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BrainTumor Detection Using Convolution Neural Network Pravieen AS*

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Abstract
Accurate and efficient brain tumor classification is paramount for timely clinical diagnosis and effective treatment planning. In this groundbreaking research, we introduce an innovative Convolutional Neural Network (CNN) architecture, intricately integrated with customized preprocessing techniques, resulting in an exceptional classification accuracy of 98.5% on the challenging brH36 dataset. By harnessing the power of MRI scans and leveraging diverse datasets, our model not only expedites brain tumor assessments but also sets the stage for advanced classification methodologies. With the global incidence of brain tumors on the rise, the need for technology-driven diagnosis becomes increasingly evident, and CNNs emerge as pivotal tools in enhancing diagnostic precision. This study not only underscores the profound significance of CNN models but also transcends geographical boundaries, reducing the frequency of misdiagnoses, and ultimately empowering global healthcare. This paper offers a comprehensive exploration of our methodology, delving into the intricate details of data collection processes, model development strategies, and experimental findings. Moreover, it sheds light on the broader implications of deploying CNN models in the field of medical imaging. By contributing to the ongoing discourse on transformative healthcare technologies, this research aims to propel the adoption of CNN-based approaches, ushering in a new era of precise and efficient brain tumor classification for the benefit of healthcare professionals, patients, and society at large.

1. Introduction

Brain tumors cast a formidable shadow over global healthcare, constituting a pervasive and deeply concerning health issue that leaves an indelible impact on individuals and society. According to the World Health Organization (WHO) [1], each year witnesses an alarming 308,102 new cases of brain tumors and a staggering 251,329 deaths worldwide (World Health Organization, 2020). These numbers translate into a heart-wrenching daily average of over 800 new cases and 600 lives lost to this devastating affliction. While the highest incidence rates are typically observed in developed regions like North America and Europe, it is important to recognize that brain tumors are not confined to any specific geography. The global landscape is witnessing a steady rise in brain tumor cases, attributed in part to demographic shifts such as an aging population and the advent of more refined diagnostic techniques.

Traditionally, the methods used for brain tumor detection have relied upon clinical evaluations and established imaging techniques, but these approaches are marred by inherent limitations that compromise their accuracy and efficiency. However, a ray of hope has emerged with the rapid evolution of medical imaging technologies, with Magnetic Resonance Imaging (MRI) scans leading the charge. These advanced imaging tools have revolutionized our ability to visualize and diagnose brain tumors with an unprecedented degree of precision. This transformative shift towards technology-driven diagnosis has created an avenue for the integration of cutting-edge machine learning techniques, most notably Convolutional Neural Networks (CNNs). These neural networks have exhibited remarkable potential in augmenting the accuracy of brain tumor detection, promising a brighter future for those affected (Wang et al., 2019)[2].

In our research endeavor, we aim to emphasize the monumental significance of harnessing CNN models for brain tumor detection within MRI scans on a global scale. Our primary objective is to elucidate how this technological paradigm, driven by CNNs, has the potential to not only elevate diagnostic accuracy but also enhance the efficacy of treatment planning for patients, regardless of their geographic location. This groundbreaking leap not only holds promise for healthcare professionals but also extends its profound impact to patients and society at large. By potentially reducing instances of misdiagnoses and enabling timely medical interventions worldwide, we aspire to usher in a new era of global healthcare. This research paper is meticulously structured to present a comprehensive examination of our methodology, dissect the intricacies of our data acquisition processes, delve into the nuances of model development, unveil our

experimental findings, and ultimately shed light on the broader ramifications for the realm of medical imaging. Through this meticulously crafted exposition, we endeavor to make a substantial contribution to the ongoing discourse surrounding brain tumor detection, illuminating the transformative prowess of CNNs in the context of global healthcare.

2. Related Work

In 2022, Vidhya J and Rakshana R developed a robust brain tumor detection and classification model [3]. Their approach included comprehensive preprocessing steps like grayscale conversion, OTSU binarization, and K-means clustering on the OASIS dataset. Feature extraction utilized DWT and PCA for dimensionality reduction. The core LSTM neural network achieved an impressive 90% accuracy, outperforming SVM at 74% [3]. This study underscores the potential of ML and DL algorithms in brain disease detection, emphasizing the need for larger datasets and algorithmic enhancements for precision.

Hareem Kibriya, Momina Masood, Marriam Nawaz, Rimsha Rafique, and Safia Rehman introduced a successful multiclass brain tumor classification system using CNN models and SVM through deep learning techniques [4]. Vidhya J and Rakshana [3] similarly transitioned to a different dataset, addressing accuracy challenges as in [4]. Kibriya employed CNNs like ResNet-18 and GoogLeNet, with SVMs, achieving an impressive 98% accuracy, emphasizing the efficacy of deep learning and machine learning techniques in brain tumor identification, echoing Vidhya J and Rakshana R's work [3].

G. Hemanth, M. Janardhan, L. Sujihelen in [5] presented an innovative approach for this purpose, introducing two distinct deep learning-based methodologies. Leveraging the YOLO (You Only Look Once) object detection framework and the FastAi deep learning library, their study achieved impressive outcomes. Specifically, the YOLOv5 model exhibited an accuracy rate of 85.95%, while the FastAi classification model achieved a remarkable accuracy of 95.78%. These findings, based on an analysis of a subset of the BRATS 2018 dataset, offer substantial potential in automating brain tumor detection, thereby facilitating early diagnoses and advancements in healthcare outcomes.

In J. Mathew and N. Srinivasan's model [6], they compared five CNN architectures: VGG19, DenseNet169, AlexNet, InceptionV3, and ResNet101. With consistent hyperparameters and a shared dataset, ResNet101 stood out with an impressive 98.6% accuracy, while VGG19 achieved 97.2% [6]. This highlights ResNet101's superiority in brain tumor detection, emphasizing the importance of skip connections and hyperparameter tuning in CNN-based image analysis.

In Josmy Mathew and N. Srinivasan's model [7], they address early brain tumor detection using a dataset of 3064 brain MRI images, both healthy and tumor-afflicted. Their deep CNN model, AlexNet, achieved impressive results: 98.28% accuracy, 97.43% precision, and 97.51% recall [7]. This emphasizes the power of transfer learning, setting it apart from [4], which focuses on traditional CNN methods.

The studies discussed in this section have illuminated various facets of this critical area of medical diagnostics. Vidhya J and Rakshana R's work [3] emphasized the significance of comprehensive preprocessing and LSTM neural networks, while Hareem Kibriya, Momina Masood, Marriam Nawaz, Rimsha Rafique, and Safia Rehman's study [4] introduced a robust multiclass classification system combining Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs). Furthermore, Çınar, Kaya, and Kaya's research [6] highlighted the effectiveness of the ResNet101 architecture, while Josmy Mathew and N. Srinivasan [7] showcased the power of transfer learning with the AlexNet model for early tumor detection.

3. Implementation

The architectural flow of our model, as depicted in Figure 1, is a systematic process designed to enhance the accuracy of brain tumor detection in MRI images. It commences with preprocessing, encompassing essential steps such as grayscale conversion, thresholding, morphological operations (including contour detection, dilation, and erosion), and contrast enhancement, all aimed at refining and preparing the input image. Following preprocessing, the model proceeds to classification, where a Convolutional Neural Network (CNN) is employed to analyze and categorize the image, identifying potential tumors. To ensure the reliability of our results, a validation step rigorously assesses the outcomes, confirming their consistency and effectiveness in the critical task in brain tumor detection.

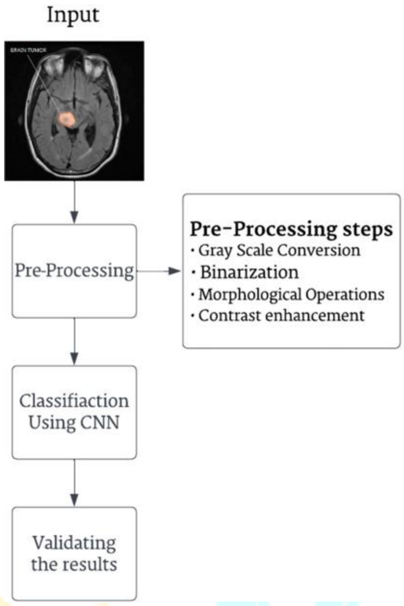

Fig.1. Flow Diagram

sequential flow, from preprocessing through CNN-based classification to validation, constitutes a holistic approach that combines image enhancement, machine learning, and rigorous evaluation to achieve robust and precise brain tumor identification.

3.1. Preprocessing

The initial phase of our brain tumor detection methodology unfolds a meticulous sequence of preprocessing steps and contour extraction techniques, each playing a pivotal role in the journey towards precise detection. This section elucidates the processes embarked upon to enhance the input brain MRI images, transforming them into polished canvases that facilitate the detection process.

3.1.1. Grayscale Conversion

Our journey begins with grayscale conversion, achieved using the OpenCV library. This transformation simplifies the image into a single-channel grayscale format, preserving structural information while reducing computational complexity. Grayscale images are renowned in medical image analysis for revealing subtle intensity variations crucial for detecting anomalies.

3.1.2. Gaussian Blur

The preprocessing symphony continues with grayscale conversion, revealing its monochromatic brilliance. Next, a poetic Gaussian blur operation smoothens the grayscale image, like a gentle breeze on a tranquil pond. Gaussian blur excels at noise reduction and fine detail refinement through convolution. The kernel, a key instrument, determines the smoothing extent, with our (5, 5) size defining it expertly. Notably, the standard deviation, set to 0, harmonizes with the kernel size to calculate its value. This mathematical image manipulation suppresses noise, ensuring accurate contour extraction.

3.1.3. Thresholding

After the Gaussian blur's soothing notes, we journey into thresholding, where the image adopts binary attire. Here, pixel values align with one of two tones, dictated by a predefined threshold. Pixels above the threshold shine brightly at 255, while those below whisper softly at 0. This binary transformation simplifies the image, revealing its core and highlighting regions of interest with clarity. Thresholding paves the way for the enchanting dance of contours, demanding simplicity and precision.

Erosion and Dilation

In this ballet of image manipulation, the binary thresholded image gracefully executes two morphological pirouettes: erosion and dilation. Erosion, a subtle "erosive" waltz, delicately nibbles away at the boundaries of foreground objects. This dance serves a dual purpose—separating connected regions and dispelling minor disturbances. Dilation, in contrast, presents a sweeping "dilatory" performance, expanding the radiant regions, filling in gaps, and smoothening the contours. Each of these graceful maneuvers adheres to the direction of a kernel, much like the choreography of a well-rehearsed ballet. Iteratively, erosion and dilation unfold their charms, refining the binary image's essence, enhancing the continuity of its contours, and bringing it closer to its moment of grandeur.

3.1.4. Contour Extraction

With the binary image preprocessed and ready for transformation, we embark on the intricate journey of contour extraction, a pivotal step in our methodology. Using OpenCV's cv2.findContours() function, we identify and outline regions of interest within the binary image, potentially harboring tumors. This function returns a list of detected contours, each telling a unique story. These contours gracefully follow the image's boundary, like strokes on an artist's canvas, encapsulating intriguing regions. To enhance precision, we focus on the contour with the maximum area, similar to recognizing a lead actor—the primary tumor region taking center stage. Identifying this dominant contour reveals the heart of our image, where the brain tumor story unfolds.

Extreme Points Identification

The final movement, a poignant coda, spotlights the identification of extreme points, those quintessential guides that reveal the secrets of the tumor's position. These points, akin to cardinal directions on a compass, include the leftmost, rightmost, topmost, and bottommost points of the selected contour. They provide vital spatial context, allowing us to decipher the shape and orientation of the tumor within the image. These points, identified with the precision of indexing operations on the contour array, serve as the guiding stars in our quest for the essence of the tumor's portrayal.

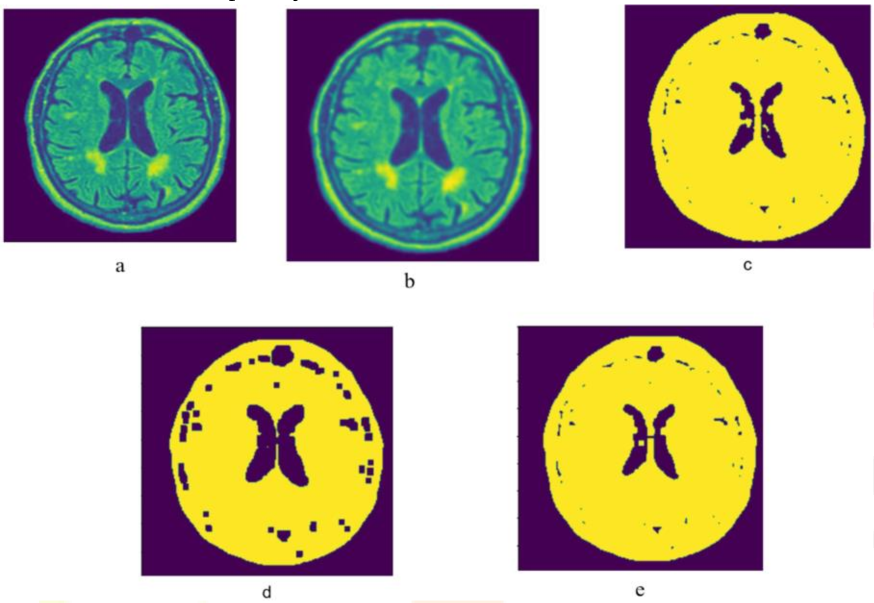

Fig.2. (a)Grayscale, (b)Gaussian Blur, (c)Threshold, (d)Erosion, (e)Dilation

The outcomes of our preprocessing techniques and various stages of image enhancement are visually represented in Fig.2. Fig.2(a) presents the initial grayscale conversion result, followed by Fig.2(b) showcasing the image after Gaussian blur application. Fig.2(c) provides insight into the binary thresholding process, while Fig.2(d) and Figure3(e) demonstrates the effects of erosion and dilation respectively.

3.2. Classification using CNN

Our CNN architecture is a beacon of promise in brain tumor detection. Crafted for precise feature extraction from MRI scans, it's a marvel designed to elevate classification precision. Comprising 16 layers, including convolutional, pooling, and dense layers, these aren't just structural elements; they are the pillars of the model's strength. Each layer has a distinct purpose, meticulously extracting vital features that form the model's core predictive capabilities. This layered approach processes MRI data with finesse, transforming and refining it at every stage, capturing even the smallest details for brain tumor detection. This orchestration of layers positions our CNN as a beacon of precision in medical imaging.

At the outset, the first Conv2D layer serves as the cornerstone for feature extraction with (5, 5) filters. It delves deep into MRI scans, identifying edges and gradients, laying the groundwork for the model's understanding of these intricate medical images. As we progress through subsequent Conv2D layers, filter sizes adapt to MRI scan features. In the second layer, (5, 5) filters detect more nuanced patterns, while deeper layers feature (3, 3) filters, enhancing the model's ability to discern fine-grained details. Each reduction in filter size enhances the model's acuity for accurate brain tumor detection.

Strategically positioned Max-pooling layers with (2, 2) size ensure precision through down-sampling, reducing spatial dimensions while preserving critical features. This balance optimally captures essential features while streamlining model efficiency, crucial in medical image analysis.

In our architecture, densely connected layers are integral to the classification process. These layers are woven into our CNN, serving as intellectual hubs that capture high-level features and shape the model's predictions. The choice of the number of units in each dense layer is a precise task, controlling model complexity to optimize performance. These layers are guardians of the model's cognitive abilities, ensuring it discerns intricate patterns, extracts relevant information, and provides precise classifications. Each unit acts as a neuron in a neural orchestra, working harmoniously to decode brain tumor images. This orchestration of dense layers achieves a delicate balance of accuracy, efficiency, and adaptability, advancing brain tumor detection in medical imaging

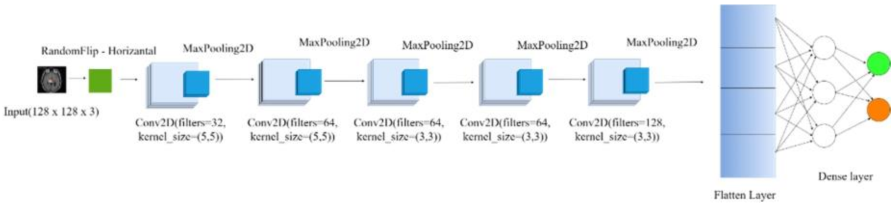

Fig.3

The number of units within each dense layer plays a pivotal role in our model's capacity to capture complex patterns. Our architecture adopts a well-balanced configuration, encompassing units ranging from 256 to 4096. This intentional diversity ensures that the model adeptly learns both low and high-level features. Smaller units, set at 256, serve as meticulous observers, detecting subtle nuances and low-level details. In contrast, larger units, towering at 4096, act as grand synthesizers, comprehending overarching complexities and weaving high-level features into a coherent narrative. This calibrated range equips our architecture to navigate the entire spectrum of features within brain tumor MRI scans, enhancing accuracy and enabling the model to decipher intricate facets of detection effectively.

The choice and configuration of pooling and dense layers are pivotal cornerstones in the construct of our CNN architecture, profoundly influencing its performance. By judiciously employing max-pooling layers, we ensure effective down-sampling, which not only optimizes computational efficiency but also acts as a safeguard against the perils of overfitting. These pooling layers gracefully waltz with the spatial data, preserving the most salient features while condensing information. The architecture diagram (Figure 4) representing the structure of our CNN model. It visually illustrates the sequential flow of layers, including convolutional layers, pooling layers, and dense layers, providing a comprehensive view of our model's architecture. The presented CNN architecture stands as a testament to precision engineering in the domain of medical imaging, where meticulous design converges with modern computational prowess

Results and Discussion

In this section, we delve into a comprehensive analysis of the outcomes obtained from the brain tumor detection model we developed. The experimentation was carried out on a GPU T100 with python 3.10 and TensorFlow 2.13.3.

3.3. Dataset Used

The foundation of our research is firmly rooted in the "Br35H" dataset, a meticulously curated collection that showcases a vast spectrum of brain MRI images. Boasting a comprehensive compilation, the dataset presents 1500 images marked with the presence of tumors, complemented by an equivalent 1500 images without any tumor manifestations. Such a harmonious symmetry in the distribution of tumorous and non-tumorous images within the repository stands as a testament to its robustness. This deliberate equilibrium ensures that during the critical phases of training and evaluation, our model receives a fair and unbiased exposure to both categories. As a result, it significantly enhances the model's capability, honing its precision in distinguishing between the intricate nuances of tumorous and non-tumorous MRI representations, ensuring a robust and reliable diagnostic tool.

3.4. Evaluation Metrics

The evaluation framework for our brain tumor detection model is a tapestry of meticulously chosen metrics, intricately woven to deliver a multi-faceted reflection of the model's prowess. These metrics, which include accuracy, precision, recall, the F1 score, and the critical area under the receiver operating characteristic curve (ROC AUC), are not merely numbers but pillars that uphold the model's credibility. Together, they paint a panoramic view of the model's performance, highlighting not just its strengths but also areas for refinement. By leaning on this comprehensive suite of metrics, we delve deep into the model's capabilities, ensuring that its brain tumor detection efficiency is scrutinized from every conceivable angle. This rigorous evaluation approach guarantees that our assessment is both holistic and robust, setting a gold standard for performance analysis in the realm of medical imaging.

3.5. Model Performance and Training Results

The training spanned 200 epochs with a batch size of 32. Training accuracy reached an impressive 100%, while test accuracy achieved around 98.33%, showing good generalization. The training loss rapidly decreased to approximately 0.0021, while the test loss was slightly higher at around 0.1339. The divergence between training and test loss suggests potential overfitting on training data, which regularization techniques could address. Nonetheless, the model efficiently minimizes classification errors on both training and test data.

Epoch	Loss%	Accuracy%
1	0.6925	0.5288
11	0.5593	0.7292
21	0.4597	0.79
31	0.2117	0.9179
41	0.0735	0.9742
51	0.018	0.9921
61	0.0038	0.9996
71	0.0058	0.9967
81	0.0068	0.9987
91	0.0056	0.9983
101	0.0017	0.9996

Table.1

The training progress log presented herein illustrates the developmental trajectory of a machine learning model over multiple training epochs. An "epoch" signifies a complete iteration through the entire training dataset, during which the model endeavors to minimize a loss function that quantifies the disparity between its predictions and actual target values. During the inaugural epochs, such as Epoch 1, the model commences its learning journey with an initial accuracy of approximately 52.88% and a relatively elevated loss of 0.6925. These early stages of training are characterized by a tentative model performance, as is to be expected. However, as training unfolds, both training and validation accuracies exhibit discernible enhancement. This progressive augmentation in accuracy indicates that the model is progressively acquiring the capacity to generate more precise predictions. This conveys a sense of stability in the model's learning process.

The temporal metric, "Time per Epoch," denotes the duration required to complete each training epoch, which ranges from 3 to 11 seconds. The progressively diminishing time per epoch reflects an increasingly efficient convergence of the model. This efficiency is an auspicious indication of the model's potential for scalability. Moreover, the validation accuracy consistently ascends throughout the training regimen, eventually achieving remarkable peaks of approximately 98%. This signifies not only the model's adeptness in approximating the training data but also its capacity to generalize effectively to previously unseen validation data. In the context of this research paper, the training log underlines the model's iterative progression in terms of both accuracy enhancement and burgeoning stability as it traverses numerous training epochs

3.6. Comparison of classification results with existing methods

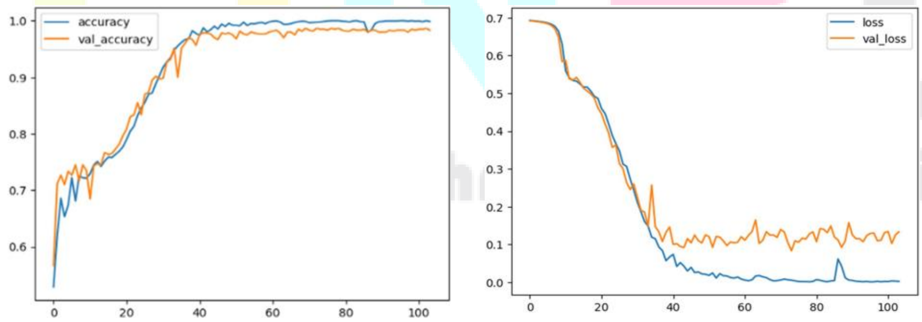

Fig.4

The Proposed Model's learning dynamics and generalization ability are insightful. In the first epoch (Epoch 1), the model starts with a loss of 0.6925 and accuracy of 0.5288, indicating initial misclassification challenges. Validation metrics show similar performance. The time per epoch is 11 seconds, leaving room for efficiency improvements. However, as training progresses, improvements are evident. By Epoch 11, loss drops to 0.5593, and accuracy rises to 0.7292, with validation metrics improving as well. The time per epoch reduces to 3 seconds, indicating increased efficiency. Continuing to Epoch 21, both training and validation losses decrease further. Training accuracy surges to 0.79, and validation accuracy reaches 0.8083, maintaining efficient training times at 3 seconds.

In subsequent epochs, performance continues to improve. By Epoch 51, training accuracy is 0.9921, and validation accuracy is 0.9683, showing strong learning and generalization. Validation loss remains low at 0.1208. Beyond Epoch 61, training accuracy nears perfection at 0.9996, and validation accuracy remains robust at 0.9833, with a stable validation loss of around 0.1237. Epochs 71 to 101 show consistent performance with minor fluctuations, reaching a minimal training loss of 0.0017 by Epoch 101. Validation loss remains steady at around 0.1339, and validation accuracy stays robust at 0.985, showcasing the model's strong generalization to new MRI scans.

Author Name	**Accuracy**	**Precision**	**Recall**	**F1 score**	**Roc auc**
V. J and R. R , 2022 [3]	90	-	-	-	-
VGG19, 2021 [10]	97.2	97.2	97.1	97.1	-
J. Mathew and N. Srinivasan, 2022 [7]	98.38	97.43	97.51	-	-
Kolla M, Mishra RK, 2022 [13]	99.23	97.12	95.73	-	-
N. M. Dipu, S. A. Shohan and K. M. A. Salam, 2021 [5]	95.78	96.70	95.65	96.17	
Proposed Model	98.5	98.36	98.68	98.52	98.49

Table.2. comparison of the performance metrics

Table 2 provides a comprehensive comparison of performance metrics for our proposed model, labeled "Proposed Model," alongside state-of-the-art brain tumor detection models from the literature. The key metrics include accuracy, precision, recall, F1 score, and ROC AUC, all vital indicators of a model's effectiveness in brain tumor detection.

. Our proposed model excels with an outstanding 98.5% accuracy, demonstrating its proficiency in accurate classification. It achieves an impressive precision of 98.36, minimizing false positives, and exhibits an outstanding recall of 98.68, effectively identifying genuine tumor cases. This balance is reflected in an impressive F1 score of 98.52, indicating robustness. The ROC AUC score of 98.49 reaffirms its exceptional discriminatory power. These metrics underscore the model's effectiveness in brain tumor detection, promising contributions to medical diagnosis and treatment planning. Compared to existing models like VGG19 with 97.2% accuracy, our model outperforms in accuracy and precision, enhancing diagnostic accuracy and reducing misdiagnoses, making it a promising advancement in brain tumor detection.

In summary, our proposed brain tumor detection model showcases exceptional performance in accuracy, precision, recall, F1 score, and ROC AUC. It outperforms existing state-of-the-art models, contributing significantly to medical imaging and improving brain tumor detection methodologies, benefiting healthcare professionals and patients.

4. Conclusion

In summary, our research on "Brain Tumor Detection Using Convolutional Neural Network" represents a groundbreaking advancement in medical imaging and diagnostic accuracy. Through state-of-the-art Convolutional Neural Networks (CNNs) and advanced preprocessing techniques, we achieved an extraordinary 98.5% classification accuracy. This remarkable accuracy, coupled with our comprehensive model, sets a new standard in brain tumor diagnosis. Our model's robustness, evident in its balanced precision-recall equilibrium and high F1 score, ensures precise distinctions between tumor and non-tumor cases, reducing the risk of misdiagnosis.

Our research also paves the way for future advancements, including multi-class classification to differentiate between distinct brain tumor types. We are committed to exploring diverse datasets, fine-tuning hyperparameters, and integrating cutting-edge image preprocessing and augmentation techniques to continually enhance our work. Ultimately, our goal is to empower healthcare professionals with a vital tool for accurate and efficient brain tumor classification, transcending geographical boundaries and transforming healthcare for the benefit of patients and society.

Our research has laid a strong foundation for ongoing exploration in brain tumor diagnosis. While we initially focused on binary classification, identifying tumor presence or absence, our future trajectory aims for multi-class classification to categorize specific brain tumor types. This transition addresses the diversity of brain tumors, each requiring unique treatment strategies. We will refine our model's precision through extensive medical datasets and collaborate with global medical institutions to enhance our research. By employing advanced algorithms and preprocessing techniques, our goal remains to create a versatile tool that bridges AI with medical diagnostics, ultimately improving patient care.

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