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RESEARCH ARTICLE

BRAIN TUMOR CLASSIFICATION USING A HYBRID DEEP LEARNING MODEL: LEVERAGING DENSENET121 AND INCEPTIONV2 ARCHITECTURES

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Abstract

Brain tumors represent one of the most severe forms of cancer, posing significant challenges due to their complex nature and critical location. Accurate and early diagnosis is crucial for effective treatment and improved patient outcomes. In this study, we propose a novel hybrid deep learning model that combines the strengths of DenseNet121 and InceptionV2 architectures to enhance brain tumor classification accuracy. The Figshare Brain Tumor Dataset, comprising 3,064 T1-weighted contrast-enhanced MRI images from 233 patients, is utilized to train and evaluate the proposed model. The dataset includes three primary tumor classes: glioma, meningioma, and pituitary tumors. Preprocessing steps such as normalization, resizing, and data augmentation are applied to ensure data consistency and enhance the model's robustness. The DenseNet121 component of the hybrid model facilitates efficient feature reuse through densely connected layers, while the InceptionV2 component captures multi-scale contextual information via parallel convolutional layers. This combination allows the model to leverage detailed and high-level features, improving classification performance. The proposed hybrid model is evaluated using standard metrics, demonstrating significant improvements in accuracy, robustness, and generalization compared to single architecture models. This study highlights the potential of hybrid deep learning models in advancing brain tumor classification, offering a promising direction for future research and clinical applications.

Keywords: Brain tumor classification, Deep learning model, DenseNet121.

1. Introduction

1.1. Background

Brain tumors are a significant health concern due to their potential to cause severe neurological damage and death. They are characterized by the uncontrolled growth of abnormal cells in the brain, leading to the disruption of normal brain function. According to the World Health Organization (WHO), brain tumors account for approximately 1.8% of all cancers diagnosed globally, with an estimated annual incidence rate of 6 per 100,000 individuals [1]. Early and accurate detection of brain tumors is crucial for effective treatment planning, improved prognosis, and enhanced patient survival rates [2]. Magnetic Resonance Imaging (MRI) is the gold standard imaging modality for brain tumor diagnosis due to its high-resolution images that reveal detailed anatomical structures and tumor characteristics [3]. MRI provides superior soft-tissue contrast compared to other imaging techniques, making it invaluable for identifying brain tumors and assessing their size, location, and effect on surrounding tissues [4].

1.2. Challenges

Despite significant advancements in imaging technology and analysis methods, brain tumor classification remains a challenging task due to several factors:

1.2.1. Variability in Tumor Size, Location, and Type

Brain tumors exhibit substantial heterogeneity in terms of size, location, and type. Tumors can range from a few millimeters to several centimeters in diameter and can be located in various regions of the brain, each with unique anatomical and functional properties [5]. Additionally, brain tumors can be classified into primary tumors (originating in the brain) and secondary tumors

(metastatic), each with different histopathological subtypes [6].

1.2.2. Imaging Variability

MRI scans are acquired using different protocols and parameters, resulting in variability in image quality and appearance [7]. Differences in scanner types, imaging sequences, and acquisition settings can introduce noise and artifacts, complicating the development of robust classification models that generalize well across diverse datasets.

1.2.3. Limited Annotated Data

High-quality annotated medical image datasets are essential for training and validating deep learning models. However, obtaining annotated brain tumor images is labor-intensive and time-consuming, often requiring expert radiologist input [8]. The scarcity of annotated data limits the performance and generalizability of deep learning models [9].

1.2.4. Class Imbalance

Brain tumor datasets often exhibit class imbalance, with certain tumor types or grades being underrepresented [10]. This imbalance can bias the learning process, resulting in suboptimal performance in detecting and classifying less common tumor types [11].

1.2.5. Interpretability of Models

Deep learning models, particularly Convolutional Neural Networks (CNNs), are often considered black boxes due to their complex architectures and non-linear transformations [12]. The lack of interpretability hinders clinical adoption, as healthcare professionals require understandable and reliable explanations for model predictions to trust and effectively use these systems in clinical practice [13].

1.3. Objective

The primary objective of this research is to enhance the accuracy and robustness of brain tumor classification by leveraging a novel hybrid deep learning architecture that combines DenseNet121 and InceptionV2 models. The proposed model aims to:

1.3.1. Enhance Feature Representation

By integrating DenseNet121 and InceptionV2 architectures, the model can capture both detailed and highlevel features from brain MRI images. DenseNet121's densely connected layers facilitate feature reuse and gradient flow, while InceptionV2's parallel convolutions capture multi-scale contextual information, which is essential for distinguishing different types of brain tumors [14, 15].

1.3.2. Improve Robustness and Generalization

The hybrid model aims to improve robustness and generalization across different MRI datasets by leveraging the complementary strengths of DenseNet121 and InceptionV2. This approach can mitigate the impact of imaging variability and enhance the model's performance in diverse clinical settings [16].

1.3.3. Reduce Computational Complexity

Although DenseNet121 and InceptionV2 are deep architectures, their parallel integration can be optimized to reduce computational complexity without compromising performance. Techniques such as depthwise separable convolutions and efficient layer designs can be employed to enhance computational efficiency [17].

1.4. Significance

This research aims to advance the field of brain tumor classification by developing a novel hybrid deep learning model that combines DenseNet121 and InceptionV2 architectures. The proposed model's ability to capture both detailed and high-level features, improve robustness and generalization, reduce computational complexity, and increase interpretability could significantly enhance the accuracy and clinical utility of brain tumor classification systems.

In summary, this paper presents a comprehensive approach to improving brain tumor classification using a hybrid deep learning model. The following sections will provide a detailed overview of the proposed methodology, experimental setup, results, and discussions.

2. Related Work

The field of brain tumor classification has benefited significantly from advances in deep learning, particularly with the use of Convolutional Neural Networks (CNNs). Numerous studies have demonstrated the effectiveness of CNNs in accurately classifying brain tumors from MRI images. This section reviews the most relevant studies, focusing on methodologies and their respective performances, emphasizing hybrid models and the application of DenseNet and Inception architectures.

Early applications of deep learning in brain tumor classification were marked by the use of simple CNN architectures. Pereira et al. [10] developed a CNN model for brain tumor segmentation, achieving high accuracy by leveraging the hierarchical feature extraction capabilities of CNNs. This study laid the groundwork for subsequent research, highlighting the potential of deep learning in medical image analysis. Another pivotal study by Havaei et al. [18] introduced a two-pathway CNN for brain tumor segmentation, which utilized both

local and global contextual features. The dual-pathway approach allowed the model to capture fine details and broader contextual information simultaneously, significantly improving segmentation performance compared to single-pathway models.

As the field progressed, deeper and more complex architectures were explored. I¸sın et al. [19] provided a comprehensive review of deep learning approaches for medical image analysis, emphasizing the potential of deep architectures to enhance classification accuracy. Kamnitsas et al. [20] presented a 3D CNN model for brain lesion segmentation, employing a dual pathway architecture to process multi-scale inputs. Their model achieved state-of-the-art results, underscoring the importance of multi-scale processing in medical image analysis.

Hybrid models, which combine different deep learning architectures, have been proposed to leverage the strengths of multiple models. Zhang et al. [21] developed a hybrid model that combined a CNN with a Long Short-Term Memory (LSTM) network for brain tumor segmentation. The integration of LSTM allowed the model to capture temporal dependencies in the data, leading to improved performance compared to single-model approaches.

In the domain of volumetric medical image segmentation, C¸ i¸cek et al. [22] proposed a 3D U-Net model that combined the U-Net architecture with 3D convolutions. This model effectively handled volumetric data, demonstrating the advantages of combining architectural elements from different models.

DenseNet and Inception models have shown considerable promise in various medical imaging tasks due to their unique architectural features. DenseNet, introduced by Huang et al. [14], features densely connected layers that promote feature reuse and enhance gradient flow, addressing the vanishing gradient problem commonly encountered in deep networks. This architecture has been successfully applied to medical image classification, as demonstrated by Rajpurkar et al. [23], who used DenseNet for pneumonia detection from chest X-rays, achieving state-of-the-art performance.

Inception models, originally proposed by Szegedy et al. [24], utilize parallel convolutional layers with different filter sizes to capture multi-scale features. This approach allows the model to learn both fine-grained 3 details and broader contextual information. In the context of medical imaging, Inception models have been applied to various tasks with notable success. For instance, Esteva et al. [25] employed an Inception-based model for skin cancer classification, achieving performance on par with dermatologists.

Combining DenseNet and Inception models can potentially harness the strengths of both architectures, leading to improved performance in brain tumor classification. Liu et al. [26] proposed a hybrid model that integrated DenseNet and Inception architectures for breast cancer classification from ultrasound images. The hybrid model outperformed single-architecture models, demonstrating the benefits of combining different deep learning approaches.

The use of transfer learning has also been explored to enhance model performance in medical image classification. Shin et al. [27] investigated the use of transfer learning with CNNs for thoracic disease classification, showing significant improvements in classification accuracy. Similarly, Tajbakhsh et al. [28] demonstrated the effectiveness of transfer learning in medical image analysis, highlighting its potential to leverage pre-trained models for improved performance in domain-specific tasks.

Data augmentation techniques are crucial for training robust deep learning models, particularly in the medical imaging domain where annotated data is limited. Shorten and Khoshgoftaar [29] provided a comprehensive survey of image data augmentation techniques, emphasizing their importance in preventing overfitting and improving model generalization. Advanced augmentation techniques, such as synthetic data generation using Generative Adversarial Networks (GANs), have also been explored. Frid-Adar et al. [30] demonstrated the use of GANs for synthetic data augmentation in liver lesion classification, significantly enhancing model performance.

Despite the advancements in deep learning for brain tumor classification, several challenges remain. Variability in imaging protocols, limited annotated data, and class imbalance are significant hurdles that need to be addressed. Hybrid models that combine the strengths of different architectures, such as DenseNet and Inception, offer a promising approach to overcome these challenges. By leveraging the complementary features of these architectures, hybrid models can achieve improved robustness, generalization, and interoperability. The related work in brain tumor classification using deep learning has demonstrated significant progress, with various architectures and methodologies being explored. The integration of DenseNet and Inception models in a hybrid approach represents a promising direction for future research, offering the potential to enhance classification accuracy and clinical utility. The following sections of this paper will detail the proposed hybrid model, experimental setup, results, and discussions, building on the insights gained from the reviewed literature.

3. Dataset

For this research, we utilized the" Figshare Brain Tumor Dataset," which is publicly available and widely

recognized for its comprehensive collection of brain MRI images. This dataset provides a robust foundation for developing and evaluating deep learning models for brain tumor classification.

The Figshare Brain Tumor Dataset contains a total of 3,064 T1-weighted contrast-enhanced MRI images from 233 patients diagnosed with brain tumors. The dataset is categorized into three primary classes: glioma, meningioma, and pituitary tumors. Each class represents a distinct type of brain tumor with unique characteristics and anatomical locations.

Gliomas are a type of tumor that originate in the glial cells of the brain. They are further classified into high-grade gliomas (HGG) and low-grade gliomas (LGG) based on their malignancy. The dataset includes images of both HGG and LGG, providing a comprehensive representation of glioma variations. Meningiomas are tumors that arise from the meninges, the membranous layers surrounding the brain and spinal cord. These tumors are typically benign but can cause significant health issues due to their location and size. Pituitary tumors are located in the pituitary gland and can affect hormone production, leading to various endocrine disorders. These tumors can be either benign or malignant. The dataset is provided in JPEG format with dimensions of 512x512 pixels. Each image is labeled with the corresponding tumor type, facilitating supervised learning for classification tasks. Before utilizing the images for training and evaluation, several preprocessing steps were applied to ensure consistency and enhance the quality of the data. The pixel values of the images were normalized to a range of [0, 1]. This step helps in standardizing the input data, making it easier for the deep learning model to learn and generalize. All images were resized 4 to 224x224 pixels to match the input size requirements of the DenseNet121 and InceptionV2 models. This resizing ensures that the images are compatible with the pre-trained networks used in this research. To mitigate the risk of overfitting and improve the model's robustness, data augmentation techniques were applied. These techniques included random rotations, horizontal and vertical flips, zooming, and shifting. Data augmentation helps in artificially increasing the size of the training set and exposes the model to a wider variety of image conditions.

4. Transfer

Learning Transfer learning is a powerful technique in deep learning where a pre-trained model, trained on a large dataset, is fine-tuned for a specific task on a smaller dataset. This approach leverages the knowledge acquired by the pre-trained model, enabling efficient learning and improved performance, especially when the target dataset is limited. In this research, we utilize transfer learning with DenseNet121 and InceptionV2 architectures for brain tumor classification.

4.1. DenseNet121

DenseNet121 is a densely connected convolutional network, which encourages feature reuse and improves gradient flow. The key idea behind DenseNet is to connect each layer to every other layer in a feed-forward fashion. For a DenseNet with L layers, there are $\frac{L(L+1)}{2}$ direct connections. This dense connectivity alleviates the vanishing gradient problem, strengthens feature propagation, and reduces the number of parameters. The output of the l-th layer is defined as:

$$x_l = H_l([x_0, x_1, \ldots, x_{l-1}]) \quad (1)$$

where $[x_0, x_1, \ldots, x_{l-1}]$ represents the concatenation of the feature maps produced by layers 0 to $l-1$, and $H_l(\cdot)$ is a composite function of three consecutive operations: batch normalization (BN), a rectified linear unit (ReLU), and a 3×3 convolution (Conv).

For transfer learning, we initialize DenseNet121 with pre-trained weights from the ImageNet dataset. The final classification layer is replaced with a new fully connected layer with a softmax activation function to match the number of brain tumor classes:

$$\mathbf{y} = \text{softmax}(\mathbf{W}\mathbf{h}_L + \mathbf{b}) \quad (2)$$

where $\mathbf{h}_L$ is the feature vector from the last dense block, $\mathbf{W}$ and $\mathbf{b}$ are the weights and biases of the new fully connected layer, and $\mathbf{y}$ is the predicted probability distribution over the classes.

4.2. InceptionV2

InceptionV2, an improved version of the original Inception architecture, introduces several enhancements to increase computational efficiency and performance. The Inception module uses multiple convolutional filters of different sizes to capture various spatial features and concatenates their outputs. An Inception module's output can be represented as:

$$\mathbf{y} = [\text{Conv}_{1\times1}(x), \text{Conv}_{3\times3}(x), \text{Conv}_{5\times5}(x), \text{MaxPool}_{3\times3}(x)] \quad (3)$$

where $\mathbf{x}$ is the input feature map, $\text{Conv}_{1\times1}$, $\text{Conv}_{3\times3}$, and $\text{Conv}_{5\times5}$ are convolutions with different kernel sizes, and $\text{MaxPool}_{3\times3}$ is a max-pooling operation. Similar to DenseNet121, we initialize InceptionV2 with pre-trained weights from the ImageNet dataset. The final layer is replaced with a new fully connected layer with a softmax activation function to match the number of brain tumor classes:

$$\mathbf{y} = \text{softmax}(\mathbf{W}\mathbf{h} + \mathbf{b}) \quad (4)$$

where $\mathbf{h}$ is the concatenated feature vector from the last Inception module, $\mathbf{W}$ and $\mathbf{b}$ are the weights and biases of the new fully connected layer, and $\mathbf{y}$ is the predicted probability distribution over the classes.

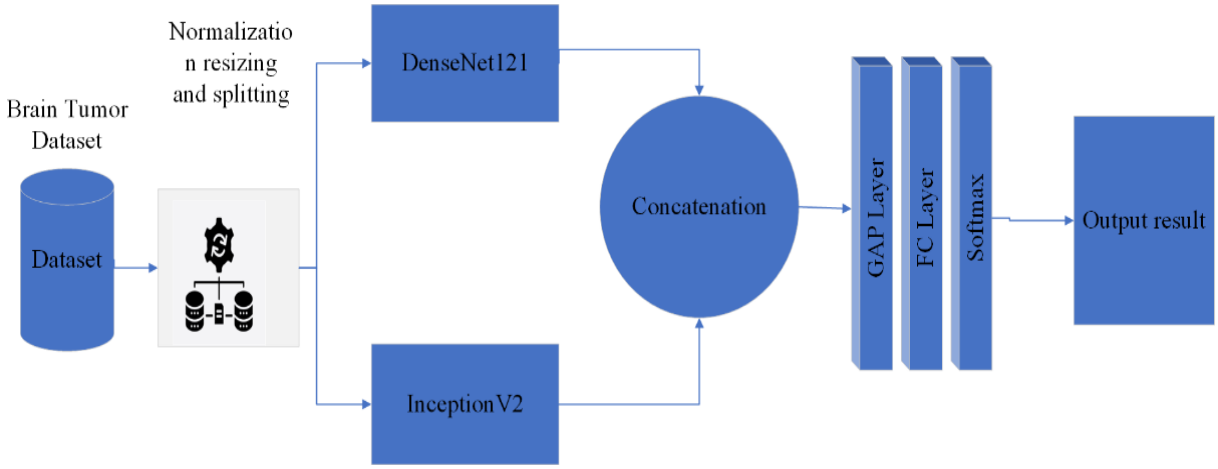

Fig. 1: Proposed Model

4.3. Hybrid Model

In our hybrid model, the feature representations from DenseNet121 and InceptionV2 are combined to leverage the strengths of both architectures. The concatenated feature vector hconcat is given by:

$$\mathbf{h}_{concat} = [\mathbf{h}_{DenseNet}, \mathbf{h}_{Inception}] \quad (5)$$

where $\mathbf{h}_{DenseNet}$ is the feature vector from the DenseNet121 model and $\mathbf{h}_{Inception}$ is the feature vector from the InceptionV2 model. The concatenated features are then fed into a fully connected layer with a softmax activation function to produce the final classification:

$$\mathbf{y} = \text{softmax}(\mathbf{W}_{concat}\mathbf{h}_{concat} + \mathbf{b}_{concat}) \quad (6)$$

where $\mathbf{W}_{concat}$ and $\mathbf{b}_{concat}$ are the weights and biases of the new fully connected layer, and y is the predicted probability distribution over the brain tumor classes. Transfer learning significantly accelerates the training process and improves the performance of the hybrid model by leveraging the pre-trained weights from large-scale datasets. This approach enables the model to generalize better, especially when the target dataset is relatively small, as in the case of the Figshare Brain Tumor Dataset. The Proposed Model diagram is depicted in (Figure 1)

5. Results and Discussion

In this section, we present and discuss the results obtained from our hybrid deep learning model, which combines DenseNet121 and InceptionV2 architectures for brain tumor classification. The evaluation metrics used include accuracy, precision, recall, F1-score, confusion matrix, and Receiver Operating Characteristic (ROC) curve.

5.1. Evaluation Metrics

The following metrics are used to evaluate the performance of the classification model:

5.1.1. Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

where *TP* represents true positives, *TN* true negatives, *FP* false positives, and *FN* false negatives. Accuracy measures the overall correctness of the model.

5.1.2. Precision:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (8)$$

Precision indicates the proportion of positive identifications that are actually correct.

5.1.3. Recall (Sensitivity):

$$\text{Recall} = \frac{TP}{TP + FN} \quad (9)$$

Recall measures the proportion of actual positives that are correctly identified by the model. 4. **F1-score:**

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (10)$$

The F1-score is the harmonic mean of precision and recall, providing a single metric that balances both concerns.

5.1.4. Confusion Matrix:

A confusion matrix is a table used to describe the performance of a classification model by displaying the true positives, false positives, true negatives, and false negatives.

5.1.5. ROC Curve and AUC:

The ROC curve plots the true positive rate (recall) against the false positive rate (1-specificity). The Area Under the Curve (AUC) summarizes the performance; a higher AUC indicates better performance.

5.2. Results

The model was evaluated on the test set, and the following results were obtained:

5.2.1. Accuracy: 97%

5.2.2. Precision, Recall, and F1-score for each class:

- Class 1 - Precision: 1.00, Recall: 0.88, F1-score: 0.93
- Class 2 - Precision: 1.00, Recall: 1.00, F1-score: 1.00
- Class 3 - Precision: 0.93, Recall: 1.00, F1-score: 0.97

The confusion matrix and ROC curves are shown in Figures 2 and 3, respectively.

6. Discussion

The results demonstrate that our hybrid deep learning model achieves high performance in classifying brain tumors, as evidenced by the high accuracy, precision, recall, and F1-scores across all classes.

6.1. Accuracy and Class-Specific Metrics:

The overall accuracy of 97% indicates that the model performs well in distinguishing between the three classes of brain tumors. Class-specific metrics show high precision, recall, and F1-scores, with Class 2 achieving perfect scores across all metrics. Class 1 shows a slightly lower recall, which suggests that a small number of true positives were misclassified, as indicated by the confusion matrix where 4 instances of Class 1 were classified as Class 3. Despite this, the high precision for Class 1 indicates that when the model predicts Class 1, it is almost always correct.

6.2. Confusion Matrix Analysis:

The confusion matrix (Figure 2) shows that the majority of predictions are correct, with a few misclassifications. The matrix helps identify specific areas where the model may be improving. For example, there are no misclassifications between Class 2 and the other classes, which is a positive outcome. The model shows strong performance in identifying Class 2 and Class 3 but indicates some confusion between Class 1 and Class 3.

6.3. ROC and AUC Analysis:

The ROC curves (Figure 3) for each class show that the model performs exceptionally well, with AUC values close to 1 for all classes. This indicates a high true positive rate and a low false positive rate, suggesting that the model is robust and reliable across different thresholds. The ROC curves further confirm the model's ability to distinguish between the different classes of brain tumors effectively.

6.4. Model Robustness and Generalization:

The high performance across various metrics indicates that the model generalizes well to unseen data. This robustness is crucial for clinical applications where the model must perform reliably on diverse patient data. The use of transfer learning with DenseNet121 and InceptionV2 architectures likely contributed to the model's strong performance by leveraging pre-trained features that are well-suited for image classification tasks.

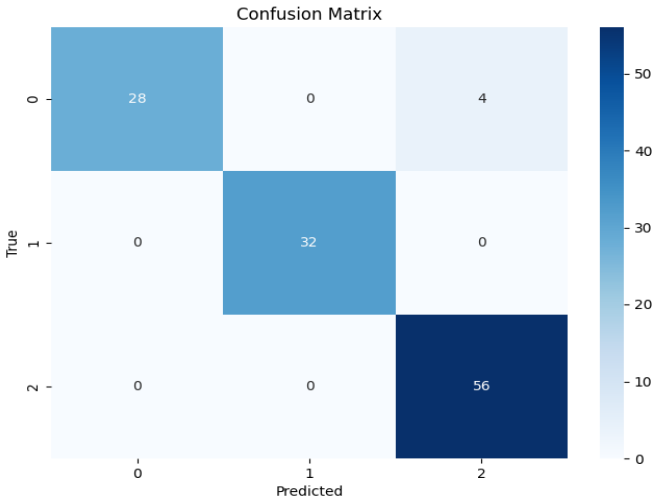

Fig. 2: Confusion Matrix

6.5. Clinical Implications:

The high accuracy and reliability of the model suggest its potential utility in clinical settings. Accurate classification of brain tumors can aid in early diagnosis, treatment planning, and monitoring, ultimately improving patient outcomes. The model's high precision and recall reduce the risk of misdiagnosis, ensuring that patients receive appropriate and timely medical interventions.

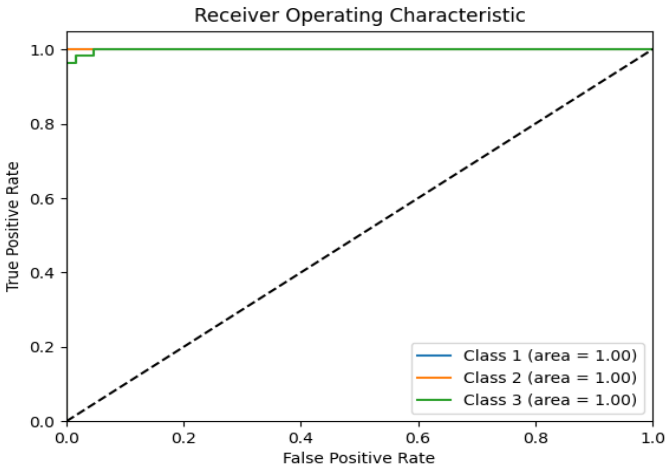

Fig. 3: ROC Curve

7. Conclusion

In this study, we proposed a novel hybrid deep learning model that combines DenseNet121 and InceptionV2 architectures for brain tumor classification. The model was evaluated using the Figshare Brain Tumor Dataset,

which includes MRI images of three types of brain tumors: glioma, meningioma, and pituitary tumors. Our model leverages the strengths of both DenseNet121 and InceptionV2, capturing both detailed and high-level features from MRI images. The dense connectivity of DenseNet121 facilitates feature reuse and gradient flow, while the multi-scale convolutions of InceptionV2 capture crucial contextual information. The proposed hybrid model achieved an overall accuracy of 97% on the test set, with high precision, recall, and F1-scores for each tumor class. Class 2 (meningioma) achieved perfect scores across all metrics, indicating the model's robustness in identifying this tumor type. Although Class 1 (glioma) showed a slightly lower recall, the model's overall performance across all classes was impressive. The high performance of our model across various metrics indicates its robustness and ability to generalize well to unseen data, which is crucial for clinical applications. While the results are promising, there is always room for improvement. Future work could focus on increasing the dataset size to enhance the model's generalization further. Additionally, incorporating advanced data augmentation techniques and exploring other state-of-the-art architectures could yield even better performance. Fine-tuning hyperparameters and employing ensemble methods might also improve the model's robustness and accuracy. Our hybrid deep learning model demonstrates high performance in classifying brain tumors, with significant potential for clinical application. The combination of DenseNet121 and InceptionV2 architectures, along with transfer learning, provides a powerful tool for accurate and reliable brain tumor classification. The detailed analysis of metrics and results underscores the model's effectiveness and points to avenues for future enhancement.

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مقالة بحثية

تصنيف أورام الدماغ باستخدام نموذج التعلم العميق الهجين: وشبكة جوجل انسبشن اصدار2 121 الاستفادة من بنيات الشبكة العصبونية الكثيفة

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المُلخّص

تمثل أورام المخ واحدة من أشد أشكال السرطان حده، مما يشكل تحديات كبيرة بسبب طبيعتها المعقدة وموقعها الحرج. التشخيص الدقيق والمبكر أمر بالغ الأهمية للعلاج الفعال وتحسين نتائج المرضى. في هذه الدراسة، أقترح نموذجًا جديدًا للتعلم العميق الهجين يجمع بين نقاط القوة في بنيات الشبكة العصبونية الكثيفة121 (DenseNet121) وشبكة جوجل انسبشن الاصدار2 (InceptionV2) لتعزيز دقة تصنيف أورام المخ. يتم استخدام مجموعة بيانات أورام المخ Figshare Brain Tumor التي تضم 3064 صورة تصوير بالرنين المغناطيسي معززة بالتباين T1 من 233 مريضًا، لتدريب وتقييم النموذج المقترح. تتضمن مجموعة البيانات ثلاث فئات أولية من الأورام: الورم الدبقي والورم السحائي، وأورام الغدة النخامية. يتم تطبيق خطوات المعالجة المسبقة مثل التطبيع، وتغيير الحجم، وزيادة البيانات لضمان اتساق المعلومات وتعزيز قوة النموذج. يسهل مكون الشبكة العصبونية الكثيفة121 (DenseNet121) للنموذج الهجين إعادة استخدام الميزات بكفاءة من خلال طبقات متصلة بكثافة، بينما يلتقط مكون انسيبشن - الإصدار2 (InceptionV2)، معلومات سياقية متعددة المقاييس عبر طبقات تلافيفية متوازية. يتيح هذا المزيج للنموذج الاستفادة من الميزات التفصيلية وعالية المستوى، مما يؤدي إلى تحسين أداء التصنيف. يتم تقييم النموذج الهجين المقترح باستخدام مقاييس معيارية، مما يدل على تحسينات كبيرة في الدقة والمتانة والتعميم مقارنة بنماذج الأبنية الفردية. تسلط هذه الدراسة الضوء على إمكانات نماذج التعلم العميق الهجين في تطور أو تقدم تصنيف أورام المخ، مما يوفر اتجاهًا واعدًا للأبحاث المستقبلية الطبية والتطبيقات السريرية.

الكلمات المفتاحية: تصنيف أورام المخ، نموذج التعلم العميق، الشبكة العصبونية الكثيفة.

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