Brain Tumor Detection from MRI Images using a Convolutional Neural Network (CNN) Approach

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Abstract: A brain tumor refers to an abnormal growth of cells in the brain, which can either be malignant or nonmalignant. In recent years, the utilization of deep learning methods has seen a notable increase in the field of medical imaging. Detecting brain tumors plays a vital role in medical imaging, aiding in the early diagnosis and treatment of brain-related ailments. The application of diverse deep learning technologies has demonstrated promising outcomes in various medical domains, such as surgical procedures and the management of different medical conditions. The proposed work implements a two-step image preprocessing and data augmentation to enhance the MRI images quality, along with a newly optimized 2D Convolutional Neural Network (2DCNN) architecture for effective diagnosis of brain tumor. Batch normalization technique with a higher learning rate is used in the architecture. The proposed architecture is a lightweight model with a limited number of convolutional, max-pooling layers and fewer epochs used for training. The research paper compares the proposed 2D CNN architecture with different machine learning models. The proposed model achieved accuracy in the range of 96% to 98% with more than 3000 MRI images used for training. The experimental findings substantiate the efficacy of the suggested approach when compared to alternative machine learning methods, underscoring its capacity to enhance clinical decision-making for the diagnosis of brain tumors.

Keywords: Brain Tumor, Deep Learning, Image Processing, Convolutional Neural Network

1. Introduction

1.1 Background and Motivation:

The brain is a highly intricate and vital organ responsible for regulating a myriad of physiological functions, encompassing cognition, emotions, memory, and sensory processes. When we refer to a brain tumor, we are discussing the abnormal proliferation of cells within the brain. The brain's rigid structure poses a considerable challenge, as it lacks the capacity to accommodate any form of expansion within its confined space. Uncontrolled cell growth, typically referred to as tumors, carries the potential to develop into a cancerous condition. Brain tumors, if left untreated or inadequately managed, can pose severe risks, even leading to fatality. Essentially, there are two primary classifications of brain tumors: primary and secondary. Primary tumors originate directly within the brain, whereas secondary tumors, often termed metastatic brain tumors, result from the migration of malignant cells from other organs to the brain. Brain tumors are further categorized as benign or malignant. Benign tumors generally grow slowly, exhibit well-defined boundaries, and seldom spread to other areas. However, they still present a risk as they can exert pressure on and damage brain tissue, potentially causing significant functional impairment. On the other hand, malignant tumors invade healthy brain tissue and are cancerous in nature. Malignant brain tumors, due to their propensity to disrupt critical brain structures, pose a life-threatening danger.

The principal diagnostic modality employed for detecting brain tumors is magnetic resonance imaging (MRI). MRI scans yield highly detailed and precise images, facilitating the detection and monitoring of brain tumors and aiding in the formulation of effective treatment plans. This MRI procedure is non-invasive, harnessing powerful magnetic fields and radio waves to generate high-resolution images of any abnormalities within the brain.

Several advanced machine learning classification techniques, including Naive Bayes, Support Vector Machines, and K-Nearest Neighbors (KNN), have been effectively utilized for the identification of brain tumors from MRI images. However, these techniques have historically exhibited relatively lower accuracy rates. In contrast, the proposed fine-tuned CNNs have demonstrated significantly improved accuracy levels, ranging between 96% to

98%.
In the CNN-based tumor detection process, MRI images undergo a series of preprocessing steps prior to the training phase. These preprocessing operations encompass tasks such as data augmentation, data cleaning, filtering, and image pre-processing. Following these initial preprocessing steps, the proposed CNN algorithm is employed to train on the MRI images. Subsequently, the trained CNN model is applied to analyze MRI scans, effectively identifying the presence of brain tumors.

1.2 Objectives

The objectives of the proposed work are to

- Develop a novel 2D CNN architecture explicitly tailored for the precise identification of brain tumors.
- Exploit the potential of deep learning algorithms to overcome the limitations inherent in conventional image processing techniques.
- Evaluate the effectiveness of the CNN model by subjecting it to rigorous testing using a well-established benchmark dataset, while also conducting comparative assessments against the most up-to-date state-of-the-art methodologies.
- Investigate the interpretability of the CNN model by engaging in the visualization of learned features and accentuating regions of notable significance within the data.

2. Related Work

2.1Review of Brain Tumor Detection Techniques:

Detecting brain tumors is a pivotal endeavor in the realm of medical imaging, and throughout the years, multiple methodologies have emerged to facilitate precise and prompt brain tumor diagnoses. Within this section, we shall explore the prevailing techniques for brain tumor detection, encompassing both traditional image processing methodologies and machine learning strategies. Our aim is to elucidate the strengths and weaknesses inherent in these approaches, underscoring the imperative demand for advanced deep learning techniques.

a) Traditional Image Processing Techniques:

Traditional image processing techniques for brain tumor detection involve a series of preprocessing steps, followed by segmentation and feature extraction. Common techniques include thresholding, region growing, edge detection, and mathematical morphology. These methods often rely on handcrafted features and heuristic rules to distinguish tumors from normal brain tissues.

Advantages:

- Well-established and widely used in clinical practice.
- Relatively fast computation time.
- Can provide good results for well-defined tumors with clear boundaries.

Limitations:

- Susceptible to noise, artifacts, and imaging variations.
- Limited ability to handle complex tumor shapes, irregular boundaries, and heterogeneous tumor regions.
- Difficult to generalize across different datasets and imaging protocols.
- Heavily dependent on the choice of parameters and thresholding techniques.
- May require manual intervention and expert knowledge for accurate tumor delineation.

b) Machine Learning Approaches:

Machine learning methodologies have demonstrated potential in the realm of brain tumor detection, harnessing the capabilities of data-driven algorithms. These techniques entail the training of a classifier using a labeled dataset comprising MRI images, enabling the prediction of tumor presence or absence in previously unseen images. Commonly employed machine learning algorithms for brain tumor detection encompass Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks (ANN).

Advantages:

- Proficiency in discerning distinguishing characteristics from the data.
- Capability to handle intricate tumor shapes and variations in image appearances.
- Enhanced capacity for generalization across diverse datasets and imaging protocols in comparison to conventional methods.

Limitations:

- Limited ability to capture high-level semantic features and contextual information.
- Reliance on handcrafted features and manual feature engineering.
- Difficulty in handling large-scale datasets due to computational and memory constraints.
- Suboptimal performance when dealing with highly imbalanced datasets.
- Limited interpretability, making it challenging to understand the decision-making process.

Due to the limitations of standard image processing techniques and machine learning approaches, deep learning techniques, particularly CNN have emerged as an alternative method in brain tumor identification. By automatically generating hierarchical representations from raw MRI data, capturing complicated spatial patterns, and providing end-to-end solutions for tumor diagnosis and localization, deep learning models have the potential to address the limitations of earlier methods.

2.2 Deep Learning in Medical Image Analysis:

Deep learning, a subset of machine learning, has emerged as a potent asset in numerous medical image analysis tasks. CNNs, in particular, have garnered significant attention and achieved considerable success in extracting pertinent insights from medical images.

a) Overview of Deep Learning:

Deep learning models are made up of numerous layers of interconnected artificial neurons that behave similarly to the neural networks in the human brain. These models are intended to learn hierarchical representations automatically from raw input data, removing the need for manual feature engineering. Deep learning is well-suited for analysing medical images due to its capacity to learn complicated patterns and representations.

b) Convolutional Neural Networks (CNNs):

CNNs represent a specialized category of deep learning models well-suited for handling grid-like data, such as images. They consist of Convolutional layers, pooling layers, and fully connected layers. CNNs function by applying convolutional filters to the input image, thereby capturing local spatial relationships and progressively acquiring more abstract features.

c) Applications in Medical Image Analysis:

Deep learning, and CNNs in particular, have demonstrated significant success in various medical image analysis tasks, including:

- Segmentation: Deep learning models can automatically segment organs, tissues, or lesions within medical images, enabling accurate volumetric measurements and region of interest localization.
- Classification: CNNs can classify medical images into different categories, such as tumor types, disease stages, or pathology classes, aiding in diagnosis and treatment planning.
- Detection and Localization: Deep learning models can detect and localize abnormalities, such as tumors, nodules, or lesions, within medical images, helping radiologists identify critical areas of interest.

2.3Review of CNN-based approaches

In reference [1], the study delved into the application of deep learning techniques, specifically leveraging the LeU-Net architecture, for the analysis of 2D MRI images with the aim of detecting brain tumors. The LeU-Net model, a specialized CNN architecture designed for image segmentation tasks, demonstrated the potential of deep learning, particularly CNNs, in providing accurate and efficient solutions for brain tumor detection in the domain of medical imaging.

Reference [2] explored the use of CNNs and Support Vector Machines (SVM) for the classification of brain MRI images. To enhance classification accuracy and prediction results, the study introduced a hybrid model that combined both CNN and SVM components.

In [3], an innovative deep learning-powered technique was developed for the detection and classification of brain tumors. This technique involved a two-stage process. First, a 3D CNN architecture was employed to extract brain tumors from the input data. Subsequently, these extracted tumors underwent feature extraction using a pretrained CNN model. The selected features were then validated through a feed-forward neural network, resulting in impressive accuracy rates on the BraTS datasets for the years 2015, 2017, and 2018.

Reference [4] introduced a hybrid approach combining Neutrosophy and CNN (NS-CNN) for the classification of tumor regions as benign or malignant. The study used CNN features extracted from segmented brain images, and

SVM and K-Nearest Neighbors (KNN) classifiers were employed for the categorization task. The results indicated that the CNN features outperformed other classifiers, achieving an average success rate of 95.62%.

In [5], the authors presented a method for brain tumor extraction from 2D MRI images, involving the utilization of the Fuzzy C-Means clustering algorithm, followed by the application of classical classifiers and a CNN. Six traditional classifiers were implemented alongside a CNN, with the CNN achieving an accuracy rate of 97.87%.

Reference [6] introduced a model for automatic brain tumor detection, combining CNN and a multilayered Support Vector Machine (SVM). The CNN was utilized for tumor detection and segmentation, while feature extraction and object detection were accomplished using a local binary pattern and a multilayered SVM classifier. The proposed method demonstrated superior performance in multiple evaluation metrics compared to existing approaches.

In [7], a hybrid paradigm was constructed, featuring a neural autoregressive distribution estimation (NADE) model and a CNN. This hybrid model was trained using MRI data to classify three distinct types of brain tumors. The results exhibited the effectiveness of the hybrid CNN-NADE model in the classification task.

Reference [8] focused on the application of a CNN for brain tumor detection in MRI images, achieving an impressive accuracy rate of 99.12%. The Softmax Fully Connected layer utilized for image classification demonstrated an accuracy rate of 98.67%.

In [9], the study employed the AlexNet model and the Region Proposal Network (RPN) from the Faster R-CNN algorithm. Transfer learning techniques were applied to enhance accuracy, resulting in improved predictions of tumor types.

3 Methodology

3.1 Data Collection and Preprocessing:

a) Data Collection

There are several open-source datasets available for Brain Tumor Images. The data used in proposed work is downloaded from Kaggle under Br35H :: Brain Tumor Detection 2020 Computer Vision Project [13] which consists of nearly 3000 images for training among which 1500 are images with Yes (tumor present) with sample as shown in figure 1 and 1500 are images with No (tumor absent) with a sample shown in figure 2 and 100 images are used for testing and 60 images are used for prediction.

Yes **No**

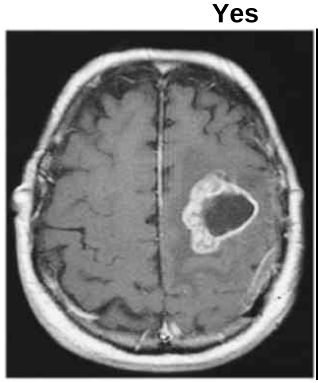

Figure 1. Tumor

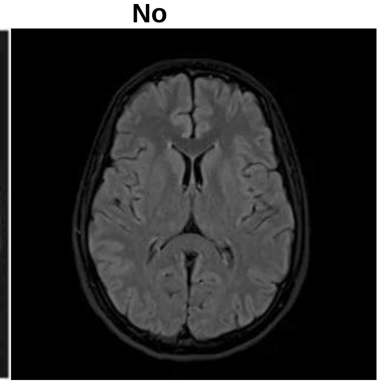

Figure 2. No Tumor

b) Pre-processing

Image preprocessing techniques are essential in deep learning, particularly when dealing with medical images such as those used in brain tumor diagnosis. The goal of image preprocessing is to improve visual information quality by removing undesirable noise and increasing contrast. In this study, MRI images from the dataset were obtained in varying sizes. To ensure compatibility with our models, we performed two key preprocessing steps: normalization and resizing.

Image Normalization

To begin, the images were normalized to ensure consistent pixel intensity values across the dataset. Normalization helps to standardize the image data and bring it within a specific range. This step is crucial for achieving reliable and consistent results during the training process.

Image Resizing

Next, the images were resized to a uniform dimension of 64 × 64 pixels. Resizing ensures that all input images have the same dimensions, which is important for maintaining consistency in the neural network architecture.

Resizing also helps to reduce computational complexity by lowering the total number of network parameters. To perform these preprocessing tasks, we utilized the OpenCV-Python package, which is a popular tool for image processing. OpenCV-Python provides a wide range of functions and methods that facilitate tasks such as image normalization, resizing, noise removal, and contrast enhancement.

Data Augmentation:
Data augmentation techniques are commonly employed in CNN-based tumor detection to increase the diversity and size of the training dataset. These approaches include applying random transformations to the source images, such as rotations, translations to create enhanced versions. Data augmentation helps improve the generalization capability of the CNN and reduces overfitting.

3.22D Convolutional Neural Network
CNNs have emerged as powerful tools for brain tumor detection from medical imaging data, particularly Magnetic Resonance Imaging (MRI). CNNs excel at automatically learning hierarchical representations directly from raw image data, making them well-suited for analyzing complex structures like the brain. Here, we will discuss the application of CNNs in brain tumor detection and their key components and processes.

a) Architecture of 2D CNN:
CNNs are composed of a series of interconnected layers, including convolutional layers, pooling layers, and fully connected layers. These components work together to process and extract information from input data. Here's a breakdown of their functions:

- Convolutional Layers: These layers employ filters to capture local spatial patterns or features within the input image. These filters are convolved with the input data to detect specific patterns, such as edges or textures.
- Pooling Layers: Pooling layers are responsible for reducing the spatial dimensions of the feature maps produced by the convolutional layers. Common pooling techniques include max-pooling, which retains the most important features within a defined window, while discarding less relevant information.
- Fully Connected Layers: These layers establish connections between all neurons in one layer with all neurons in the subsequent layer. They play a crucial role in high-level feature extraction and classification. Activation functions, such as ReLU (Rectified Linear Unit) and softmax, are applied to introduce non-linearity and enable the network to learn complex relationships within the data.

In the proposed 2D CNN model, the architecture is described as follows:

- Input layer with 64x64x3 input units, indicating an input image size of 64x64 pixels with three color channels (e.g., RGB).
- Three convolutional layers, each followed by a ReLU activation function and a Max Pooling layer with a size of 2x2. These layers are responsible for extracting and processing spatial features from the input data.
- Two dense layers: The first dense layer contains 64 units with a ReLU activation function, enabling the extraction of high-level features. The second dense layer has 2 units and employs a softmax activation function for classification, allowing the model to make predictions.

This architecture, as illustrated in Figure 4, represents a common configuration for a 2D CNN used for tasks like image classification, including the specific layer types, activation functions, and layer sizes used in the model.

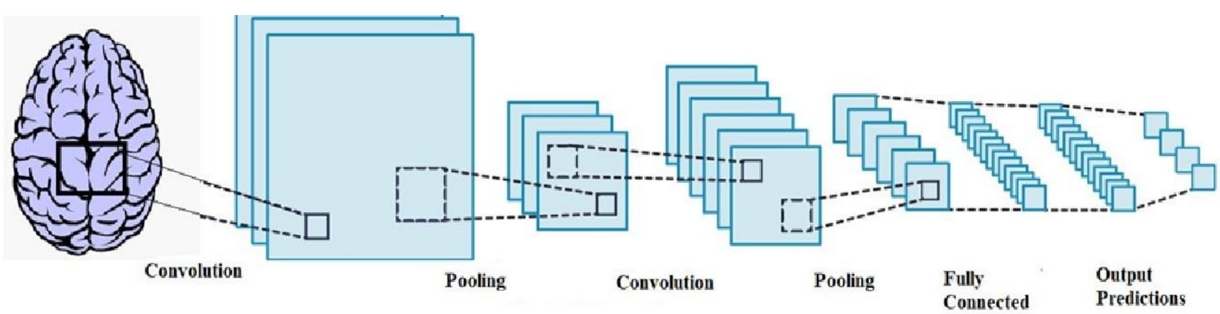

Figure 3. Architecture of brain tumor detection using CNN

The Convolution, pooling layers and fully connected layers for the proposed CNN model is as shown in figure 3

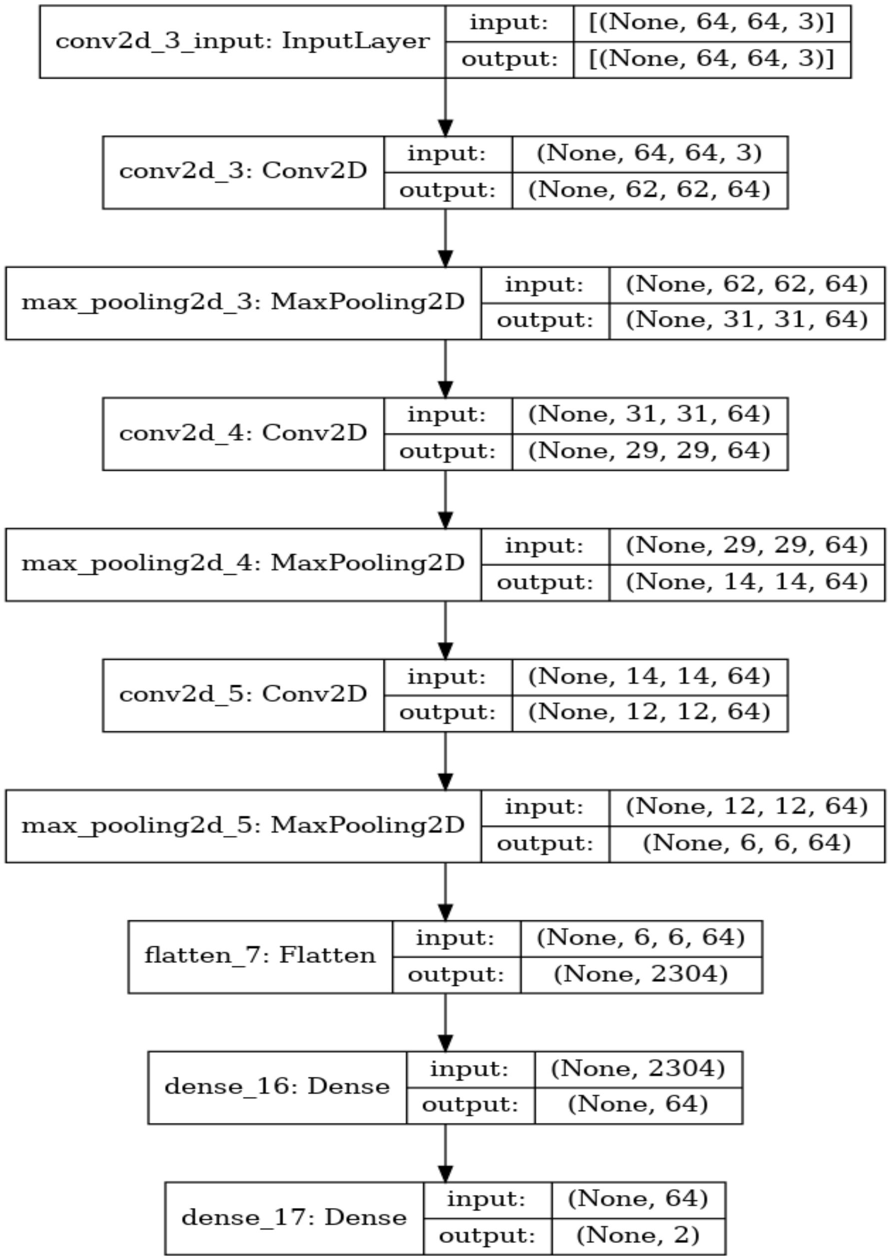

Figure 4. Structure of Proposed 2D CNN

3.3**Model Training and Optimization:**

Training Process:

The training of a Convolutional Neural Network (CNN) for brain tumor detection requires a labeled dataset containing MRI images. This dataset is typically split into two subsets: the training set and the validation set. The CNN undergoes a training process called backpropagation, where it iteratively adjusts its internal parameters to minimize the disparity between its predicted tumor labels and the actual labels within the dataset.

The training process consists of two main phases: forward propagation and backward propagation. During forward propagation, input data is passed through the network, and predictions are generated. In the subsequent backward propagation phase, the network's parameters are updated based on the computed loss or error between the predictions and the ground truth labels. This iterative process continues until the network converges to a state where its performance on the validation set meets the desired criteria.

Parameter Optimizations:

To enhance the performance of the 2D CNN architecture, specific key parameters have been optimized:
- The 2D CNN model is trained over a course of 10 epochs, representing the number of complete passes through the entire training dataset.
- The selected optimizer for the training process is Adam, a widely used optimization algorithm known for its efficiency.
- The loss function chosen for the model is sparse categorical cross-entropy, a suitable choice for binary classification tasks.

CNN-based approaches have demonstrated exceptional effectiveness in brain tumor detection, surpassing traditional image processing methods and other machine learning algorithms. They excel in handling complex tumor shapes, irregular boundaries, and diverse tumor regions, ultimately leading to improved accuracy and efficiency in tumor detection. Additionally, the interpretability of CNNs can be improved by visualizing learned features and highlighting regions of interest, which aids in gaining a deeper understanding and validating the model's decision-making process.

4. Experimental Results

In this section, we provide an overview of the performance evaluation of the CNN on the MRI dataset, presenting the results and outcomes of our analysis.

4.1. Experimental Setup

The experiment is carried on Windows Operating System: 8 with Processor: Intel core i5 64-bit, quad-core,2.5 GHz minimum per core, Ram: 4 GB. Kaggle platform is used for experimentation using python libraries for image processing, CNN and performance measurements.

4.2 Performance Evaluation Metrics

In the realm of evaluating the performance of a brain tumor classification method, a variety of metrics are employed to provide a comprehensive assessment. While accuracy serves as a fundamental metric, gauging the correctness of both tumor (T) and non-tumor (NT) classifications in binary classification, it is crucial to augment accuracy with additional metrics, including recall and precision. Accuracy is a widely recognized indicator for evaluating classification performance, representing the proportion of samples that are correctly classified.
Accuracy can be expressed as follows:
Accuracy = (TP + TN) / (TP + TN + FP + FN)
Where TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative
Precision, another important metric, quantifies the proportion of true positives relative to all entities identified. In simpler terms, it allows us to assess how effectively a model retrieves only true positive results while minimizing irrelevant items.

Precision can be calculated as:
Precision = TP / (TP + FP)
Sensitivity, also known as recall, measures the probability that a positive test result is returned when a patient has a tumor. It represents the true positive proportion.

Recall (Sensitivity) can be defined as:
Recall (Sensitivity) = TP / (TP + FN)
Specificity, a vital metric in binary classification tasks such as medical diagnostics, including brain tumor detection, assesses a model's ability to accurately identify negative instances or cases. The specificity formula is as follows:

Specificity = TN / (TN + FP)
These metrics collectively provide a comprehensive understanding of a classification model's performance, considering its ability to correctly identify positive and negative instances, minimize false positives and false negatives, and balance precision and recall in the context of brain tumor detection and classification.

4.3Quantitative Results:

Python has been used to create the 2D CNN model along with Keras, TensorFlow library, using the data set available from Kaggle notebooks. The proposed 2D CNN model's training accuracy and training loss are shown in Figures 5 and 6, respectively.

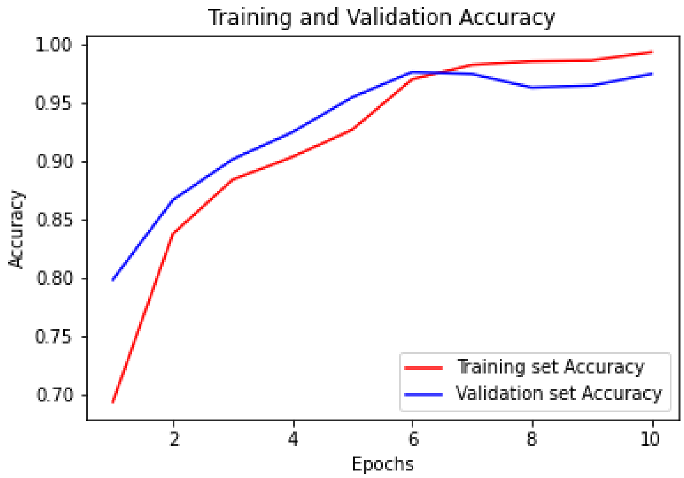

Figure 5. Accuracy of Training and Validation Data

Figure 6. Loss of Training and Validation Data

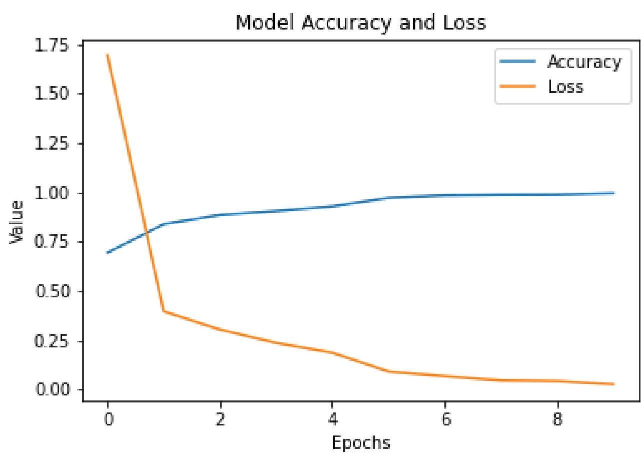

Figure 7. Model Accuracy vs Loss

In the context of the accuracy metric, it is evident from Figure 7 that both the training and validation datasets exhibit a favorable convergence trend. Furthermore, with each successive epoch, there is a consistent reduction in the discrepancy between the training and validation losses. This pattern suggests that the model is progressively assimilating information during the training process.
Regarding the loss metric, it is worth noting that as the training progresses, the accuracy and loss metrics begin to exhibit a gradual divergence. This phenomenon may indicate that the training process should be concluded earlier

to prevent overfitting or excessively specialized learning.

a) Comparison of 2D CNN with KNN, Bayes, SVM Classifier:

The Tabular representation shown in Table 1 depicts that 2D CNN model performs better than other machine learning classification models measured in terms of Accuracy, Sensitivity and Specificity metrics. The figure 8 shows accuracy analysis, figure 9 shows specificity analysis and figure 10 shows sensitivity analysis of 2D CNN model w.r.t Naïve Bayes, KNN and SVM on the given data set.

Table 1. shows the comparison of 2D CNN results with that of other machine learning classification models like Naïve Bayes, KNN and Support Vector Machines(SVM) on the given data set.

Table 1. Performance Metrics Analysis

Ref No	Classification Model	Accuracy	Sensitivity	Specificity
[9]	Support vector machine (SVM)	87–94%	78.5–93 %	62–91.5%
[10]	K nearest neighbor (KNN)	85–90%	81.1–82.6%	63.6–94%
[11]	Naive bayes	68.2–83.4%	60.2–83.4%	62–80%
	2D CNN	91-99 %	95-99%	96-99%

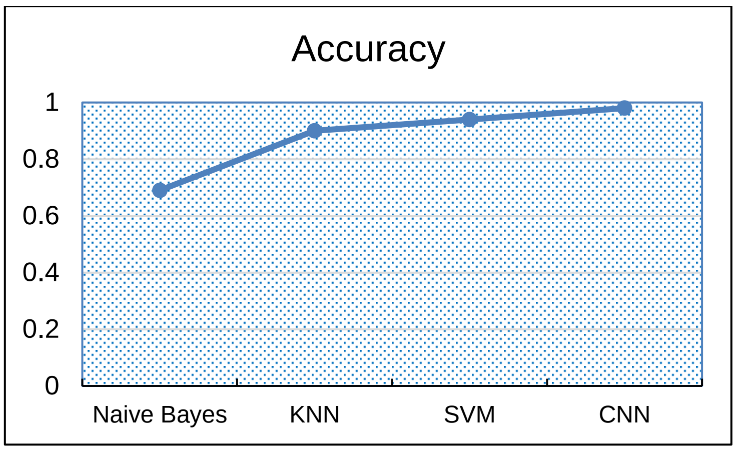

Figure 8. Accuracy Analysis

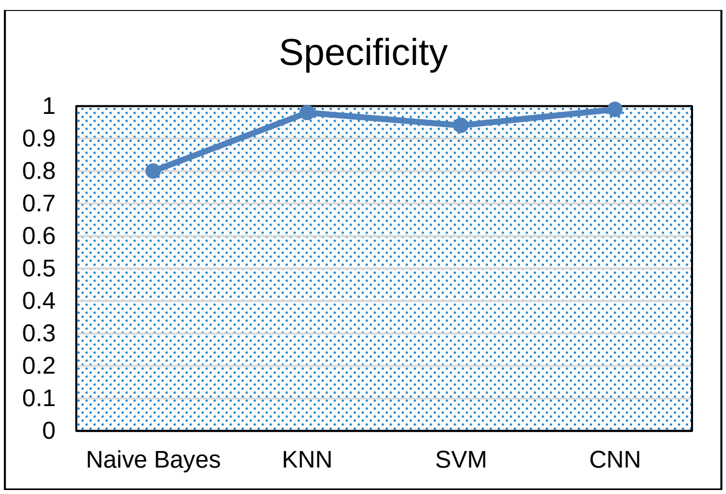

Figure 9. Specificity Analysis

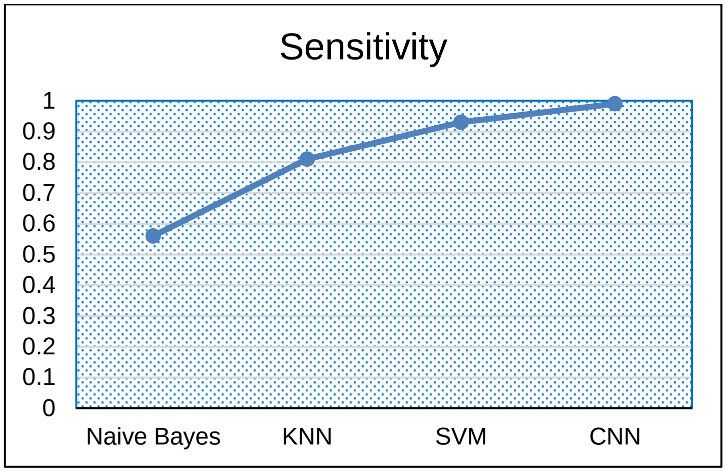

Figure 10. Sensitivity Analysis

4.4Results and Discussions

The proposed system functions as a binary classifier for the detection of brain tumors using MRI images, making use of a dataset comprising over 3000 images sourced from the Kaggle platform. A pivotal component of this system lies in its preprocessing stage, where it diligently enhances the quality of input MRI images by eliminating noise and applying augmentation techniques to ensure optimal data quality.

At the core of this system resides an optimized 2D CNN architecture, custom-tailored for the specific task of brain tumor detection. This CNN model stands out for its streamlined design, featuring a reduced number of convolutional and max-pooling layers. Despite its simplified structure, this model attains remarkably high accuracy levels with a reduced number of training epochs.

Experimental results validate the superiority of the 2D CNN classification model over other machine learning techniques, such as KNN, Naïve Bayes, and SVM, based on performance metrics like accuracy, specificity, and sensitivity. This underscores the effectiveness and dominance of the proposed approach in the realm of brain tumor detection.

In summary, the system brings innovation through its advanced preprocessing techniques, optimized CNN architecture, and superior performance when compared to alternative classification methods. It offers a dependable and precise tool for the detection of brain tumors from MRI images.

5. Conclusion:

The proposed work has successfully developed an automated approach that utilizes a highly optimized 2D CNN to classify brain tumors from meticulously preprocessed and augmented MRI images. This method has achieved an impressive accuracy rate of 98% in binary classification, surpassing the performance of alternative approaches. These results are anticipated to provide valuable assistance to medical professionals in their decision-making processes and have been integrated as a supportive tool for doctors.

Looking ahead, future research endeavors are aimed at constructing a comprehensive system for tumor detection, segmentation, and classification employing deep learning techniques. This includes expanding the dataset, fine-tuning hyperparameters, and exploring advanced feature extraction methods. Furthermore, there is potential to extend the approach for the detection of other brain abnormalities and enhance categorical classification of different tumor types.

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Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

The manuscript author contributed to the study conception and design. Material preparation, data collection and analysis were performed by Tanveer I. Bagban. The first draft of the manuscript was written by Tanveer I. Bagban. The author approved the final manuscript.

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