Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7766257

AN ANALYSIS OF CONVOLUTIONAL NEURAL NETWORK AND SUPPORT VECTOR MACHINE FOR MULTICLASS BRAIN TUMOR DETECTION

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ABSTRACT: -Clinical diagnosis now plays a bigger part in today's healthcare system. Since brain cancer is the deadliest disease in the world, it is a significant concern in the field of medical imaging. Magnetic resonance imaging-based early and precise diagnosis may be beneficial for brain tumor evaluation and prognosis. In order for radiologists to employ computer-aided diagnostic procedures to assist them discover brain tumors, medical images need to be identified, segmented, and classed. There is an urgent need for an automated method since radiologists find the procedure of manually identifying brain tumors to be laborious and prone to mistakes. The method for precisely identifying and classifying brain tumors is thus introduced. There are five stages recommended for the procedure in terms of the tools and techniques used. To find the image's edges in the beginning, the original image is stretched with a linear contrast. The creation of a deep neural network architecture specifically designed for the goal of segmenting brain tumors occurs in the second stage. Finally, transfer learning is used to train a modified MobileNetV2 architecture for feature extraction. Finally, a controlled entropy-based method and a multiclass support vector machine (M-SVM) were used to choose the best features. Last but not least, M-SVM is used to classify images of meningioma, glioma, and pituitary tumors.

KEYWORDS: Biomedical image processing; brain tumor; deep learning; linear contrast stretching; segmentation.

I. INTRODUCTION

At this time, the expenditures associated with treating people who have brain tumors are the highest of all types of cancer. Because of the rapid proliferation of particular cell types, people of any age can experience the development of brain tumors. [1] A brain tumor is an abnormal growth of tissue that can form anywhere in the brain or central spine. This development interferes with the brain's normal function. [2] The location, size, and surface area of these large tumor cells are the three factors that determine whether they are malignant (cancerous) or benign (non-cancerous). The terms "primary" and "secondary" tumor locations refer to the stages of cancer cells that have developed the most recently. While cancer cells are still considered benign, this stage of the tumour is referred to as the primary tumour region. Primary brain tumors are those that begin in the tissue of the brain itself. With the appropriate therapy, these tumors can be cured or at the very least made more manageable. Secondary tumors are cancers that began in another organ but have now progressed to the brain from where they originated. The presumptuous patient's tumor can be cured only by the use of appropriate surgical procedures or radiation therapy [3]. Monitoring the progression of brain tumors is essential to the patient's chance of survival [4]. This is because brain tumors pose a threat to healthy brain tissue. Meningiomas are a type of tumor that has the potential to spread to the brain and spinal cord. The tumors themselves are made up of three different layers of meningeal tissue [5]. Meningiomas frequently take the form of lobar masses that are asymmetrical and have sharp borders [6].

The patient's age, the size of the tumor, and the location of the tumor all have a role in determining the patient's likelihood of survival after being diagnosed with meningioma. Clinginess to the point of obsessiveness, recurrent headaches, and weakness in the limbs are all symptoms of meningioma. The tumors of benign meningiomas have a diameter of less than 2 millimetres, whereas the tumors of malignant meningiomas can have a diameter of as much as 5 centimetres [7]. If discovered and treated in a timely manner, the vast majority of malignant meningiomas are curable.

Magnetic resonance imaging (MRI) has become one of the most prevalent methods for making this diagnostic [8]. This is due to the fact that there are various distinct types of MRI that can be utilized for the detection of brain cancer. It is of the utmost importance to accurately diagnose and treat brain tumors because of the possibility that they will claim the patient's life. The only approach to protect patients from potential harm is to perform full brain scans on them and look for signs of the disease as early as possible in its progression. There are a variety of MRI techniques, and each one has its own distinct settling time [9]. These techniques allow for the detection of diverse types of brain tissue. If only one modality of an MRI is used, it may be difficult to diagnose brain tumors due to the fact that their form and location can be unpredictable. When looking for tumors, comparing data from many MRI techniques is extremely important [10]. When contrast enhancement is used, T4-Gd MRI can show a bright signal at the tumour edge. FLAIR MRI can use water molecules to suppress signals in order to differentiate cerebrospinal fluid (CSF) from areas of edoema. T1weighted MRI can be used to distinguish tumor tissue from healthy tissue. T2-weighted MRI can be used to outline areas of edoema, resulting in clear image areas.

Calculating area, determining uncertainty in segmentation area, and segmenting tumours are difficult tasks [11]. This is due to the structural complexity and unpredictability of brain tumors, as well as the high volatility and intrinsic features of MRI data, which include the fluctuation of tumour size and form. The process of manually segmenting a tumor takes a significant amount of time, and medical professionals may see differences in the results of the segmentation due to variations in the form and structure of the tumor. On the other hand, meningiomas may be distinguished from one another with relative ease, whereas gliomas and glioblastomas provide more of a challenge [12]. Therefore, it is of the utmost importance to offer a method of automated segmentation in order to make this difficult operation more manageable.

When performed manually, detecting and monitoring brain tumors takes a significant amount of time, and there is a high risk of making an error [13]. We need to come up with a strategy for replacing the manual operations with automated ones as soon as possible. The current methodologies, which rely on labelling methods to identify sick regions in the brain and are unable to detect internal peripheral pixels, are not compatible with the procedures that are used to detect brain tumors, hence these approaches cannot be used. We prefer MRI over CT scans due to the contrast agent's capacity to reveal the damaged region in a clearer light with MRI (CT). Hence, MRI modalities are utilized in a wide variety of diagnostic strategies with the purpose of diagnosing brain cancer.

In recent years, a wide variety of different strategies have been proposed for the automatic classification of brain tumors. These strategies can be broadly categorized as either Machine Learning (ML) or Deep Learning (DL) approaches, depending on whether they prioritize feature fusion, feature selection, or the underlying learning mechanism. In recent years, a number of different strategies have been proposed for the automatic classification of brain tumors. In machine learning systems, feature selection and feature extraction are essential building blocks for categorization [14,15]. On the other hand, systems for deep learning may learn by manually extracting attributes from pictures. MRI analysis and other types of medical image analysis make extensive use of the most recent deep learning (DL) techniques, in particular convolutional neural networks (CNNs), which boast an astonishing level of precision [16,17,18]. Even though these drawbacks can be mitigated through the use of transfer learning [19], they still exist when compared to traditional machine learning approaches and include the requirement for a large training dataset, a high complexity of time, low accuracy for applications where only small datasets are available, and expensive GPUs that eventually increase the cost to the user. Transfer learning can be used to mitigate these drawbacks. In addition, if one is familiar enough with a variety of deep learning parameters, training methods, and topologies, the task of selecting the appropriate deep learning model may appear to be a daunting one. Among the machine learning-based classifiers that have been applied to the classification and detection of brain tumors are Decision Tree, Support Vector Machine (SVM), Random Forest (RF), fuzzy C-mean (FCM), Convolutional Neural Network (CNN), Nave Bayes (NB), K-Nearest Neighbor (KNN), and Sequential Minimal Optimization (SMO) (DT). The computational and geographical complexity of the CNN implementation has been lowered, making it simpler to put into practice. These classifiers have garnered a lot of academic interest in general because to the relatively small datasets that are required for training, the low cost of computation, and the ease with which untrained individuals can adopt them.

The unique strategy of segmenting and classifying brain tumors is expected to result in advances such as the ones listed above.

During this stage of pre-processing, we utilize a method known as linear contrast stretching in order to improve the appearance of the image's edge details;

Built from the ground up a 17-layer convolutional neural network (CNN) architecture that was designed exclusively for the segmentation of brain tumors;

Transfer learning from a modified version of MobileNetV2 was utilized by our team in order to get the datasets necessary for deep feature extraction;

In order to accomplish this, we make use of an entropy-controlled technique for picking features, in which the top features are selected in accordance with the value of the entropy. In order to classify the final features, a multi-class support vector machine (SVM) classifier is utilized. Also, a comprehensive statistical analysis and comparison with state-of-the-art methods are carried out in order to validate the consistency of the suggested methodology.

II. RELATED WORKS

MR imaging is frequently used in contemporary medical practices for the purpose of diagnosing brain cancer [8,14]. In this section, we take a closer look at the effectiveness of current methods for detecting and classifying brain tumors. In recent years, a significant number of research projects on the detection, segmentation, and categorization of brain tumors have been carried out. Even though there have been a number of articles [20,21,22] highlighting its significance, the medical community continues to emphasize how important the subject is. This study proposes a strategy for identifying and describing brain tumors in greater detail. The differentiation of brain images for the purpose of diagnosing brain malignancies can be accomplished through the use of either generating or discriminating techniques [17,23]. Maqsood et al. [4] presented a method for identifying brain tumors that utilized fuzzy logic in conjunction with the U-NET CNN architecture. It involved enhancing the contrast, utilizing an edge detection method that was based on fuzzy logic, and classifying the data using U-NET CNN. In order to achieve this goal, we first apply a contrast enhancement technique to the source pictures as part of the pre-processing phase. Next, we use a fuzzy logic-based edge detection technique to locate the edges in the contrast-enhanced images. Finally, we apply a dual tree-complex wavelet transform at various scale levels. In brain imaging, features are extracted from deconstructed sub-band pictures and then classified using the U-NET CNN classification approach. This allows for the differentiation of meningioma from other types of tumors that can occur in the brain. The proposed method achieved a performance that was 98.59% better than that of other algorithms that are considered to be state-of-the-art.

Researchers Sobhaninia et al. [24] constructed a CNN model for segmentation using brain MRI by utilizing a LinkNet network. They combined different viewpoints in order to increase the model's performance, and the end result was a dice score of 0.79. An adaptive neuro-fuzzy inference classification strategy is used by Johnpeter et al. [25] to identify and locate tumors in brain MRI scans; nonetheless, this network appears to be quite advanced. Our technique improved the appearance of tumor regions utilizing histogram equalization rather than employing edge detection on the brain images. The finished product has an accuracy percentage of 98.1 percent of the time.

Togacar et al. [26] developed a network that they named BrainMRNet by applying the modulo and hypercolumn techniques to their work. The initial photographs went through a preprocessing step before being delivered to the attention module for further examination. The picture is delivered to the convolutional layer, which then processes it depending on the attention module, which regulates the areas of the image that are brought into focus. The hypercolumn technique is utilized to a significant degree across the convolutional layers of the BrainMRNet model. Because the data obtained from each consecutive layer were kept in the array tree of the final layer, we were able to raise accuracy to 96.05% by employing this method. Kibriya et al. [27] developed a method for classifying brain tumors that is based on the combination of a large number of diagnostic criteria. In order to resolve the issue with the data, we begin by using the minimum-maximum normalisation strategy to the initial photographs, and after that, we apply the massive data extension to the images that have been pre-processed. A combination of a support vector machine (SVM) and a k-nearest neighbour (KNN) classifier that was trained using data from the GoogleNet and ResNet18 deep CNN models produced the final output, which had an accuracy of 97.7%. Using a CNN that was developed by Sajjad and colleagues [28], it is possible to detect and classify brain tumors. The authors were able to reach an accuracy rate of 94.58% by utilizing a Cascade CNN algorithm for segmenting the tumors in the brain and a fine-tuned version of VGG19 for classifying the tumors. Both of these methods were used in conjunction with one another. In order to locate tumors in MRI scans of the brain, Shanthakumar [29] used a technique called watershed segmentation. This segmentation methodology, which takes use of a predefined labelling scheme to attain this outcome, was able to improve the accuracy of tumor segmentation to 94.52%, making it one of the most accurate segmentation methods available. Prastawa et al. [30] demonstrated that it is possible to distinguish between different tumor areas in MR images of the brain. Even though this method has an 88.17% success rate, it is only able to identify the abnormal boundaries on the outside of the tumour region; it cannot identify the boundary that runs through the middle of the tumor.

In order to categorize brain tumors, Gumaei et al. [31] proposed using a hybrid feature extraction method that was founded on a regularized extreme learning machine (RELM). The min-max normalization contrast enhancement method is utilized for preprocessing, a hybrid PCA-NGIST method is utilized for feature extraction, and the RELM method is utilized for the classification of brain tumors. This job had a precision rating of 94.23% across the board. A fine-tuned, pre-trained VGG19 model improved outcomes for Swati et al. [32], who reported an average accuracy of 94.82% when applied to contrast-enhanced magnetic resonance imaging (CE-MRI). After addressing the problem of overfitting using the ResNet50 CNN model and global average pooling, Kumar et al. [33] proposed a technique for diagnosing brain tumors that had an accuracy rate of 97.48% on average. These ground-breaking innovations have captured the attention of a large number of people in the field of medical image analysis. It was suggested by Veeramuthuet al. [4] that brain pictures may be categorized using machine learning in conjunction with an understanding of brain architecture.

By utilizing Multi-Level Discrete Wavelet Transform, it is possible to simplify the process of decomposing the image and then subsequently obtaining its characteristics. An approach known as PNN-RBF training and classification is utilized in order to categorize the degree of severity of the sickness depicted in the brain image. Sanjeev and his colleagues developed the hybrid technique that is currently being used [5]. A genetic algorithm is used to narrow the feature set, a discrete wavelet transformation (DWT) is used to filter out extraneous information, and a support vector machine (SVM) is used to categorize the various forms of brain tumors. This combined method. Gopal et al. [6] proposed an approach that is based on the feed forward backpropagation of the neural network as a way to improve the efficiency of motor imagery categorization (FFBPNN). Classifying medical images can be done using a variety of methods, some of which include artificial neural networks (ANN), fuzzy clustering techniques (FCM), support vector machines (SVM), decision trees (DT), K-nearest Neighbors

(KNN), and Bayesian classification. An artificial neural network, along with supervised learning methods such as SVM and KNN, is an example. One such category of techniques that can be used to organize data into meaningful categories is known as unsupervised learning methods. Examples of this technique are K-means clustering and the Self-Organizing Map.

Yet, the transition from features that were manually constructed to those that were machine-learned has been a slow one. Before AlexNet's breakthrough, a number of different approaches to learning features were already in use. Bengio et al. [7] are going to do an exhaustive investigation of the methodologies. Examples of this approach include main component analysis, picture patch clustering, and dictionary techniques, to name just a few. Toward the end of their research, in a chapter titled "Global Training of Deep Models," Moosa et al. [8] will implement CNNs that have been instructed from the very beginning to the very end. In this discussion, we will concentrate on the foundational models, and we will ignore the models that are more surface-level. applying conventional feature learning methods to photographic images of medical conditions. Ravi et al. (2017) [9] provides a more in-depth analysis of the role that deep learning plays in health informatics, including a brief discussion of its application to the interpretation of medical pictures. For additional information, you can refer to this review.

Shen et al. (2017) [10] presented the findings of a study that focused specifically on the application of deep learning to medical image interpretation. While they do cover a lot of ground, we feel that certain key aspects have been missed, despite the fact that they cover a lot of ground. The categorization and identification of brain tumors from MR images is made possible with the help of medical image segmentation, which is a process that is vital for the quick planning of treatment. Techniques for the Categorization of MRIs

There are a significant number of tumors in the brain. For examining head tumors, the diagnostic approach of choice is imaging of the patient's brain using magnetic resonance imaging (MRI). Conventional methods of machine learning frequently assign a categorization to a brain tumor based on an arbitrary characteristic or the judgement of a radiologist. This can be problematic when trying to diagnose and treat the disease. In this particular investigation, we distinguish between benign and malignant tumors on MRI scans of the brain by employing an ensemble modeling approach that makes use of the SVM and CNN classifier [5].

In addition, when it comes to recognizing brain tumors, threshold-based segmentation management creates fuzzy borders and limitations, which might be a challenge.

Deep learning was used to develop a model for detecting and diagnosing brain tumors. This model was constructed using Resnet-50 and TL. These experiments are accurate to a 95% degree on average. The fivefold crossvalidation was achieved by the researchers through the application of block-wise based transfer learning. Accuracy of 95% Their method, known as CEMRI, was evaluated with the help of a benchmark dataset made up of T1-weighted MR images. Using the neural network architecture developed by Google to classify MRI scans of the human brain. We were able to attain a classification accuracy of 98%. A classification strategy that is based on support vector machines is used here [7]. Two uses of convolutional neural networks (CNN) include feature extraction and classification. This structure makes use of four layers total, with two of those layers being convolutional and the other two being fully connected. Transfer learning was used in a study that used nine deep learning models to successfully identify brain tumors with a TL accuracy of 97.39% [7]. The study was conducted.

They switched to deep learning mode so that they could investigate the MR data further. When the suggested method was used for the classification of MRI scans, it was shown to be successful 98.71 percent of the time. The findings were surprising when one takes into account the limited scope of the study. In every regard, CNN's plans were completely accurate. In addition, VGG attained 96 percent accuracy, which is higher than the results obtained by ResNet50 (89 percent) and InceptionV3 (89 percent). Accuracy of 75% [8] According to CNN, contemporary buildings are intended to perform at lightening speeds while retaining a 98.24 percent accuracy rate. This is a feat that is considered nearly impossible. It is strongly advised that multi-scale analysis of MRI imaging of brain tumors be performed using CNN. They tested the proposed model on the MRI image dataset, and discovered that it had an accuracy of 97.3 percent in categorizing the pictures [9]. The CNN model gathers data for feature extraction using two convolutional layers and two fully connected layers. This allows the model to categorize brain tumors. They had a success rate of 97% when it came to classifying brain tumors [10].

The researchers classified MRI scans of the brain into healthy and sick categories by using a convolutional neural network ResNet34 model and a transfer learning approach [20]. They took a greater number of images in order to achieve a level of accuracy of one hundred percent by employing a technique for enhancing data photographs of brain tumors to determine whether or not they are normal [11].

A combination of the ANN model and the optimization approach of the Gray Wolf Optimizer was used (GWO). They were able to attain an accuracy in their classifications of 98.91 percent by using GWOANN. They demonstrated a deep CNN network that had been trained using ResNet-50 and brain MR [12]. The accuracy of the model was brought up to 97.48% with the assistance of the proposed method for the improvement of the data. It was hypothesized that a Capsnet CNN model might achieve an accuracy of 90.89 percent by using an MRI of the brain as training data [13]. [14] found that an ensemble model made up of three independent convolutional neural network classifiers was able to achieve an accuracy of 98%.

The findings of the study suggested that transfer learning could be utilized in the classification of brain tumors. For the completion of this job, a CNN with either the DenseNet-2, VGG-16, or VGG19 architecture or the ResNet-50 architecture was selected. During the course of this inquiry, we utilized FigureShare. The created model was modified with the assistance of a public test bed after using 3064 magnetic resonance imaging (MRI) data to differentiate between three distinct forms of brain tumors. The findings showed that the dataset hosted on Figshare, which is accessible to the public, encouraged the sharing of information. The development of the ResNet-50 model was a successful endeavor. Typically within 99.02 percent of the target value. The group began up in 2020 where they had left off in 2020, and continued to use the same dataset in an effort to increase the diagnostic accuracy for brain cancer. It is recommended that CNNs contain two layers of convolution for feature extraction and two levels of completely linked layers for classification [16]. This CNN approach was successful in providing an accurate diagnosis in a total of 97.39% of instances with brain cancer. Researchers were able to determine numerous distinct subtypes of brain tumors by analyzing the data at their disposal. Several other classifiers, including as KNN, ANN, RF, and LDA, were utilized in this process. The KNN model and the NLBP feature extraction approach were combined in order to achieve the 95.56 percent accuracy that was sought after [17]. When working with a brain to discover and categorize tumors, the limitations of the aforementioned methods of transfer learning—intrusiveness, complexity, and susceptibility to sampling errors—must be overcome. This is because dealing with a brain presents a number of unique challenges. A paucity of study has been conducted on the reliability and efficacy of such approaches, which is a systemic problem. As a consequence of this, transfer learning models have been developed for the purpose of employing in the diagnosis and classification of malignant brain tumors. Deep learning, a novel and very effective classification strategy, was used to categorize the images, and region-based CNNs were utilized to categorize the various types of tumors (faster R-CNN). Khairandish et. al. [1] presented an explanation of how brain tumors truly behave, and it presents a clear image of this stage thanks to the assistance of numerous approaches and the analysis of research studies using a range of criteria. The analysis is carried out with regard to the dataset, proposed model, proposed model performance, and type of method utilized in each individual study. The majority of the papers that were analyzed, which ranged from 79% to 97%, included reliable data. In that order, they used the techniques known as Convolutional Neural Network, K-Nearest Neighbor, K-Means, and Random Forest (highest frequency of use to lowest). In this case, the Convolutional Neural Network provided the best accuracy, which Someswararao et al. measured at between 79 and 97.7%. et al. [2] used various machine learning approaches, most notably the CNN model, in order to establish a new and novel method for detecting cancers in MR images. This study coupled a CNN model classification task for evaluating whether or not a person has a brain tumor with a computer vision task for automatically cropping the brain from MRI data. The goal of the study was to determine whether or not a patient has a brain tumor. Convolutional Neural Network and K-Means Clustering were two additional methods that were utilized; however, Convolutional Neural Network provided the highest accuracy, which was approximately 90%. Choudhury, et. al. al. [3] suggested a brand new CNN-based system that has the ability to differentiate between various MRI images of the brain and identify them as either tumorous or not. The accuracy of the model was found to be 96.08%, and its f-score was found to be 97.3. In order to generate results in 35 epochs, the model employs a CNN consisting of three layers and takes only a few preprocessing steps. The importance of predictive therapeutic and diagnostic applications of machine learning is going to be the focus of this particular research project's primary objective. Support Vector Machine, Convolutional Neural Network, k-Nearest Neighbour, Boosted trees, Random forest, and Decision Trees were some of the other methods that were utilized in this study. In order to detect, categorize, and segment brain tumors, the suggested approaches are guaranteed to be very effective and accurate. Automated or semi-automatic precision

The application of particular methods is required in order to accomplish this goal. Throughout the course of this investigation, CNN was put to use in order to recognize and classify data by making use of a suggested automatic segmentation strategy. Some of the other methods are convolutional neural networks, conditional random fields, support vector machines, and genetic algorithms. The CNN method has the highest efficiency and accuracy ratings, coming in at approximately 91% and 92.7%, respectively. In [1] and in this paper, we analyze MRI images using GLCM features and a Multilayer Perceptron neutron. The MLP technique involves forwarding the network with one or more layers positioned between the input and output layers. Segmentation with thresholding, feature vector extraction with GLCM by declaring the four angles that are energy, entropy, contrast, and variance, and model learning are all components of the suggested method that make use of this neural network technology. Segmentation is accomplished with thresholding. Feature vector extraction with GLCM is accomplished by declaring the four angles that are energy, entropy, contrast, and variance. Pictures that have previously been processed by filtering or equalizing before being thresholded. The process of reducing the amount of data by selecting features from it is called data extraction. A neural classifier receives its initial training based on the properties that were retrieved. The proposed ISO method is put through its paces with the use of twenty magnetic resonance imaging (MRI) scans of the skull. After the histogram has been normalized, the segmentation process is used to cut off the parts of the picture that contain the tumor. This makes it possible to make a more precise determination of where the tumor is located within the MRI. In addition, the images that were retrieved are put to use in a phone conversation.

In this investigation, we look for evidence of brain tumors in MRI scans using a method known as support vector machine (SVM) analysis. A statistically-based supervised learning system known as the Support Vector Machine (SVM) is described here. DWT being used to represent a picture. The use of a Simulink model is required whenever SVM classification is carried out. This article presents a prototype that was developed with support vector machines (SVM) and demonstrates how it is possible to achieve both high performance and high accuracy in detection. While attempting to categorize tumors, the first step is to select the suitable photographs for examination (known as "preprocessing"). After determining the size and shape of the tumor, the following stage, known as feature extraction, is carried out. After this step, the data from the images are fed into a support vector machine to be trained. After that, the SVM classification is performed utilizing the DICOM format. At long last, a tumor is identified as the likely culprit. The predictive values (PPV) are judged to be 81.48 percent, and the negative predictive values (NPV) are determined to be 82 percent. There were 5 genuinely positive responses, 22 genuinely negative responses, 5 genuinely positive responses, and 5 genuinely negative responses. [3]

For the purpose of this investigation, we employ the CNN technique to identify MRI images. The use of MRI scans, which are then processed to increase precision, is required for the diagnosis of brain tumors. The fundamental components of a convolutional neural network are the neurons and the convolution layers (CNN). The behavior of a system might be more clearly stated using clustering, which is a technique used to locate naturally recurring groups within massive data sets. The purpose of cluster analysis is to unearth previously concealed patterns in extensive datasets. Patch extraction is utilized in imaging to help discover the places where malignancy is present. The architecture of CNN is designed to make the most of the two-dimensional nature of the pictures it receives as input. Postprocessing for MRI scans includes a number of different steps, including segmentation, detection, and extraction, among others. Better segmentation is one of the benefits that come with using the system. MRI scans have an accuracy rate of 88%, on average. The application of a neural network results in an increase in accuracy.

The MRI pictures used in this research are recognized with the assistance of a Recurrent Neural Network, as described in [4]. (RNN). An initial application of the BP NN activation function was made in order to scale the number of nodes in the network both up and down. The log sigmoid function was used to reduce the number of nodes in the hidden layer from 270 to 230. Initially, the number of nodes in the hidden layer was set at 270. By increasing the number of nodes in the RNN to 300, we have, at long last, accomplished the highest possible level of performance. We utilize an Elman network since we find it to be the most effective. The amount of performance mistakes also increases in proportion to the number of nodes in the network. When compared to other ANN systems, it was discovered that Elman networks, when applied to the process of recognition, were significantly faster and more accurate. Our ratio was 76.47%, which was significantly lower than Elman's 88.14%.

III. CNN FOR BRAIN TUMOR DETECTION: A CASE STUDY

The process of segmenting and classifying images has a number of obstacles, one of which is the absence of a standard model that is generally applicable. However, selecting the most appropriate method for each particular circumstance. Developing a good public image can be a difficult task. Hence, there is no one approach that is generally recognized for the recognition and classification of pictures. It continues to be a significant obstacle for AI vision systems. The method did not take into account the categorization of photos depicting various clinical illnesses, types of illness, or stages of disease. It is susceptible to overfitting since the system has a significant number of pure nodes in high concentration.

The developers came up with the idea of employing deep learning to automatically detect brain tumors through the use of MRI scans, and then they analyzed the findings to assess how well the concept performed.

The Importance of the Work That Is Being Suggested

- Histogram equalization can be achieved by employing a cutting-edge boosted adaptive anisotropic diffusion filter. This causes the image to be improved.
- There are two stages to the segmentation process. In the first phase, a brain section is performed, and the area affected by the tumor is isolated with the use of a hybrid deformable model that combines a fuzzy method with a superpixel-based adaptive clustering.
- The features are extracted based on the texture and the tetrolet transform, and then the features that have been extracted are integrated with an optimization technique developed by Harish Hawk.
- The purpose of the proposed method is to differentiate between normal brain tumors and abnormal brain MRI pictures using the CNN classifier.

Tumors are groups of abnormally forming brain tissue that are grouped together, and they have the potential to cause irreparable damage to the central nervous system.

In addition to this, the multiplication of tumor cells may result in aberrant mental capacities. It is also essential to keep in mind that many distinct types of tumors can cause the slow expansion and eventual death of brain cells [1]. This is an important fact to keep in mind. But, if a person with a brain tumor is identified at an earlier stage, there are many more treatment options available to them, which significantly increases their chance of survival. Classifying benign tumors using a large number of MRI images is a technique that is both time-consuming and labor-intensive. However, benign tumors develop more slowly and pose less risk than malignant tumors. The utilization of magnetic resonance imaging allows for the production of photographs of a superior clinical quality (MRI). This imaging technology is frequently utilized by medical practitioners in order to detect issues in the brain. illuminating the progression of malignancies throughout the course of time. MRI pictures play a significant role in the process of automatic medical analysis [2]. They do this by providing anatomical specifics, which makes the visual representation of the various parts of the brain better. Using MRI imaging, researchers have developed a number of methods for diagnosing and categorizing different types of brain tumors. There is a wide range of methodologies, ranging from more conventional approaches to medical image processing to the most cutting-edge methods of machine learning.

Deep learning (DL) is a type of machine learning that allows users to learn from data that is both unstructured and unlabeled without the supervision of a person. In recent years, DL techniques and models have been proved to be effective in handling a wide variety of challenging problems. These problems require a high degree of accuracy and depend on hierarchical feature extraction as well as data-driven self-learning. Deep learning has been put to use in many other domains, including pattern identification, object detection, voice recognition, and decision-making [3]. This is only one of its numerous applications. The requirement for an enormous amount of training data is the most significant challenge that machine learning must overcome. As an illustration, in the sector of healthcare, there is a dearth of medical data that is readily available to the general public and that may be utilized to educate deep learning models.

Concern over the safety of individuals' private information is the primary driver behind this decision. As a result of this, the medical industry has placed a significant amount of emphasis on transfer learning in order to compensate for the dearth of data. Here is an example of transfer learning, which is when a deep learning model that was initially trained for one task is subsequently applied to a different problem. In this case, the original task was used to train the model. In circumstances in which there is insufficient training data, this approach is frequently taken [4]. In this study, we make use of transfer learning to develop a deep learning model that is able to recognize and categorize different types of brain tumors based on MRI data. The suggested model can be constructed with just these three pre-trained deeps if necessary:

This article demonstrates a CNN-based, wholly automated method for recognizing and categorizing different types of brain tumors.

We make use of models that have already been pre-trained in order to extract more, deeper information from MR pictures of the brain. We tested three pre-trained models and an ensemble of these pre-trained models plus CNN models on a dataset of brain MRI images with two classifications (normal/tumor).

The current study differentiates between benign and malignant brain tumors by employing densenet121 and densenet169 in conjunction with transfer learning on datasets obtained from Kaggle. MRI is a powerful tool that can improve the detection of tumors, as well as their categorization and the ability to estimate their growth rate.

A. Data Pre-processing phase

Data Preparation The size of the training dataset is a factor that must not be overlooked when developing deep convolutional neural networks. The initial iteration of the model was constructed with the help of the Picture Data Generator in Keras TensorFlow.

The image dataset is enhanced with random modifications so that the proposed system can be trained on a sufficient number of MRI pictures (rotations, height and breadth shifts, brightness changes, etc.). Because of how precisely the settings for the data augmentation were chosen, the proposed classifier will never be shown the same picture twice.

B. Data augmentation

The number of datasets that are used during training has a significant impact on the ultimate performance of deep convolutional neural networks. There is a strong association between the two. We added more MRI photographs to the initial dataset so that the suggested system could learn more effectively from the MRI pictures it was shown. TensorFlow is updated in Keras by utilizing the ImageDataGenerator function in order to make adjustments (pivots, scale adjustments, and brightness). What steps were taken to enhance the data so that the suggested classifier would be able to produce accurate identifications? You will never get the opportunity to observe a replica of yourself. The model's capacity for generalization is increased as a result of this procedure.

C. Both Crop and Re-sizing

The first step in this procedure is to take the brain and move it away from the background of the picture [19]. The method presented here makes use of OpenCV to locate the extreme points of a bounding box. It is important to note that the MRI pictures that were used in this study came in a variety of sizes, each of which was determined by the location from which the image originated. The photographs are scaled down to 64 by 64 by 1 pixel so that there is consistency.

D. Division of the Data

In this analysis, we divide the data into a number of distinct subcategories. During the course of three distinct phases, the suggested method will be put to the test, validated, and improved upon. an examination of the comprehensive education system as a case. With the first subset, it is possible to fit the model. This is around 80 percent of the entire dataset. The portion that was left has been eliminated. The testing and validation of the system will both proceed at the same pace of 80% each.

E. The Convolutional Neural Network

sometimes known as CNN, has become widely used because of its improved ability to categorize images. CNN is able to automatically acquire features by utilizing the data that is provided to it. The DL architecture in question is a well-known one that features feedforward connections between each tier. These networks are able to learn complex functions with the assistance of deep architecture, which is something a simple neural network is unable to do [20]. CNN is the brains behind computer vision, which has applications include the classification of objects, the monitoring of activities, and the creation of medical images. Because it contains an inbuilt filter, its preprocessing is much simpler and more compact than the preprocessing of other neural classifiers. The following are some of the components that make up a typical CNN architecture:

i. Convolution

ii. pooling
iii. activation
iv. and a dense layer
v. are each stages along the way in the classification process.

F. Transfer Learning (TL)
It is a deep learning approach that is used to handle the same problem by combining an existing model that has been trained on a large dataset with a new model that has been trained on a dataset that is completely different from the first dataset. CNN operates more effectively when it is provided with a greater quantity of data. The usage of TL can be beneficial in CNN circumstances in which the datasets are limited. The field of TL has grown significantly over the past several years, finding applications in object identification, medical imaging, and picture categorization [21]. Huge Datasets, such as ImageNet, were leveraged to train the models so that they can extract relevant properties. Applications that work with smaller data sets, such the data from MRIs of the brain, are quite prevalent. The amount of time necessary to finish training is cut down significantly thanks to TL, which is one of its many advantages. procedures, avoiding tight fits, training using fewer data, and motivating higher performance are all ways to achieve this goal. The training for the CNN model has been completed using ResNet in our investigation.

IV. CONCLUSION

When it comes to classification, dense convolutional layers neural circuits, often known as CNNs, have been the subject of extensive research in both established and emerging industries. Assessing the performance of a deep neural network model for a classification algorithm connected to the detection of brain cancer is the purpose of this research article. The application of the extension to the ResNet model demonstrates that the deep learning algorithm utilized in natural image processing is capable of providing higher efficiency in the analysis of medical data. This is shown by the fact that the extension was implemented. The Magnetic Resonance Imaging (MRI) brain was scanned in an effort to locate the malignant brain tumor that was presented as a solution. A unique boosted adaptive anisotropic diffusion filter is employed for noise removal, and there are numerous phases involved in the process before the tumor component of the brain image can be detected. The tumor region can then be extracted using segmentation. The suggested approach makes use of the extraction of textural features. CNN classifiers are used for the classification, and the proposed system achieved 98.3 percent accuracy. In the near future, we want to perform enhancements using perfusion-based MRI scans, which are technically challenging.

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