Automated Brain Tumor Detection and Classification Using Convolutional Neural Networks

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Abstract— This study unveils a novel methodology by employing Convolutional Neural Networks (CNNs) for the automated identification and classification of brain malignancies. The proposed method utilizes a comprehensive collection of high-resolution brain MRI scans from various datasets. It accomplishes this by employing cutting-edge image preprocessing techniques and a meticulously designed CNN architecture. The three-step procedure comprising preprocessing, feature extraction, and classification guarantees a reliable depiction of tumor characteristics. Convolutional neural networks (CNNs) that employ machine learning are capable of learning discriminative features independently from unprocessed image input. The superiority of the proposed method in identifying and classifying brain tumors is apparent, given its impressive accuracy of 99.76%. This study indicates that the system effectively assesses medical images, suggesting the potential for enhanced neuroimaging diagnosis.

Keywords— Brain Tumor, Convolutional Neural Networks (CNNs), Medical Image Analysis, Image Preprocessing, Classification.

I. INTRODUCTION

Brain tumors represent a significant public health issue and therefore, prompt and accurate diagnosis is crucial for determining the most effective course of treatment [1]. Traditional methods of diagnosis rely on the arduous and subjective manual assessment of brain scans using computed tomography (CT) or magnetic resonance imaging (MRI) by certified radiologists, who are susceptible to human error [2]. This research paper presents an innovative approach for brain tumor detection that leverages a state-of-the-art Convolutional Neural Network (CNN) constructed upon Multi-Scale Feature Fusion. This approach involves the meticulous collection and preparation of data prior to entrusting it to human experts for evaluation. This paper employs a variety of techniques, including image enhancement, noise reduction, and standardization, to ensure that the data is of the utmost quality [3]. The proposed methodology is built upon the fusion of CNN and Multi-Scale Feature Fusion [4]. A multitude of CNN branches with varied kernel sizes and dilation rates are required for feature map fusion to function across receptive field widths that vary. The aim is to instruct the network to identify both large-scale details and small-scale patterns concurrently. By enabling the detection of both subtle and obvious features in images of brain lesions, the multi-scale methodology substantially improves the model's sensitivity. This enhances the adaptability of the model even further, permitting it to manage a greater variety of tumor diameters and levels of complexity. An Attention Mechanism is also integrated in the methodology to enhance the CNN classification [5]. This approach enhances the discriminatory capability of the network by dynamically placing emphasis on critical regions during the process of feature extraction [6]. The continuous integration of spatial attention modules subsequent to particular convolutional layers serves to emphasize crucial regions, thereby augmenting the precision and interpretability of tumor localization [15]. This study provides a comprehensive overview of how the proposed CNN architecture incorporates these innovative methods to ensure precise brain tumor detection and also presents an innovative and all-encompassing methodology for detecting brain tumors through the integration of supplementary branches that utilize diverse attention processes, kernel diameters, and dilation rates. The proposed solution offers a more methodical and sophisticated means of identifying brain malignancies when compared to conventional manual review methods. Incorporating a Multi-Scale Feature Fusion and Attention Mechanism into CNN enhances, among other things, its sensitivity, adaptability, interpretability, and precision.

II. LITERATURE REVIEW

M. A. Hafeez et al [11] introduces a methodology to automatically classify MRI images of the brain in order to detect the presence of malignancies such as pituitary tumors, meningiomas, and gliomas using CNN as the solution. Based on 30,64 T1-weighted brain CE-MRI images acquired from different patients, a CNN design with 15 layers is implemented. This algorithm attains an exceptional level of accuracy, specifically 98.6 percent, leading to remarkable results. Y. Bhanothu et al [12], proposes a method that automatically detects and classifies brain malignancies in MRI images by combining two algorithms. Initial steps involve cleaning and normalizing the patient dataset and then partitioned into two image sets: one for testing purposes and the other for training. The training data is used for learning the patterns and testing data is used for evaluation. With stochastic gradient descent training, faster R-CNN is capable of attaining an exceptional peak training accuracy of 98.4%. ZainEldin et al [13] proposes an BCM-CNN model utilizing the ADSCFGWO method, which is predicated on convolutional neural networks, to optimize its hyperparameters. The most advanced model currently utilized for the diagnosis of brain tumors is the Inception-ResNetV2. This approach integrates an exhaustive assessment and outperforms traditional classifiers in terms of performance. Ch.Amulya et al [14] comprises two steps for classifying MRI brain tumors. This paper integrates KNN and SURF. The first step involves the extraction of features using SURF and SIFT. Then these extracted features are then classified using the KNN classifier. The integration of SURF and KNN yields results in the classification of brain tumors having an accuracy of 96.22%. T. A. Jemimma et al [16] proposes the utilization of a convolutional neural network (CNN) trained with the Watershed Dynamic Angle Projection (WDAPP-CNN) for the purpose of classifying and segmenting brain tumors. This system aims to address several challenges in medical imaging, including the detection of brain tumors, segmentation, extraction of features, and classification. The textured features are extracted from segments that have been accurately segmented using the Watershed technique for tumor localization using the Dynamic Angle Projection Pattern (DAPP). Subsequently, the gathered variables are utilized by a convolutional neural network (CNN) classifier to validate or invalidate the existence of anomalies in the MRI brain image. This methodology implements cutting-edge image processing techniques and deep learning methodologies. The primary aim is to enhance the efficacy and precision of the procedure. K. Priyadharshini et al [19] proposes an innovative method named Supportive Intelligence for Tumor Detection (SITD) that uses AI to forecast brain cancers. Diverse techniques of image processing and deep learning are utilized. Early identification is essential for successful treatment of brain tumors due to their reputation for being difficult to detect in the initial phases. SITD aims to improve and simplify tumor diagnostics by providing a rapid, automated, and reliable method. This paper examines the research about brain cancer diagnosis through magnetic resonance imaging (MRI) and the potential utilization of advanced learning, transferable learning, and quantum computing in this field. W. Ayadi et al [18] presents a system designed to segment various forms of brain tumors, in response to the critical need for timely and accurate diagnosis. A computerized CAD system is indispensable for the diagnostic process in managing brain tumors, which present a substantial threat to global health due to the high likelihood of erroneous classification and its deleterious consequences.

III. PROPOSED WORK

A. Data Acquisition and Preprocessing:

Improving the quality and utility of the obtained data is a critical component of the preprocessing procedure, which serves as a foundation for subsequent analysis. Image enhancement is employed for highlighting critical elements and improving the clarity of minute details in brain imaging. This is achieved through the implementation of algorithms and filters like Gaussian filters which improves brightness, contrast, and clarity, thereby emphasizing possible sites of tumors. Improving the visibility of these areas facilitates the subsequent examination. Concurrently, noise reduction methodologies are implemented to rigorously analyze the image data with the purpose of removing any anomalies or disruptions. In this process, filters are implemented to distinguish the target data from extraneous noise. By eliminating extraneous noise, the signal-to-noise ratio is enhanced and the dataset's overall quality is improved. An enhanced signal-to-noise ratio facilitates the CNN's ability to differentiate minute details within the images and diminishes the probability of distortion, thereby leading to a more precise analysis. Implementing standardization procedures is critical for ensuring data consistency and uniformity, especially concerning the intensity levels observed across various examinations and to accomplish this, the range or magnitude of the image's pixel intensity levels must be standardized. The flowchart of image preprocessing is depicted in Figure 1.

Errors arising from discrepancies in imaging parameters or apparatus have the potential to disrupt the analysis process entirely; thus, their prevention is of the utmost importance. When input intensity values are uniform, convolutional neural networks (CNNs) exhibit enhanced capability in consistently and robustly representing features. As a result, CNN's capability to consistently identify significant patterns in various situations is enhanced. In order to ensure that all scans are captured within the same general region, geometric normalization techniques are applied. By adopting this methodology, the effects of discrepancies resulting from variations in patient location or scanner configuration can be mitigated. Through the maintenance of a consistent spatial orientation, geometric normalization enhances the consistency of the dataset. This reduces the probability that variables will be deemed confounding in the analysis. A number of preprocessing procedures have optimized and refined the dataset to ensure a dependable and robust brain tumor diagnosis.

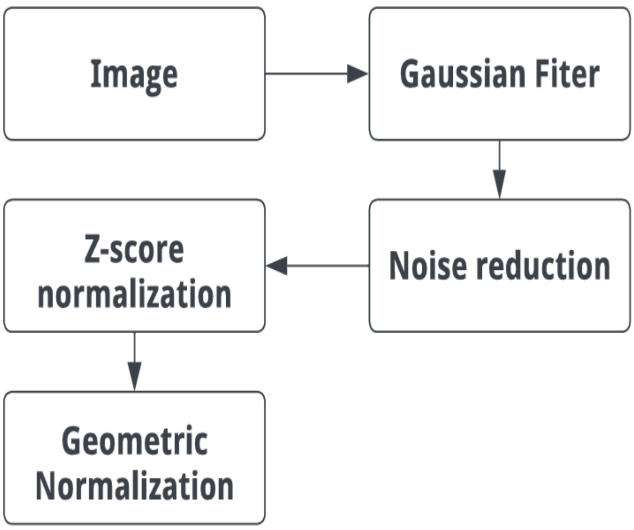

Fig 1. Flowchart of Image Preprocessing

B. Feature Extraction using CNN Network:

CNN is a customized deep learning model designed for image recognition and extracting features. This system is characterized by the use of a multi-layer stack to progressively learn more intricate representations of input images. The input layer of a convolutional neural network (CNN) receives the raw pixel values of the input picture. Subsequently, characteristics are derived from the input image by convolutional filters or kernels within a convolutional layer. These filters analyze local data in the input image by multiplying pieces individually which identifies spatial patterns, edges, or textures. The depth of a convolutional layer is determined by the quantity of filters employed to isolate specific input features. Following the convolutional layer, the max-pooling layer is added which decreases the spatial dimensions of the feature maps. It decreases the resolution of feature maps by choosing the highest value from a set of values inside a specified area, preserving important data. Downsampling improves the computer's efficiency by reducing its sensitivity to spatial translations. These layers facilitate feature extraction from hierarchies by adding extra pairs of convolutional and max-pooling layers. The layers work together to capture more intricate and complicated patterns as the network becomes deeper. The architecture of the proposed system is depicted in Figure 2.

The condensed data is inputted into interconnected layers to enable the network to utilize the acquired characteristics for decision-making. A densely networked architecture is produced when the neurons of each layer are interconnected within a fully connected network. Output layer, which is located at the end of the CNN, is responsible for generating predictions or classifications. When diagnosing brain cancers, neurons in the output layer usually indicate distinct classes such as tumor and non-tumor. The softmax activation function is a standard method to transform output values into probability distributions and is employed in the output layer of the network, making it easier to assign the most probable class. Backpropagation training method improves the CNN's capability to identify important characteristics and patterns in brain tumor images by making frequent modifications to parameters. The decision-making process utilizes flattening and fully connected layers. The network is a proficient tool for identifying brain malignancies as it can independently learn and differentiate complex patterns in brain scans.

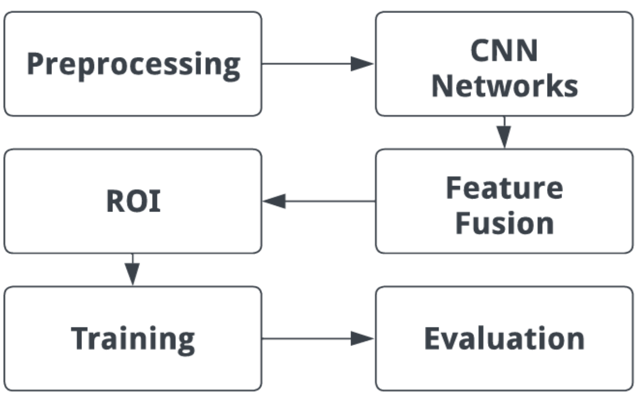

Fig 2. Flowchart of Proposed System

C. Multi Scale Feature Fusion:

This phase is crucial in our proposed brain tumor identification method as it improves the Convolutional Neural Network's capacity to effectively capture both broad and detailed information. This technique enhances the comprehension of brain imaging by combining feature maps from various convolutional layers with variable receptive field sizes to capture both intricate details and broader patterns. Multi-Scale Feature Fusion employs different CNN branches with diverse kernel sizes and dilation rates where the branches describe methods for acquiring characteristics of different sizes. The network is trained to understand both local and global contexts by using convolutions with different kernel sizes. The network's multi-branch architecture aids in feature extraction and enables it to adjust to varying tumor sizes and complexity levels.

Concatenation is a technique that involves merging feature maps from different sizes to create composite representations by integrating them along the channel dimension. Summation keeps important information from each scale by merging feature maps element-wise. Integrating these fusion processes into the model improves its ability to represent features, enabling it to discern subtle patterns across various spatial hierarchies more accurately. Multi-Scale Feature Fusion enhances sensitivity significantly. The network improves its ability to detect crucial and nuanced characteristics in brain tumor images by integrating data from multiple dimensions. This method improves the model's capability to identify anomalies of different sizes and complexities, which results in a more thorough and reliable detection. Employing the multi-scale technique enhances the model's resilience. Using data from several scales helps the network make precise predictions, allowing it to better handle variations in tumor characteristics like size and shape. Adaptability is crucial since tumors can present in a diverse range of ways.

D. Attention Mechanism:

This paper employs a Region of Interest (ROI) Attention Mechanism to train Convolutional Neural Networks (CNNs) for brain cancer detection. This mechanism directs the CNNs' training towards the most crucial areas of medical pictures which improves the model's ability to differentiate by continuously emphasizing important areas during feature extraction. Integration of spatial attention modules following convolutional layers into the CNN structure is done to implement the ROI. This module chooses and highlights important components in the incoming image. The attention mechanism prioritizes prominent qualities in different regions to promote successful tumor identification by giving varying levels of importance. Self-attention mechanisms are integrated into the spatial attention module which allows the network to independently focus on various components of each visual. and ensures that the Convolutional Neural Network (CNN) can modify its focus dynamically to accommodate the complexity of tumor situations. The self-attention mechanism aids the model in identifying subtle patterns and anomalies, enhancing the accuracy and quality of decision-making. The ROI Attention Mechanism improves the accuracy of tumor localization. Enhancing the accuracy and reliability of brain tumor localization is achieved by reducing the chances of false positives and focusing the model's attention on crucial regions.

E. Training and Evaluation:

The network is trained to identify distinguishing features in a dataset by adjusting its parameters. During evaluation, the model is tested using data it has not been exposed to before. A modified version of the cross-entropy loss, typically utilized for classification tasks, is applied to measure the difference between the real tumor labels and the predicted ones. The loss function guides the optimization process and helps the network minimize classification mistakes and improve its capability to differentiate tumor regions from non-tumor regions. We employ the popular Adam optimizer for deep learning applications to fine-tune the CNN and it enhances convergence efficiency by combining momentum with adaptive learning rates to avoid local minima in the model. This optimizer accelerates the training process, leading to faster convergence and enhanced overall performance. To improve generalization and avoid overfitting, utilization of dropout regularization is employed while training. Dropout randomly deactivates a portion of neurons with each forward pass to decrease the network's dependence on any single feature and regularization enhances the model's capability to adapt to variations in input data during training and deployment. Augmentation is utilized to improve the model by introducing variety into the training dataset. Augmentation techniques improve the model's capacity to apply knowledge to unfamiliar material by instructing it on consistent characteristics and structures using random rotations, flips, and zooms added to the training dataset. Various techniques are used to validate and evaluate the output values and retrain it for better accuracy and reliability. The model involves binary classification of the dataset and its performance is evaluated using the below formulas.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{6}$$

Each of the above formulas is used to calculate the positive and negative predicted values with the actual classification and depicts the performance and reliability of the model. Performance metrics value of the testing dataset is calculated using the above formulas and then using K-Fold Cross Validation technique the best model is chosen. This technique helps in identifying the best model through various iterations.

IV. RESULTS

Table 1 presents the primary performance metrics for the brain tumor detection system utilizing Convolutional Neural Networks. Accuracy, Precision, F1 Score, and Recall are metrics that provide a thorough assessment of the model's categorization performance. These metrics are crucial for assessing the reliability of medical image analysis by measuring the system's capacity to detect tumors accurately and minimize false positives and negatives. The model has strong performance in identifying positive cases, with an accuracy of 99.76% and a precision of 99.85%.

Table 1. Performance Metrics

Metrics	**Value (%)**
Accuracy	99.76%
Precision	99.85%
F1 Score	98.63%
Recall	98.26%
Sensitivity	96.6%
Specificity	99.3%

Table 2 showcases the performance metrics of our system against two existing systems by Y. Bhanothu and Ch. Amulya. In terms of accuracy, the proposed system achieves the highest score of 99.76%, outperforming both Bhanothu's and Amulya's systems. Similarly, the proposed system demonstrates superior precision at 99.85%, compared to Bhanothu's 77.60% and Amulya's 94.37%. These results highlight the effectiveness and reliability of the proposed system in brain tumor classification than previous systems.

Table 2. Comparison with Existing Systems

Metrics	**Proposed System**	**Y. Bhanothu [12]**	**Ch.Amulya [14]**
Accuracy	99.76%	98.4%	96.22%
Precision	99.85%	77.60	94.37%

The score value is 0.98, as indicated by the ROC curve in Figure 3. The receiver operating characteristic (ROC) curve graphically represents the discriminative capability of the model, thereby illustrating the trade-off between specificity and sensitivity. A precision of 0.98 is indicative of outstanding accuracy in the comparison of true positive and false positive frequencies.

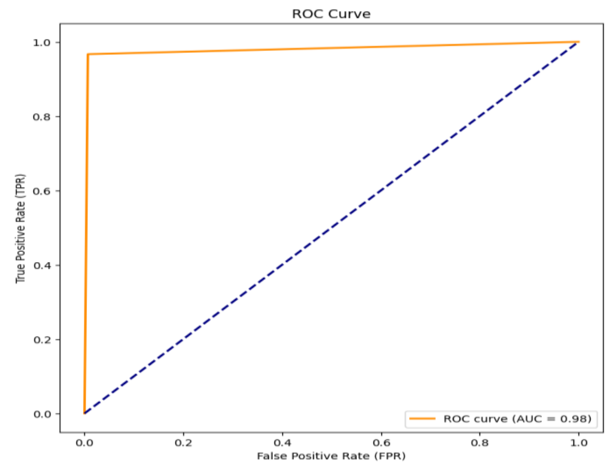

Fig 3. ROC Curve

Figure 5. shows the relationship between accuracy over each epoch and depicts the improvement of the model during the training in learning patterns and classifying the output and the loss over each epoch is depicted in Figure 5 and it shows the decrease of loss over each training epoch and making the model better at classification without error.

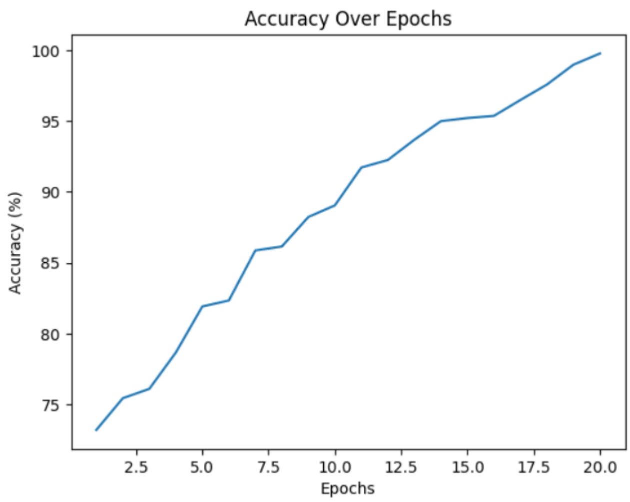

Fig 4. Accuracy Over Epochs

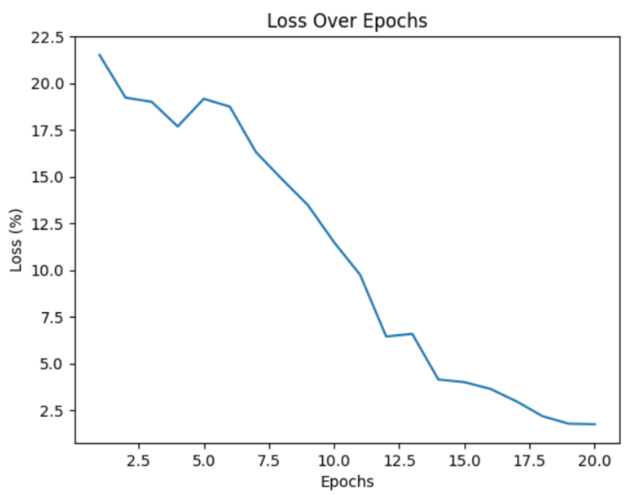

Fig 5. Loss Over Epochs

The evaluation is done by the confusion matrix which serves as an exceptional instrument for evaluating the performance, providing valuable insights into its merits and areas requiring improvement. It is illustrated in Figure 6.

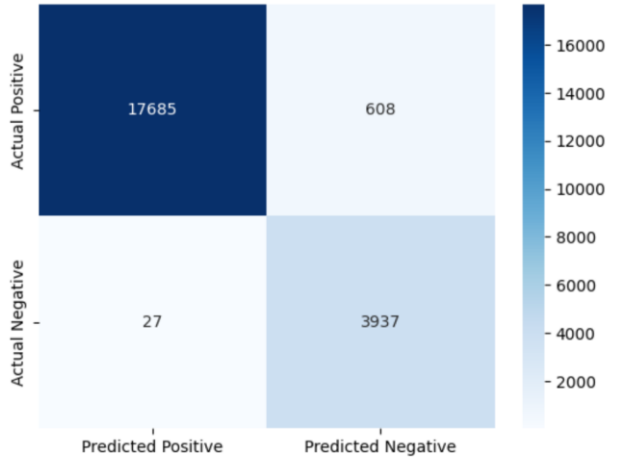

Fig 6. Confusion Matrix

V. Conclusion

In conclusion the proposed methodology of combining Convolutional Neural Networks with Multi-Scale Feature Fusion and ROI attention processes has proven efficient in detecting brain cancers which enhances the model's capacity to recognize intricate patterns, leading to more precise and reliable outcomes. This method is a significant advancement towards creating a dependable and flexible system for automatically detecting brain tumors in medical imaging with an accuracy of 99.76% and a precision score of 99.85%. Therefore, this study has improved the technique of detecting brain tumors with more efficiency and reliability.

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