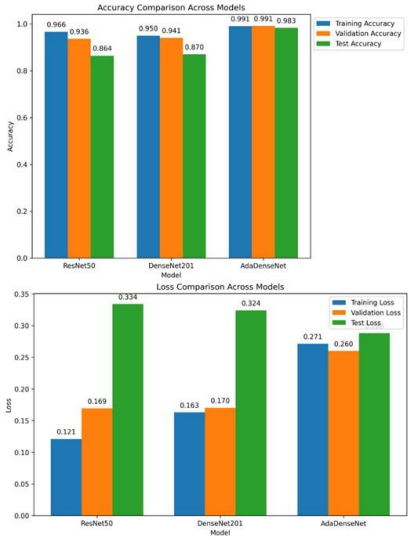

Figure 12. Accuracy and Loss comparison across models

Figure 13 illustrates the progression of training accuracy across 50 epochs.

Journal of Information Systems Engineering and Management
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Research Article

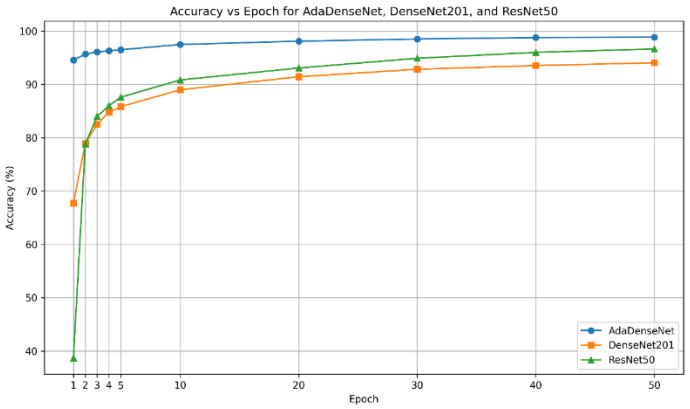

Figure 13. Accuracy Comparison per epoch for all the models

Table 3. Comparison of machine learning model

Algorithms	***Accuracy with dataset used in this study (in 50 epochs)***
DenseNet201	91.77%
ResNet50	92.0%
AdaDensenet	98.86%

Our proposed model demonstrated superior performance in classifying brain tumor images compared to traditional deep learning architectures such as DenseNet201 and ResNet50 and emerged as a standout performer in our comprehensive evaluation. All three models were trained using identical preprocessing steps, data augmentation strategies, and optimization parameters to ensure a fair and consistent comparison. Despite these controlled conditions, AdaDensnet outperformed the baseline models, achieving a remarkable accuracy of **98.86%**, while DenseNet201 and ResNet50 attained only **91.77%** and **92.0%** accuracy respectively, in 50 epochs (as shown in Table 3).

6. LIMITATIONS AND FUTURE SCOPE

The suggested AdaDensnet model has some limitations even though it achieves notable accuracy. One significant limitation is the dataset's moderate size and low heterogeneity, which may limit the model's capacity to generalize across a variety of real-world clinical scenarios. Furthermore, using solely 2D MRI pictures could miss important information found in other diagnostic data or 3D volumetric scans. Despite the use of techniques like regularization, dropout, and early halting, the high training accuracy raises the possibility of overfitting. Due to its lack of explainability features, which are crucial for clinical acceptance and confidence, the current model likewise operates as a black box. Moreover, minor tumor characteristics may have been lost when photos were resized to a consistent resolution.

There are a number of ways to increase its efficiency and generalizability. Cross-validation with multi-institutional or publically accessible external datasets may be used in future study to evaluate robustness. Predictions can become more transparent and clinically significant by improving interpretability using methods such as Grad-CAM. Diagnostic performance may also be improved by using multi-modal data, such as CT scans, patient demographics, or genomic markers. Additionally, model compression and optimization approaches could be used to investigate delivering the model in real-time or on devices with limited resources. Lastly, to lessen reliance on annotated dataset, which are frequently scarce in medical imaging tasks semi-supervised or self-supervised learning techniques could be used.

7. CONCLUSION

Our proposed brain tumor classification model AdaDensenet achieves an impressive accuracy of 98.86% after 50 training epochs, outperforming standard architectures like DenseNet201 and ResNet50. The model demonstrates

perfect discrimination capability, achieving AUC scores of 1.00 for all tumor classes as shown in the multi-class ROC curves, highlighting its exceptional ability to distinguish between categories with high precision. Although the study faces certain limitations, including a limited dataset size and high computational requirements, future research can explore federated learning, domain adaptation, and advanced attention mechanisms to further enhance model performance. Beyond its technical merits, AdaDensenet shows great promise for remote diagnostics, making AI-based healthcare more accessible in underserved regions. It can also support personalized treatment planning by aiding in tumor classification and predicting disease progression. However, challenges such as data privacy, clinical validation, and computational requirements must be addressed for wider adoption. Overall, AdaDensenet represents a meaningful step toward bridging the gap between artificial intelligence and real-world clinical applications, combining accuracy, interpretability, and efficiency to advance the future of AI-assisted radiology and telemedicine.

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