A Convolutional Neural Network-Based Method for Classifying and Segmenting Brain Tumors

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ABSTRACT:

In this study, we provide a Convolutional Neural Network-based model for fully autonomous segmentation and classification of brain tumors. Our concept differs from other efforts in that the input images are processed along various processing pathways at three different spatial scales. The natural functioning of the human visual system served as inspiration for this technique. The suggested neural model does not require pretreatment of input pictures in order to remove portions of the skull or vertebral column beforehand. It can interpret MRI scans containing Meningioma, glioma, and pituitary tumors in sagittal, coronal, and axial perspectives. Worldwide, there is a high fatality rate from brain tumors. Medical professionals must visually analyze the images and mark out the tumor areas, a process that takes time and is prone to error. Automated methods for early brain tumor identification have recently been developed.) However, due to their high false-positive outcomes and low accuracy, these approaches have issues. An efficient tumor identification and classification approach is required to extract robust characteristics and perform accurate disease classification.) This study proposes a novel deep feature-based multiclass classification method for brain tumors.) Min-max normalization is used as a preprocessing step for MR images before considerable data augmentation is undertaken to address the data problem. A single feature vector created by combining deep CNN features from transfer learned architectures such as AlexNet, GoogleNet, and ResNet18 is then loaded into SVM and K-nearest neighbor (KNN) to make a prediction. The suggested method's classification effectiveness is enhanced by the unique feature vector, which contains more data than the independent vectors. The recommended method also performed better than the existing methods and produced good accuracy; as a result, it may be used in a clinical context to categorise brain tumors using MRIs.

Keyword— Brain Tumor, Classification, Segmentation, Convolutional Neural Network, MRI, Artificial Intelligence

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3579

INTRODUCTION:

Brain tumors are among the most deadly brain conditions that can result from abnormal cell growth inside the skull. There are two different types of brain cancers: primary tumors and secondary tumors. Primary brain tumors, which solely affect the brain, account for 70% of all malignancies, in contrast to secondary brain tumors, which begin in other organs such as the breast, kidney, or elsewhere before migrating to the brain. According to NBTF study [1], there are approximately 29,000 primary brain tumor cases diagnosed in the US alone each year, and 13,000 individuals die as a result. Similar to this, thousands of individuals worldwide die from primary brain tumors each year. Gliomas, meningiomas, and pituitary tumors are the three most typical forms of brain tumors. Glioma tumors are caused by the uncontrolled proliferation of glial cells, which make about 80% of the brain. Compared to other primary malignancies, it has the highest fatality rate. Meninges, the membrane that surrounds and protects the brain, is where Meningioma tumors develop. The pituitary gland, on the other hand, is where the pituitary tumor develops and is in charge of manufacturing a variety of essential hormones. The pituitary tumor can cause hormonal abnormalities and irreversible vision loss despite being benign [2].

Making an early and accurate diagnosis of brain tumors is essential to protecting patients from side effects [3]. Depending on the technique's objective, various methods can be employed to detect brain tumors. Computed tomography (CT), magnetic resonance imaging (MRI), and ultrasonography (US) are three of the often employed techniques [4]. Magnetic resonance imaging (MRI), which conducts exams without the use of potentially dangerous ionizing radiation like X-rays, is the most widely used noninvasive imaging method. Additionally, it creates clear images of soft tissues and is capable of acquiring modalities with a variety of parameters, including as FLAIR, T1, and T2 [5].

Because tumors often vary in form, severity, size, and location, it can be difficult to determine the type of a tumor. Usually, after thoroughly examining the photographs, the medical personnel meticulously mark out the tumor spots. Usually, the surrounding healthy tissues conceal the tumor's borders. This makes the manual visual inspection identification process time-consuming and liable to tumor misunderstanding.

Additionally, for manual tumor detection, the radiologist's experience is essential [6]. The various tones of grey shown in MRI images should be recognized as being invisible to the unaided eye. When radiologists want to visually assess the depth of the tumor or determine the type of tumor to reduce the chance of a biopsy, automated systems are appropriate [7, 8]. MRIs that are noisy due to variances in imaging devices or radiologists who are overworked are two other prominent causes of tumor misdiagnosis.

Many researchers have proposed CAD-based methods for brain tumor detection. Conventional ML-based algorithms have the disadvantage of using a human feature extraction technique.) E features are extracted from training photos prior to classification [9].

Brain tumors can be categorized using machine learning- and deep learning-based algorithms (DL and ML).

ML-based systems employ manual feature extraction and segmentation, which are time-consuming and prone to mistake, prior to classification.)

These techniques frequently require the assistance of a specialist with extensive knowledge in order to locate the appropriate feature extraction and segmentation algorithms for precise tumor diagnosis. The performance of these systems is therefore unstable when working with larger databases [10]. On the other hand, DL-based algorithms do these tasks automatically and have proven to be extremely beneficial in a range of applications, including medical image analysis. One of the most popular DL models, convolutional neural networks (CNN), is commonly employed because of its dependable performance and weight-sharing structure. From training data, it can automatically extract both low-level and high-level characteristics. As a result, these processes are of interest to scientists and researchers [11, 12].

Feature fusion is a method that combines several low-level and high-level features into a single feature vector, enhancing the discrimination performance of the model by minimizing the need to employ the feature vector from a single model. By using a feature fusion-based approach, it is possible to extract from MRIs the discriminative and informative features required for accurate tumor classification. To demonstrate the efficacy of the suggested strategy, we assessed our model using a well-known brain tumor dataset and a number of quantitative indicators [13]. The following are the primary contributions of the proposed system:

We created a completely automated hybrid system that combines (a) transfer learning CNN models for deep feature extraction and (b) ML classifiers to accurately classify the various forms of brain cancers.

The proposed technique consists of the following five main elements: Image intensity normalization (ii), extensive dataset augmentation (iii), feature extraction using several CNNs, including AlexNet, ResNet18, and GoogLeNet (iii), fusion of deep features vector (iv), cutting-edge performance for classifying brain tumors from MR images (v), and tumor type classification using SVM and KNN (iv).

Concatenating deep characteristics into one vector increases the discriminating power (iii). In spite of a variety of challenges, such as a complex background, ill-defined tumor boundaries, changeable tumor location, and other MRI artifact concerns, it delivers reliable tumor classification.

REVIEW OF LITERATURE:

Early tumor detection and categorization are crucial for ensuring that a patient receives effective treatment. With the use of automated healthcare systems, specialists can now treat patients more successfully thanks to outstanding technical breakthroughs. To overcome problems with medical image diagnosis, researchers have suggested investigations based on ML and DL-based algorithms [14]. One of the most well-known DL models, CNN, has developed significantly in a number of fields, including image processing. Brain tumors can be detected using CNN-based systems, which can assist medical practitioners in determining the best treatment for their patients. According to data from that year, more than 200 DL-based studies on medical images were anticipated, and 190 of those employed CNNs [11]. Several of the most well-known CNNs are used for current medical image classification applications, including AlexNet [15], VGG [16], and GoogLeNet [17].

Mzoughi et al. [18] presented 3D CNN architecture for glioma brain tumour categorization into low-grade gliomas (LGG) and high-grade gliomas using the entire volumetric T1-Gado MRI sequence from the Brats 2018 dataset (HGG).

Local and global contextual information was incorporated into the architecture, which used small kernels and lower weights and was based on a 3D convolutional layer and deep network. The system's accuracy was 96.49%. Maqsood et al. [19] suggested an edge detection and U-NET model-based method for identifying brain tumors. The U-NET architecture is used to classify the features that are extracted from decaying sub band images and identify Meningioma in brain imaging. The tumor segmentation framework also conducts edge detection fuzzy logic and enhances image contrast.

Togacar et al. [20] used the hyper column method and attention modules to construct BrainMRNet. The visuals were preprocessed before transmission to the attention modules. Convolutional layers are fed images that contain areas that attention modules have determined to be significant. In order to detect brain tumors and glioma tumors, the authors of Khawaldeh et al. [21] created a CNN model that improved pretrained architecture and had a 91% overall accuracy. The accuracy of the system was 96.05%. Hypercolumn is one of the primary methods employed by the BrainMRNet model in the convolutional layers. The system attained this precision by maintaining the features retrieved from each layer in the final layer's array structure. The research in [18–21] has one major flaw: they only perform binary classification of brain cancers and ignore multiclass classification, demanding more investigation to identify the type of tumor. Despite the large quantity of research done in this area, more effort is still needed to establish a reliable and useful method for categorizing brain MR images. According to recent studies, methods based on transfer learning could be used to detect brain tumors. As an illustration, the authors of Sajjad et al. [22] demonstrated a multimodal CNN-based tumor categorization system. After initially segmenting the MR images with input cascade CNN and a tweaked VGG-19, they were able to identify the images with 94.5% accuracy. The method is computationally inefficient because CNNs are used for segmentation and classification. Deep features from AlexNet and VGG16 were integrated by Ari et al. [23] and then classified using an ELM (Extreme Learning Machine). The system had a 96.6% accuracy rate in the study, which used MRI images from the freely available Figshare, Rider, and REMBRANDT datasets. Using VGG16, VGG19, and AlexNet, Noreen et al. [24] retrieved the deep features. After that, ensemble classifiers were used to categories the characteristics. ResNet, Inception-V3, and VGG-16 were all employed by Saxena et al. [26] to achieve the highest accuracy of 95%. With an accuracy of 94.8%, Swati et al. [25] classified brain tumor MRI images using fine-tuned AlexNet and VGG. The authors of Abiwinanda et al. [27] on the other hand, suggested five CNN designs to classify brain tumors and achieved the highest validation accuracy of 84.1%. However, the algorithms' overall performance was poor, therefore they must be tested before being used in real-time.

It should be noted that relatively simple CNNs cannot extract sophisticated high-level properties, resulting in generally poor accuracy. Alanazi et alsystem .'s for diagnosing brain tumors [28] utilized cutting-edge 22 layered CNN architectures and achieved a maximum accuracy of 96.8%. However, only a few imaging samples are used to test and train the suggested approach. The classification accuracy of the work, which used MRI scans from the Kaggle dataset, was 92.13%. A Hierarchical Deep Learning-Based Brain Tumor categorization technique was proposed by Khan et al. [29]. However, the method needs to be examined before being used in a clinical environment for the classification of brain tumors because of its poor overall accuracy.

Anaraki et al. [30] employed Genetic Algorithms (GA) to find the best CNN architecture with the lowest processing costs for the categorization of brain cancers. When classifying glioma, meningioma, and pituitary cancers from MRI scans, they reached 94.2% accuracy. GA was unable to determine the appropriate CNN design, which resulted in below-average accuracy overall.) Information-theoretic methods, wavelet packet Tsallis entropy for feature extraction, Bayesian fuzzy clustering (BFC) for image segmentation, nonlocal mean filter for image demising, scattering transform, and classification of brain tumors were all employed by the authors of Raja [31]. However, this approach requires a lot of processing effort and is computationally inefficient. Afshar et al. [32] used Capsule Networks to identify and classify brain lesions with an accuracy of 90.89%. The model performs better when trained on segmented images, and CapsNets are particularly sensitive to the backgrounds of images. As a result, the architecture is complex.

PROPOSED APPROACH:

1. Convolutional Neural Network and Implementation Details

We suggest a multi-pathway CNN design for tumor segmentation in this paper. Each pixel in an MRI image (slice) is processed by the CNN architecture, which classifies each pixel using one of four possible output labels: 0 for a healthy region, 1 for a Meningioma tumor, 2 for a glioma tumor, and 3 for a pituitary tumor.

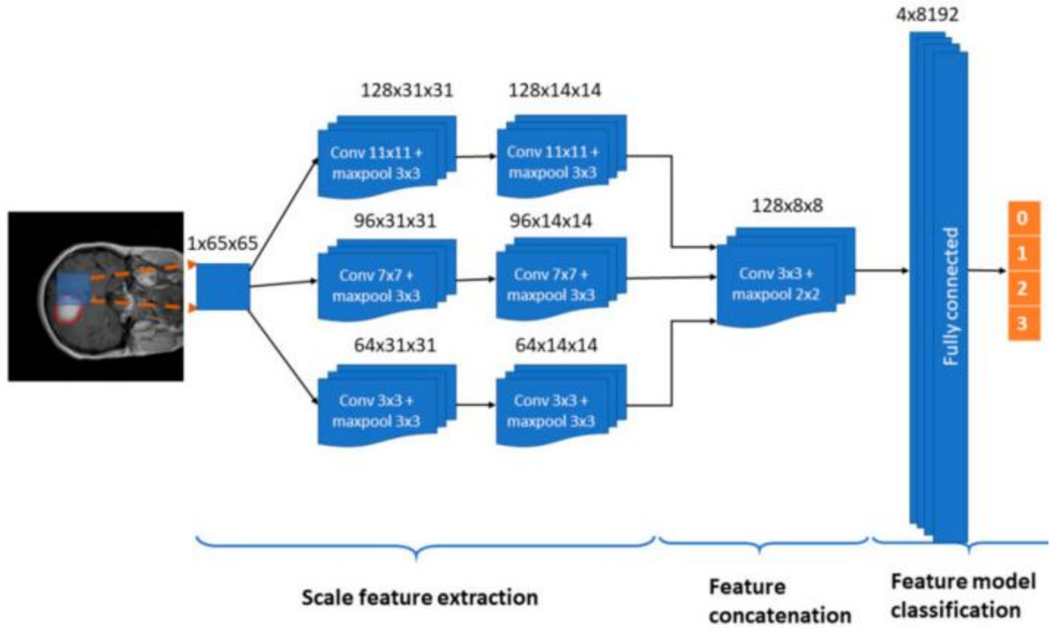

Figure-1: The proposed Convolutional Neural Networks (CNN) architecture.

We employ a sliding window in our method, which allows us to classify each pixel using a N N neighborhood or window as the input to our CNN architecture. Three convolutional pathways with three size (big, medium, and tiny) kernels are applied to each window to extract the features. We decided on a window size of 65 by 65 pixels and kernel sizes of 11 x 11, 7 x 7, and 3 x 3 pixels for our solution. Following preliminary configuration testing in which both 33 x 33 and 75 x 75 pixel window sizes were examined, the choice of window size was made.

A 3 3 max-pooling kernel with a stride value of 2 and two convolutional stages with ReLU rectification make up each pathway. The large, medium, and tiny paths, respectively, have 128, 96, and 64 feature maps. With the supposition that the window features retrieved using various filtering scales serve to define the three types of tumor to be categorized, we propose the usage of more maps for bigger scales.

In a convolutional layer with a 3 3 kernel with a ReLU activation function and a 2 2 max-pooling kernel with a stride value of 2, scale features from the three routes are combined. The output from this stage moves onto a fully connected stage, where 8192 scale features are concatenated to form the classification algorithm for the four different types of prediction label. The model has a dropout layer before the fully linked layer to prevent over fitting. In the last layer, a softmax activation function is used.

PytorchTM has been used to implement the suggested CNN. The neural network has close to three million trainable parameters (2,856,932). With a Linux environment, an Intel Core i7 CPU, and an Nvidia GTX1080 T1-11GB GPU, all tests have been run. The average prediction time per image during the 5-day training session was 57.5 s.

This paper proposes a revolutionary deep CNN-based MRI-based method for categorizing and diagnosing brain cancers. The workflow diagram is displayed in Figure 1. Before being fed into three separate CNN models for feature extraction, MRI images are first normalized and improved. SVM and KNN are used to classify the deep feature vectors once they have been combined into a single feature vector. The suggested method can be used to accurately classify a variety of brain tumors, including pituitary, glioma, and meningiomas. It is dependable and efficient.

1.1 Data Processing:

Equation (1) describes the initial preprocessing of MRI images from the dataset using min-max normalization (1). The normalization technique scales the intensity levels in an image between [0, 1].) The minimum value of the feature is changed to 0 and the maximum value is changed to 1.

$$f(x, y) = \frac{f(x, y) - Z_{\min}}{Z_{\max} - Z_{\min}}, \qquad (1)$$

Where the minimal pixel value is denoted by Zmin, and the maximum pixel value is denoted by Zmax, and f stands for the brain picture.

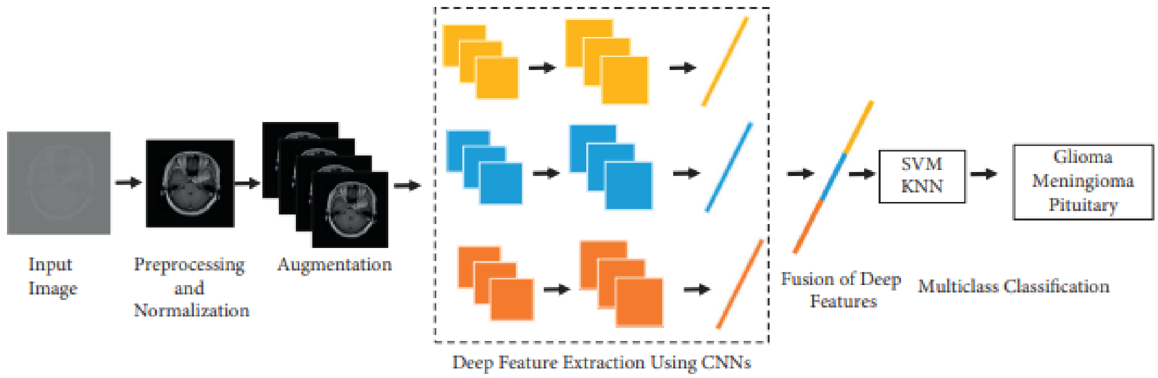

Figure-2: Diagram showing the suggested method's architecture

The next step is to rescale these images to match the input layer size of the CNNs.) Preprocessing steps help network training by accelerating learning and resolving memory issues.

1.2 Image Augmentation:

The dataset used for this work contains a small number of MRI samples; hence the pre-processed images have been enhanced artificially utilizing a number of augmentation methods. Models often have a bias toward identifying the new instances as the majority class types because of the unequal class distribution; however, this problem can be solved by artificially enlarging the dataset. The photos are improved using left/right mirroring, salt and pepper noise with density (d) of 0.003, x-axis image flipping, and 45-degree rotation with bilinear interpolation. Each pixel's output value is a weighted average of the pixels in its nearest 2-by-2 neighborhood.

1.3 Extraction of Deep Fractures:

1.3.1 Convolutional Neural Network:

Because of CNNs' impressive performance, academics are employing those more often, which has encouraged them to develop solutions to issues that were previously thought to be insurmountable. Recently, scientists have created a large number of CNN designs to address a range of issues in many different domains, including medical image identification [33]. CNN is constructed of numerous layers that are stacked on top of one another. The feature extraction module, which employs convolutional layers to learn the features and pooling layers to minimise the size of the image, and the classification module, which employs a fully connected (FC) layer to categories an image, are the two fundamental components of CNN's design.

1.3.2 Adaptive Learning:

For CNNs, larger datasets typically produce better results than smaller ones do. To train CNN models from scratch, a significant amount of resources are required. Therefore, transfer learning is used when developing a sizable training dataset or distinctive CNN architecture is not feasible.

A model that has already been trained on bigger datasets, like ImageNet [15], can be utilized as a feature extractor on a smaller dataset assignment. Transfer learning is applied in a variety of fields, including as medical image diagnosis and luggage X-ray screening [34]. By using this technique, it is possible to develop distinctive deep learning models without requiring a significant dataset or a protracted network training period.

We used AlexNet [15], GoogLeNet [17], and ResNet18 [35] as deep feature extractors in our work since CNN designs may acquire significant features without any human supervision. Furthermore, because the Figshare dataset is not particularly large, we use a transfer learning strategy to build our feature vector. Because creating a deep learning model from scratch uses a lot of computing resources, we use transfer learned models to help learn target domains using source domains and learning tasks [35, 36]. In the proposed study, we applied a transfer learning method by adjusting the FC, Softmax, and Classification layers of the final three CNN layers to meet the requirements of our target domain. Figure 6 shows the general designs of (a) AlexNet, (b) ResNet, and (c) GoogleNet. The AlexNet network was developed by Alex Keizhevsky, and it has 8 learnable layers, of which 3 are convolution layers (CLs) and 5 are fully connected layers (FC layers) [15].

The model is commonly used by researchers to solve classification issues because of its dependable performance and lightweight design.

A variant of the Inception network called the GoogLeNet was developed by Google researchers. There are 9 inception modules and 22 layers in the CNN. The design works well [17] because it preserves spatial information in images even after image reduction.

The ResNet18 architecture consists of 18 layers in total, comprising 17 CLs, an FC layer, and an additional softmax layer for classification. The CLs use a 33 kilobyte kernel. ResNets use shortcut connections that bypass one or more levels, which reduces the training loss even if their outputs are simply added to the outputs of stacked layers, not increasing computing complexity. The shortcut connections in ResNet18 eliminate two levels [35]. The input size is the dimension required for an input image. The depth of the architecture is a representation of how many consecutive CLs or FC layers there are between the first layer and the classification layer. The parameter shows the total amount of parameters that the entire network is capable of learning.

1.4 Classification:

The novel feature vector is presented to well-known classifiers at this stage, including SVM and KNN. SVM, a supervised learning method that belongs to generalized linear classifiers, optimizes the margin between the hyper plane and the dataset in order to improve accuracy and avoid over fitting. In contrast to Thomas Cover's KNN, which was developed in 1992 and has been effectively used for regression and classification issues in a variety of areas, Vladimir Wapnik and his team's classifier was first presented in 1992 [38, 39]. Since the early 1970s, it has been applied in a wide range of statistical applications. A supervised learning model is used to determine the separation between a test sample and a set of (k) training samples. The classifier assigns the test sample to the category that, among its k nearest training instances, has the highest percentage

[40]. Both classifiers are widely utilized in handwriting recognition, medical image issues, etc. because of their superior performance.

CONCLUSION AND FUTURE SCOPE:

This research presents a novel deep feature fusion-based approach for classifying brain cancers from MR images. The framework's suggested features are taken from a range of low-level and high-level architectures, with varied depths and designs, such as AlexNet, GoogLeNet, and ResNet18. These traits are then integrated using a serial fusion technique to produce a single vector. Strong combination features that are SVM and KNN-classified are present in the distinct feature vector. When tested on 15,320 MR images, the proposed approach exhibited a 99.7% accuracy rate, a recall value of 1.0, a precision score of 0.99, and a f1-score of 0.99. In comparison to independent CNN feature vectors, the novel feature vector performed better.

Furthermore, the feature fusion method aids in getting around the limits of a single CNN model, resulting in improved performance, particularly for larger datasets. The gathered data show how successful and durable the proposed approach to classifying brain tumors is. As a result, the recommended framework can aid radiologists in accurately classifying and identifying brain tumors. Future research will look into VGG, DenseNet, and other CNNs in addition to machine learning classifiers like Random Forests and Ensemble learning. More MRI datasets will also be collected utilizing various imaging modalities and new tumor classifications for categorization.

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