



Performance Analysis of Brain Tumor Detection Using Convolutional Neural Network

Dr. S. S. Shirgan, Kanchan Waghmare

Department of Electronics & Telecommunication,

N.B.N.Sinhagad College of Engineering, Solapur, India.

Abstract: Brain tumors are the most common and deadly cancer, with just a few months to live in the most advanced stages. As a result, therapy planning is a crucial step in improving the quality of life of patients. Tumors in the brain, lung, liver, breast, prostate, and other organs are regularly assessed using several image modalities such as computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound pictures. In this study, MRI images are used to diagnose brain tumor in particular. An MRI scan, on the other hand, collects so much data that manual classification of tumor vs. non-tumor in a given period is unfeasible. It does, however, have some drawbacks (for example, reliable quantitative measures are only available for a restricted number of photos). As a result, to lower the rate of human fatalities, a reliable and automatic classification technique is necessary. Due to the large geographical and structural variety of the brain tumor's surrounding environment, automatic brain tumor classification is a difficult task. This research proposes the use of Convolutional Neural Networks (CNN) classification for automatic brain tumor identification. If a tumor is discovered, the system classifies it and informs the patient about the stage of the tumor he is likely to experience. Our system gets 99.25% accuracy.

Keywords: CNN classifier, MRI image processing, Brain tumor detection.

INTRODUCTION

With billions of cells, a brain tumor is one of the most important organs in the body. Uncontrolled cell division results in an abnormal group of cells known as a tumor. The two types of brain tumors are low grade (grades 1 and 2) and high grade (grades 3 and 4). A low-grade brain tumor is referred to as "benign." Malignant is another term for a high-grade tumor. A benign tumor differs from a cancerous tumor. It does not spread to other parts of the brain as a result. A cancerous tumor, on the other hand, is referred to as a malignant tumor. As a result, it spreads to other sections of the body fast and endlessly. It causes immediate death. A brain MRI scan's main goal is to detect tumors and model tumor progression. The majority of this information is employed in the diagnosis and treatment of tumors. A magnetic resonance imaging (MRI) scan contains more information than a CT or ultrasound image concerning a medical image. An MRI scan provides detailed information on the brain's structure as well as the detection of abnormalities in brain tissue. Since it became possible to scan and freight medical images to the computer, researchers have given innovative automated ways for identifying and cataloguing brain cancers using brain MRI images. In recent years, however, Neural Networks (NN) and Support Vector Machines (SVM) have emerged as the most popular methodologies for their successful implementation. Deep Learning (DL) models, on the other hand, have recently become a hot topic in machine learning, as the subterranean architecture can efficiently represent complex relationships without requiring as many nodes as superficial architectures like K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) can (SVM). As a result, they rose to the top of their respective domains of health informatics, such as medical image analysis, medical informatics, and bioinformatics, in a short period of time.

A brain tumor is a development of cells in the brain that is abnormal. It's possible to have a primary or secondary brain tumor. A primary brain tumor arises in the brain or nearby tissues, such as the brain-covering membranes (meninges), cranial nerves, pituitary gland, or pineal gland, whereas a secondary brain tumor arises when cancer cells from other

organs, such as the lung, kidney, or breast, migrate to the brain. Mutations in the DNA of primary brain tumors cause them to grow. The abnormal cell can develop while the normal cell dies as a result of these mutations. It can injure the brain and possibly endanger one's life. In this study, we present a CNN model for correctly classifying brain cancers. As a result, treatment for the tumor can begin as soon as possible.

LITERATURE REVIEW

M. Siar and M. Teshnehab [1] A Convolutional Neural Network (CNN) was utilized in this survey to perceive a danger using frontal cortex Magnetic Resonance Imaging. Pictures from alluring resonance imaging (MRI) [2]. [11] The CNN was the essential place where pictures were used. The portrayal accuracy of the Softmax Fully Connected layer 98.67 percent of the photos were powerful. [7] CNN's precision is moreover crude. 97.34 percent was obtained using the Radial Basis Function (RBF) classifier. The Decision Tree (DT) classifier has a victory speed of 94.24 percent. Furthermore, Author utilizes the Sensitivity benchmarks as the accuracy essential. Unequivocally and Precision are two estimations used to review network execution.

Ramkumar, G. et.al [3] another systematic and method taking into account the Deep Convolutional Neural Network Algorithm (DCNNA) is proposed in this investigation, which researches a wide scope of 3X3 part regions. The suggested Brain Tumor Segmentation with DCNNA methodology supports the connection using the BRATS dataset and achieves incredible results involving resemblance co-capable estimations in the extents of 0.886, 0.833, and 0.773. In addition, in the essential grouping of the Web-based Tumor Investigation environment, comparable estimations are stayed aware of. The proposed dealing with times of partitioning on mind disease portrayals join a cushy based method.

Mohsen, Heba et.al [4] The maker of this paper used a Deep Neural Network classifier, which is one of the DL models, to detach a dataset of 66 frontal cortex MRIs into four characterizations: normal, glioblastoma, sarcoma, and metastatic bronchogenic carcinoma developments. The classifier was used connected with the discrete wavelet change (DWT), a solid component extraction methodology, and head parts assessment (PCA), and the results were extremely incredible across all show means.

T. Hatami, M et.al [5] The Random Forest computation is used to suggest a frontal cortex development division approach in this paper. The prescribed technique is applied to frontal cortex alluring resonance pictures, and execution estimates like the Dice Similarity Coefficient (DSC) and computation accuracy not totally settled forever, yielding 98.38 and 97.65 percent, independently.

G. Manogaran et.al [6] The under section and over bits of the psyche malignant growth areas are poor down in this study using a superior balanced gamma flow based AI method for managing perceive the anomaly with modified ROI revelation. Additional data lopsidedness in the inconsistency zone has been reviewed by matching the edge coordinates and assessing the mindfulness and selectivity limits using an AI method. Kesav, N., et.al [8] Author offer a procedure for frontal cortex malignant growth assessment that uses a low- multifaceted nature framework to lessen the execution time of a traditional RCNN plan. To organize Glioma and strong malignant growth MRI tests, we recently used a Two Channel CNN, a low-convoluted designing, which was productive with a 98.21 percent precision. A while later, this comparable designing is utilized as a part extractor in a RCNN to recognize disease areas in a Glioma MRI test that has been arranged from a past stage, and the development region is constrained using hopping boxes.

[9] This paper is about the distinguishing proof of frontal cortex malignant growth using an assist vector with machining based interface including GUI in Matlab. Both first and second solicitation features are associated with the recuperated components. Rule part examination is used to decrease these components to the legitimate level. The part SVM is furthermore arranged using these features [7]. From there on out, an assist vector with machining is used to arrange the data.

Ajay S. Ladkat et.al [12] Tuning of matched channel is a huge principle which is presented in this paper. This maker's paper contains how to tune and change matched channel response for really division of Hard Exudates. It moreover contains graphical tried results for different potential gains of sigma and how precision of the computation varies with it. Experimentation gives 99.62% precision of collection of exudate - non-exudate pixels and subject level accuracy is considered 93.75% in perceiving the uncommon (with exudates) and customary (without exudates) pictures independently.

A. S. Ladkat et.al [13] For taking care of an image [10], exercises should be performed on each pixel. Expecting these exercises are performed continuously it will require some venture. So to reduce the time, there is need of equivalent dealing with on all of the pixels. So that rather than dealing with each pixel exclusively, technique on all of the pixels is done look like at a time. By performing Parallel assignments speed of taking care of is extended on a very basic level when stood out from progressive one. So it will moreover help with performing video taking care of in faster manner. For equivalent dealing with NVIDIA Graphics cards used. Equivalent computation is performed on CUDA C stage.

PROBLEM STATEMENT

Brain tumors are a diverse collection of central nervous system cancers that develop within or near the brain. Furthermore, the tumor's position in the brain has a significant impact on the patient's symptoms, surgical therapeutic alternatives, and the possibility of receiving a clear diagnosis. There are certain algorithms that can extract all fine spatial features of an MRI image, such as the thresholding method, region expanding, and utilizing simply the k-means algorithm, but none of these algorithms can extract all fine spatial characteristics of an MRI image. As a result, these algorithms have a flaw in that they are unable to recognize the brain tumor in the image.

PROPOSED SYSTEM

The primary purpose of this study is to develop an efficient automatic brain tumor classification system with high accuracy, speed, and simplicity. Using Fuzzy C Means (FCM) based segmentation, texture and shape feature extraction, and SVM and DNN based classification, traditional brain tumor classification is carried out. The level of difficulty is low. However, the

computation time is long, and the precision is poor. A convolution neural network-based classification is included in the suggested system to improve accuracy and reduce computation time.

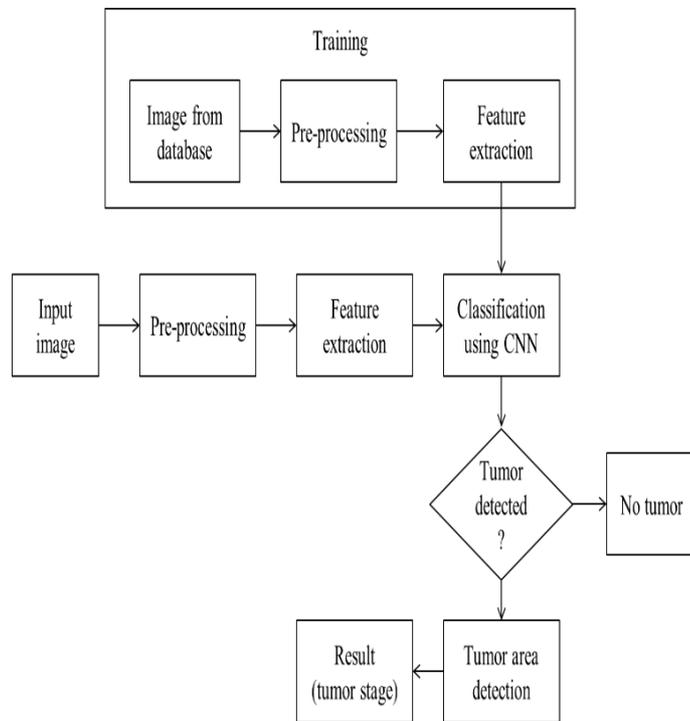


Fig 1: System Architecture

The input image is a combination of a database image (for training) and a real-time image (brain tumor detection). Both the input and output are intensity images, hence pre-processing is a frequent moniker for actions with images at the lowest level of abstraction. Pre-processing is used to improve image data by suppressing undesired distortions or enhancing certain visual qualities that are relevant for later processing. It is vital to establish a measure to compare parts of photos before addressing feature point extraction.

These measurements are used to extract and match features. Aside from the basic point feature, a more complex feature is also available. The feature extraction approach is used to extract features from a huge set of visual data while maintaining as much information as feasible. To train CNN, a dataset is provided. CNN is used to classify the data.

ALGORITHM – CNN

In our system we use CNN for detection of brain tumor. It classifies the images and gives the accurate output that detects the brain has tumor or not as well as if the brain tumor detects then which stage is suffer from this time.

Brain tumor are detected using the CNN classification algorithm. Artificial Intelligence has made considerable strides toward bridging the gap between human and computer capabilities. To reach astounding outcomes, researchers and hobbyists alike focus on a range of aspects within the subject. Computer vision is one of numerous disciplines in this category. The goal of this field is to enable machines to see and understand the world in the same way that humans do, and to apply that knowledge to tasks such as picture and video recognition, image analysis and classification, media reproduction, recommendation systems, natural language processing, and so on. Deep Learning advances in computer vision have been constructed and improved over time, largely through the usage of a single algorithm: the Convolutional Neural Network.

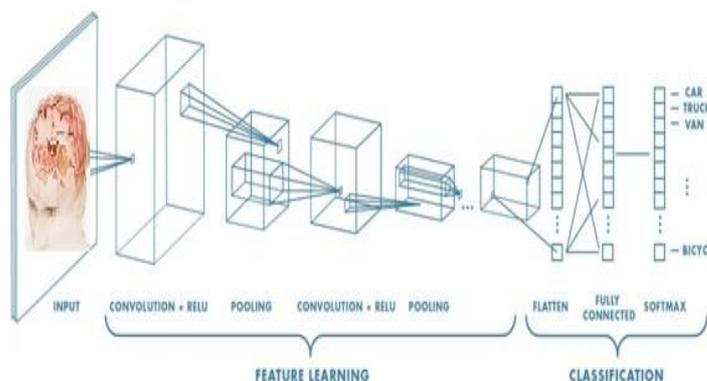


Fig 2: Architect CNN

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning framework that can take an information picture, allocate pertinence (learnable loads and inclinations) to different perspectives/objects in the picture, and recognize them.

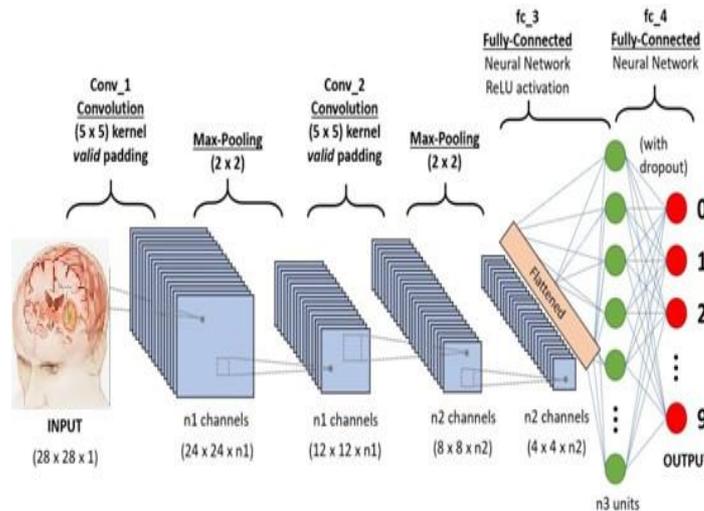


Fig 3: A CNN sequence to classify handwritten digits

The amount of pre-processing required by a ConvNet is much less than that required by other classification methods. ConvNets can learn these filters/characteristics with adequate training, whereas simple techniques require hand-engineering of filters. A ConvNet's architecture is inspired by the Visual Cortex's organization and is similar to the connectivity pattern of Neurons in the Human Brain. Individual neurons can only respond to stimuli in the Receptive Field, a tiny portion of the visual field. To span the entire visual field, a number of comparable fields can be piled on top of one another.

RESULTS AND DISCUSSION

Confusion Matrix

	Class 1	Class 2
Class 1	0281	2
Class 2	3	379

Overall Accuracy: 99.25%

Performance Parameter

Class	Accuracy	Precision	Recall	F1 Score
1	99.25%	0.99	0.99	0.99
2	99.25%	0.99	0.99	0.99

Fig 4: Confusion Matrix and Performance Parameter

The confusion matrix class 1, class 2 training modules can be seen in the diagram above. In class 1, the input photos are 0281, and we achieved accuracy of 99.25 % and precision of 0.99 % while training the classifier as a train with the supplied input database. Because the 0281 classifier failed to classify two photos as an output form of a brain tumor, recall was reduced to 0.99 %, and F1 score was also reduced to 0.99 %.

In class 2, the input photos are 379, and we achieved accuracy of 99.25 % and precision of 0.99 % while training the classifier as a train with the given input database. As a result of the 379 classifier failing to detect three photos as an output form of a brain tumor, recall has been reduced to 0.99 %, and F1 score has been reduced to 0.99 %.

We can conclude that our system's performance is better with 99.25 \% after looking at the above performance parameters.

CONCLUSION

In the field of medicine, brain tumor classification is critical. We focused on constructing a CNN classifier that can classify tumor in this research. The suggested system begins by pre-processing the image data. Filtering photographs is part of the pre-processing. The CNN model is then used to classify the photos. The classification results are also labelled as either tumor or normal brain images. CNN is a deep learning approach that consists of a series of feed forward layers. The python programming language is also employed in the implementation. We can conclude that the accuracy of our system is 99.25%. Our system is better accuracy as well as time consuming process than the existing system.

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