IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 5, Issue 3, January 2025

Brain Tumor Detection using Convolutional Neural Network

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Abstract: *Detecting brain tumors in their early stages is crucial. Brain tumors are classified by biopsy, which can only be performed through definitive brain surgery. Computational intelligence-oriented techniques can help physicians identify and classify brain tumors. Herein, we proposed two deep learning methods and several machine learning approaches for diagnosing three types of tumor, i.e., glioma, meningioma, and pituitary gland tumors, as well as healthy brains without tumors, using magnetic resonance brain images to enable physicians to detect with high accuracy tumors in early stages. Brain tumors refer to the abnormal growth of cells in the brain's tissues. Detecting these tumors and accurately determining their size can be challenging when planning treatment. Magnetic resonance imaging (MRI) utilizes strong magnets to produce detailed images of the body's interior, including the brain. Compared to traditional imaging methods, MRI provides clearer visualization of the brain, making it a common approach for identifying brain tumors.*

Keywords: Brain Tumer, MRI, Deep Learning, Artificial Intelligence, CNN.

I. INTRODUCTION

Brain tumor studies are one of the most popular topics in the academic community today. In general, the cancer tumor classification is the segmentation of tumor regions and the classification of the tumor [1], [2], [3]. This vital organ is located in the center of the nervous system. Therefore, tumors that occur in the brain cause life-threatening disease, and, in such cases, early diagnosis is vital. The features to be used for the classification of brain tumors play an important role in determining the class to which the tumor belongs. Nowadays, Convolutional Neural Network (CNN) method is the best in feature extraction [4], [5], [6], [7]. In a recent study on brain tumor segmentation, Havaei et al. [8] proposed a two-way CNN which takes both pixel properties and the possibilities of neighboring pixels into account. Usman et al. [9] segmented brain tumors to calculate the density, density differences, neighborhood and wavelet patterns of these segmented brain tumors and classify these by using the random forest classifier. Cheng et al. [10] obtained the characteristics of the tumor region by using the density histogram, gray level co-occurrence matrix (GLCM) and bag-of-words (BoW) methods, and increased the accuracy of brain tumor classification thanks to these features. Afshary et al. [11] displayed a correct recognition performance of 86.56% by using capsule networks (CapsNets) method for brain tumor classification.

In recent years, deep learning has prevailed against the conventional image processing methods. There are a number of studies that indicate the superiority of deep learning algorithms to conventional methods [12], [13], [14]. The principal stage in image classification with conventional image processing is the feature extraction, which requires specialized knowledge. Compared to the conventional image processing, the most prominent advantage of deep learning algorithms is the elimination of the need for feature extraction. CNN technology displays superior performance in image classification and pattern recognition compared to conventional methods. As it performs well in image recognition, segmentation, and recognition, it is widely used in image and video recognition.

The CNN consists of various algorithms that can be learned by the process layers (linear and non-linear). The formation of features is among these layers. Since CNN displays remarkable performance in image recognition, segmentation, and classification, it can be considered superior to other classical methods. The parameters such as input, convolution, flattened linear unit, pooling layer were investigated in the CNN architectures, and architecture with 5 convolution layers was preferred as the most suitable architecture. In the classification layer, which is the last layer of CNN

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architectures, the softmax classifier is used as a conventional classifier. Unlike other studies, Support Vector Machine (SVM) [15] and K-Nearest Neighbor (KNN) [16] classifiers were used instead of softmax classifier in the present study.

In many studies on image processing, Fuzzy Set (FS) is used to analyze fuzziness. However, FS is sometimes unable to solve some problems. Neutrosophic Set (NS) is a recent method that has displayed a high success in image processing applications. NS is more successful than FS in terms of solving uncertain situations. Thanks to its superiority, it provides successful results particularly in edge detection and segmentation applications. The relationship among Classical set, FS and NS are given in Fig. 1. In the Classic Set, the T and F subsets are 0 or 1, and I subset is 0. In the fuzzy set, I subset is 0, f subset set is 1, and t + f is 1. In NS, $0 \leq (t, i, f)$ subsets ≤ 1 [17]. The NS approach has recently been used to perform segmentation successfully in the field of biomedicine [17], [18] and other related fields [19], [20].

We developed the neutrosophic expert maximum fuzzy-sure entropy (NS-EMFSE) segmentation method in [18]. In the present study, we proposed the Neutrosophic Expert Maximum Fuzzy-Sure Entropy Set – Convolutional Neural Network (NS-EMFSE-CNN) hybrid classification method by combining neutrosophic expert maximum fuzzy-sure entropy (NS-EMFSE) segmentation and Convolutional Neural Network approaches. In the proposed NS-EMFSE-CNN, the MRI image in DICOM format is initially pre-processed and segmented using NS-EMFSE. The features obtained following the convolution layers of CNN were given to the inputs of classifiers such as SVM and KNN. Next, using the CNN method, the tumor in these segmented MRI images is classified as malignant or benign. For the artificial learning models used in this study, the k-fold cross-validation method was preferred in the division of the data sets as training and test data. Here, a 5 – cross-validation method was used. It was observed in the present study that SVM displayed the highest performance with an accurate recognition rate of 95.62%.

The main contributions of the present study can be summarized as follows:

1. CNN architecture is used as a feature extractor to avoid manual feature extraction.
2. These features are used in various classification (SVM-KNN) algorithms.
3. The CNN structure was used with Neutrosophy for image processing for the first time.
4. A new hybrid method called NS-EMFSE-CNN using segmentation and classification is proposed.
5. The classification performance of Brain Tumor images with NS-EMFSE-CNN method was higher compared to conventional CNN classification.

II. LITERATURE SURVEY

In this section, we discuss the many ways in which machine learning and deep learning have been applied to the study of infectious brain tumors and the interpretation of medical images. Over the past two decades, medical image analysis has attracted a lot of attention and research interest because of the wide range of uses it offers in healthcare, particularly in the investigation and diagnosis of patients. In order to classify brain images and analyze brain architecture, studies suggest machine learning-based strategies [9]. Abd-Ellah et al. [31] conducted an in-depth study of the available methods for diagnosing brain MRI scans, comparing and contrasting the strengths and weaknesses of traditional machine learning and deep learning approaches. Additionally, the authors presented a new semi-automatic segmentation approach for images of brain tumors [32]. For 3D MRI segmentation, this model made use of a T1W configuration. Another CNN-based architecture was presented for breast cancer picture categorization [33]. This system's maximum accuracy for tumor segmentation and localization was due to its architectural design, which extracted data from fitting scales. In addition, GoogLeNet, InceptionV3, DenseNet201, AlexNet, and ResNet50 were used in a CNN-based model for diagnosing brain tumors [34]. The results indicated that the proposed method was able to detect and categorize cancers in MR images with high precision. Overall, the corpus of work shows substantial advancement in segmenting and classifying brain tumors from MRI scans, as well as their 3D visualization. However, there is still a requirement for innovative methodologies to increase the efficacy of feature extraction, tumor classification, and localization.

The authors of this work [35] proposed several methods for exploiting MR images to spot brain tumors. The researchers looked into the effectiveness of using 3D CNNs, SVMs, and multi-class SVMs for segmentation improvement. In a variety of medical image processing tasks, including brain tumor detection, deep learning approaches, and CNNs in

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particular, showed outstanding efficacy. When compared to other machine learning classifiers, the results from using deep learning approaches to classify and segment brain tumors were superior.

An alternative study [36] presented a deep learning neural model to extract features from MR images, which were then used as input for machine learning classifiers such as Naive Bayes, Support Vector Machines, and Multilayer perceptrons. When using SVMs, the proposed method attained a classification accuracy of 96%. Kumar et al. [37] conducted a study that included the examination of several machine learning and deep learning techniques for brain tumor detection and segmentation, including support vector machines, k-nearest neighbors, multi-layer perceptrons, Naive Bayes, and random forest algorithms. Notably, the classic SVMs had the highest classification accuracy at 92.4%. For brain tumor detection in MRI, the scientists further presented a bespoke CNN architecture with five layers, which reached an amazing accuracy of 97.2%. Similarly, Khan et al. [38] developed a method for classifying and segmenting brain cancers in MRI images using VGG19 CNN architecture and K-means clustering. The suggested method first transformed the input MR modality into slices, then preprocessed the intensities using a statistical normalization strategy. The overall precision of their method was 94%.

A technique for fusing 2D and 3D MRI images was reported by the authors of [39]. They suggested utilizing DenseNet for classification and unique 3D CNN architectures for segmentation of multi-modal pictures. On the test set, the proposed method performed admirably, with an accuracy of 92% using DenseNet and 85% using the individualized 3D CNN models. Brain tumor categorization was proposed by Kang et al. [40] using machine learning classifiers and a deep CNN feature ensemble. The authors conducted their experiments using datasets of varying sizes. When compared against other machine learning and deep learning classifiers, an SVM using a radial basis function kernel performed best. Another research paper [41] developed a machine learning network- based automated brain tumor classification system for identifying high- and low-grade glioma illness images. The scientists used an extreme gradient boosting model to classify cancers of the central nervous system, including the brain, with accuracies of 90% and 95%, respectively. A new ensemble model, “Adaptive Fuzzy Deformable Fusion,” was introduced in [42]. This model improved classification and segmentation by fusing the Fuzzy C- Means Clustering technique with the deformable snake method. The experimental findings showed that the ensemble method outperformed individual models and obtained a classification accuracy of 95%. To determine how to tell benign from malignant brain tumors, Mehrotra et al. [43] investigated several pre-trained CNN algorithms based on deep learning. Various optimizers, including Adam, RMSprop, and stochastic gradient descent (SGD), were used to complete the objectives. As the research showed, when AlexNet was properly calibrated, it excelled at medical imaging tasks. To classify 253 brain tumor images (155 tumors and 98 non- tumors), Grampurohit and Shalavadi [44] built a unique CNN architecture and used VGGNet. Overfitting was mitigated by employing data augmentation and preprocessing strategies to boost sample diversity. Overall, the validation accuracy for the bespoke CNN model was 86%, whereas it was 97% for VGGNet on one dataset.

The authors of [45] reviewed several methods of image editing known as “image preprocessing”, which led to substantial enhancements in classification accuracy. Global thresholding, adaptive thresholding, the Sobel filter, the high-pass filter, median blurring, histogram equalization, dilations, and erosions were among the methods presented. In addition, 3762 pictures of brain tumors were analyzed by a pre-trained Resnet101 V2 model that relied on transfer learning to achieve a 95% rate of accuracy. Another study [46] presented a genetic algorithm (GA)–CNN hybrid for detecting glioblastoma and other brain cancers. An appropriate CNN architecture was chosen automatically with the help of the genetic algorithm in this method. The authors were able to correctly identify glioma, meningioma, and pituitary cancer in 90.9% of cases, and in 94.2% of cases overall.

Majib et al. [47] offered a novel method that combines the VGGNet architecture with a stacked classifier: VGG- SCnet. In order to facilitate faster and more effective training for automated brain tumor identification from MRI scans, the scientists fine-tuned a pre-trained VGG-16 model with additional layers recommended by their approach. The most notable contours were used to pinpoint the area of interest throughout the data preparation phase. The dataset’s class imbalance was fixed using augmentation methods. The sixth layer of the VGG-16 network was used for feature extraction because it contained fewer features. Finally, tumor detection in imaging was accomplished by employing a layered classifier.

In the context of medical imaging, image preprocessing techniques are utilized to generate an accurate representation of the anatomical structure of the human body, as discussed in [48]. Specifically, in the case of MRI images, they are

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employed to identify and locate tumor cells within the affected human brain. In another paper [49], the authors presented a unique method that used multimodal information fusion in tandem with CNNs to spot brain cancers in 3D MRI scans. The method improved upon multimodal 3D-CNNs in order to capture the unique features of brain tumor lesions using many imaging modalities. Additionally, in [50], the researchers investigated the use of VGGNets, GoogleNets, and ResNets, among other CNN designs, in the context of brain tumor classification. According to the findings, ResNet-50 outperformed GoogleNet and VGGNets, with an accuracy rate of 96.50%, compared to 93.45% and 89.33%, respectively. In addition, ResNet-50 is 10% more accurate than VGGNet and GoogleNet while taking 10% less time to process data.

One notable study by Akkus et al. [51] focused on brain tumor segmentation using a random forest classifier. The authors utilized a combination of handcrafted features, including intensity, texture, and shape features, to train the classifier. Their approach achieved competitive performance on the BraTS 2015 (Brain Tumor Segmentation 2015) dataset, demonstrating the potential of machine learning for accurate tumor segmentation. Pereira et al. [11] proposed a deep-learning-based framework for brain tumor classification. They employed a deep CNN architecture and demonstrated superior performance in distinguishing between different tumor types compared to traditional machine learning methods.

III. METHODOLOGY

The methodology of the present study is illustrated in Fig. 1. Major steps in the present study comprise brain tumor dataset selection, pre-processing MRI images, feature extraction, and classification by various classifiers.

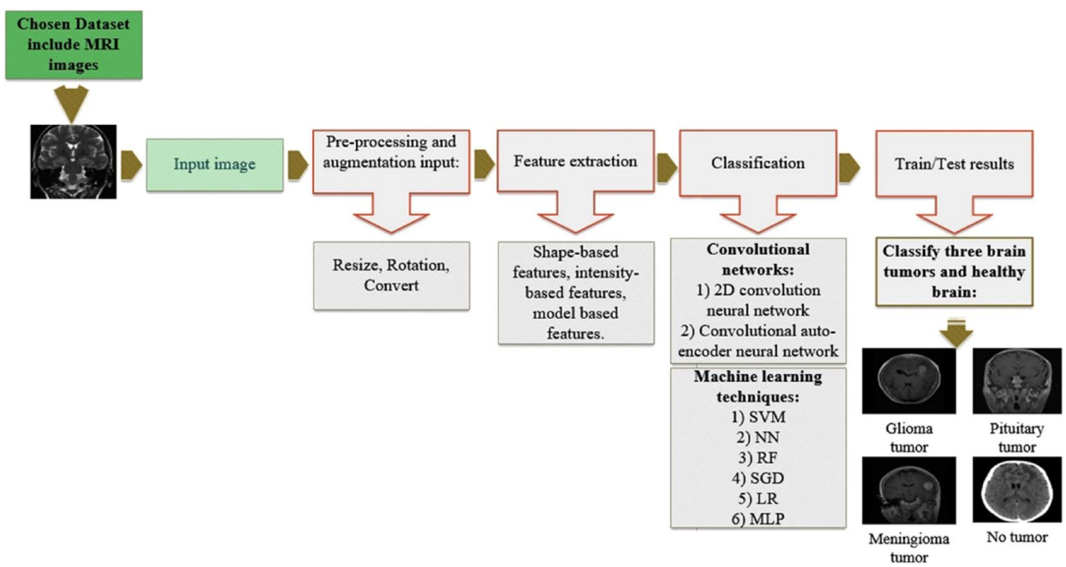

Fig. 1. Block Diagram

Dataset

The applied image-based dataset comprised 3264 T1-weighted contrast-enhanced MRI images [31]. There were four types of images in this dataset: glioma (926 images), meningioma (937 images), pituitary gland tumor (901 images), and healthy brain (500 images). All images were in sagittal, axial, and coronal planes. Figure 2 presents examples of the various types of tumors and different planes. The segment of tumors has been branded with a red outline. The number of images is different for each patient

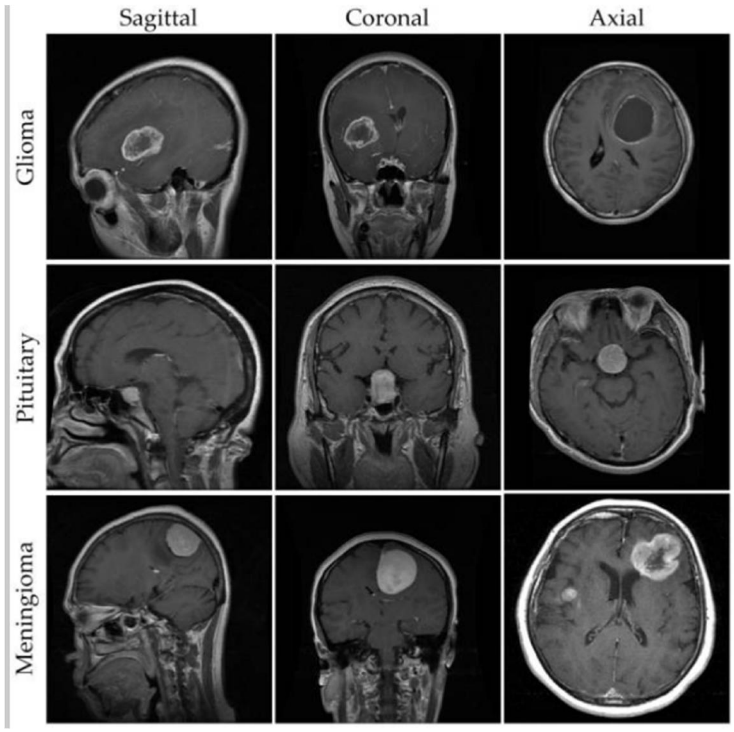

Fig. 2. A sample of MRI images from the brain tumer dataset

Data augmentation and image pre-processing

Magnetic resonance images from this dataset had distinct sizes. These images represented the networks' input layer, so they were resized to 80*80 pixels. Each image was converted in two directions to augment the dataset. The first change included image rotation by 90°, and the second was flipping images vertically. Our chosen dataset was augmented three times, which resulted in 9792 images.

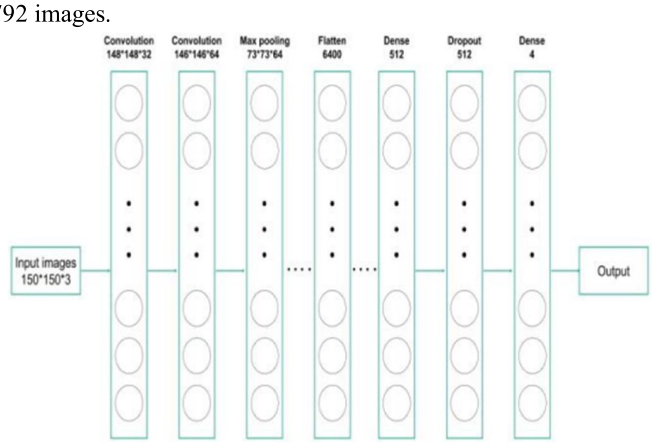

Fig. 2. Proposed Methodology for tumor Detection using 22n layer

Proposed Methodology Using CNN

CNNs are widely utilized for image processing and fall under the category of deep neural networks. They are composed of node layers, which typically include an input layer, one or more hidden layers, and an output layer. The objective of our study was to create an exemplary model using a CNN architecture that could effectively classify the type of tumor from 2D Brain MRI images. A CNN architecture with 22 layers has been specifically designed for brain tumor

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detection. The comprehensive model includes a total of 23 stages, incorporating multiple hidden layers. Notably, this model has exhibited impressive abilities in accurately detecting and localizing tumors within the brain

Overall Architecture of Brain Tumor Detection

Image analysis of brain tumors is challenging, since these tumors can vary widely in size, shape, and location. Researchers have proposed several different methods for detecting anomalies in data that cannot be directly observed, each with their own set of advantages and disadvantages. The availability of a benchmark dataset capable of assessing the efficacy of state-of-the-art procedures is vital for the objective assessment of the performance of these methods. Different devices can produce brain tumor images with varying degrees of sharpness, contrast, number of slices, and pixel spacing. Here, we describe the architecture and technological details of the proposed system that make it possible to detect brain tumors in photos quickly and accurately. Brain tumor picture preprocessing, enhancements, training, and evaluation are shown in Figure 2. Several potential methods for detecting and describing brain tumors have been proposed, and these have been covered in prior research. Unfortunately, these methods have only been successfully implemented in a select few studies, with mixed outcomes at best. The suggested method's primary focus is on providing accurate brain tumor detection in MRI scans. YOLOv7 was selected as the model to be used in this investigation because of its demonstrated efficacy in detecting brain tumors

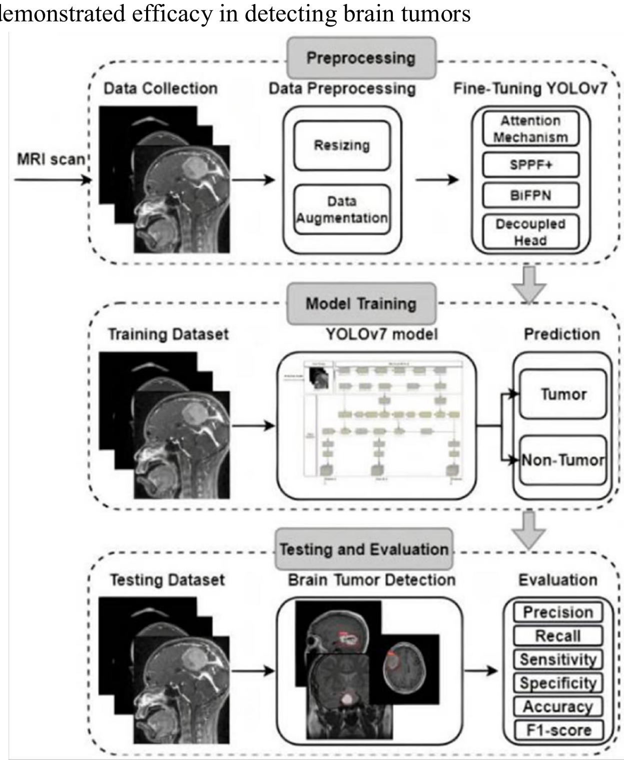

Fig. 4. Overview of the proposed brain tumor detection based on optimized YOLOv7

Dataset Collection

To ensure the validity of our findings, we used an openly available MRI dataset obtained from kaggle.com [64,65]. MRI scan images are included in this collection, since they are the gold standard for diagnosing brain tumors. Glioma (2548 images), pituitary (2658 images), meningioma (2582 images), and no tumor (2500 images) were the four subsets that made up our dataset of brain tumors. Images were all scaled to 512 pixels on the horizontal and vertical dimensions. We used 8232 MRI images (or 80% of the dataset) for training in our analysis, whereas 2056 MRI images (or 20% of the dataset) were set aside for testing. Brain tumor photos from various categories are shown as examples in Figure 1. For each type of brain cancer (glioma, pituitary, and meningioma), Table 1 provides the number of pictures in various views such as axial, coronal and sagittal. It is important to keep in mind that medical photos, in contrast to

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natural images, are more complicated and necessitate a greater level of skill to ensure appropriate analysis and interpretation. The brain tumor dataset was labeled with oversight from a medical specialist to ensure precision and consistency. This physician's expertise was crucial, as it established criteria for how the dataset should be labeled. However, not all brain cancers have characteristic imaging findings; therefore, depending entirely on image analysis can be risky. As a result, pathology analysis is essential for diagnosing brain cancers. Our dataset featured abnormal language descriptions annotated by a medical expert to give rich context for model training.

Data Pre-processing & Augmentation

The brain tumor photos were subjected to a series of pre-processing stages aimed at standardizing the dataset so that it could be used in classification problems. Here is a rundown of what was undertaken in advance: The RGB photographs were converted to grayscale, creating a monochrome version of the pictures. The data were simplified, and the computing burden was lessened as a result. Images were resized such that they all had the same 640×640 resolution. This action guaranteed that all photos were the same size, guaranteeing uniformity in the subsequent processing steps. Noise in the photos was reduced and the output quality was improved by using a Gaussian blur filter. This filtering method softens the image while keeping the important details. Images were sharpened and complicated features were extracted using a high-pass filter. This filter sharpens the focus on edges and fine details, making it easier to make out critical image elements. The morphological processes of erosion and dilation were used to change the size and form of an images' features. Erosion was used to lower the number of white areas (tumors) and highlight gaps, while dilatation was utilized to enlarge the white areas and fill gaps

2D CNN

Figure 3 shows the proposed architecture for the two-dimensional CNN. A set of 9792 data was used in this study, 90% (8812) of which was employed as the training data and 10% (980) as the testing data. The proposed network had several layers, including convolution, which possessed two convolutional layers with 64 filters. Moreover, two convolution layers included 32 filters, and the others have 16. The final two convolutional layers make the desired network filters with a length of 8. The layers in this network have a 2*2 kernel function.

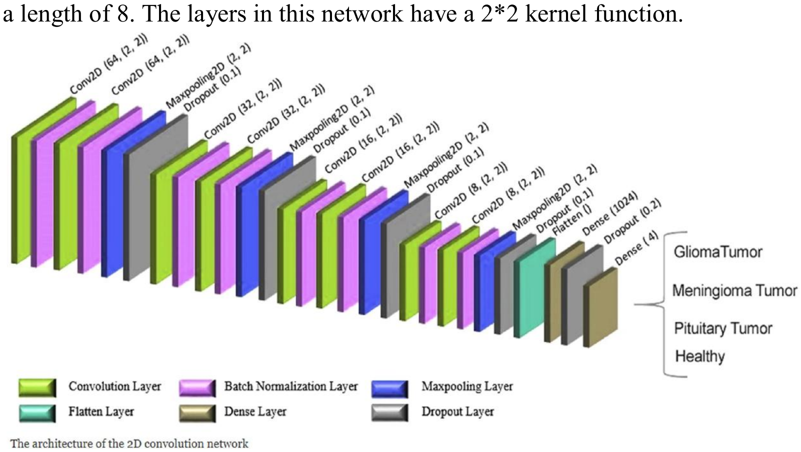

Fig. 5. The architecture of the 2D convolution network

IV. CONCLUSION

To reduce global death rates, diagnosis of brain cancers is essential. Brain tumors can be difficult to identify because of their complex architecture, size variability, and unusual forms. In our research, we used a large collection of MRI scans of brain tumors to overcome this obstacle. We showed that a state-of-the-art YOLOv7 model could be improved by transfer learning and fine tuning in order to detect gliomas, meningioma, and pituitary brain tumors in MRI data. Our suggested CNN model demonstrates the substantial influence of deep learning models in tumor identification and demonstrates how these models have changed this field. Using a huge collection of MRI images, we found some encouraging findings in the diagnosis of brain cancers. We used a wide range of performance measures to measure the effectiveness of our deep learning models. When compared to standard techniques of categorization, the proposed technology not only detects the existence of brain tumors, but also pinpoints their precise location within the MRI images. This localization allows for fine-grained categorization without laborious human interpretation. The proposed solution, in contrast to segmentation techniques, uses a little amount of storage space and has a low computational cost, making it portable across a variety of systems. Not only did the suggested approach achieve better accuracy than prior efforts using bounding box detection techniques, it also outperformed those techniques when applied to meningioma, glioma, and pituitary brain cancers. The results were improved, and the problem was tackled with the help of picture data augmentation, even though the dataset was relatively small. Using the available data, we obtained an accuracy of 99.5% in our analysis. The proposed method for detecting brain cancers in medical images has achieved this accuracy.

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