Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Identifying Brain Tumor Using X-Ray Images with Deep Learning

Dr.M.Veeresha[1]M.tech,Ph.D, Mrs.N.Rama Devi[2]M.tech,(Ph.D), Annareddy William Carey Reddy[3] ,Lakkaboyina Telugu Manjunadha[4], Sreenivasula Reddy Undela[5] , Shaik Farvez Hussain[6] ,Gajula Venkata Mahesh[7]

[1]Professor, Department of Computer Science and Engineering and Nandyal
[2]Assosiate Professor,Department of Computer Science and Engineering and Nandyal
[3,4,5,6,7]Department of Computer Science and Engineering, Santhiram Engineering College,Nandyal
E-mail: ramadevi.cse@srecnandyal.edu.in

Abstract:

Tumor of the Brain begins in the Brain and quickly metastasizes to other parts of the body. Brain X-ray or MRI analysis is the first step in making a rapid and preliminary diagnosis of a Braintumor. In comparison to magnetic resonance imaging (MRI), an X-ray picture is a more cost-effective diagnostic technique for detecting and visualizing Braintumors. This research proposes a unique method for evaluating the extent of tumors in the Brains using X-ray imaging analysis. Images of Brains damaged by tumors often show a change in the microstructure of the Brain in the area of the disease. For this evaluation, we combine many approaches. To differentiate between normal and defectiveBrains, the suggested method uses feature extraction and a support vector machine (SVM). A method using digital geometry is used to pinpoint areas where the tumor has taken hold. A decision tree classifier may be used to characterize the current stage and grade of the illness, as well as the underlying pattern of Brain degradation. On top of all that, the procedure creates a computer-aided diagnostic tool that physicians and EMTs can utilize with ease. When comparing experimental results on several test cases with the truth as determined by clinical findings, the implications drawn from the experiment are encouraging.

I.INTRODUCTION

Evaluation of X-ray images is one of the most cost-effective first-line screening methods for detecting Braintumors. According to published reports in the medical literature, the first signs of a primary Braintumor are often misdiagnosed as something else, such as a Brain fracture, swelling around a Brain, a new Brain growth, or swelling in the soft tissues around a Brain. Braindamage by the tumor may often seem different on an X-ray than the healthy Brain and tissue around it. Brain cells in a tumor-affected area absorb X-rays at a different rate than Brain cells in a tumor-free area. Therefore, Brains that have been impacted by tumors seem to have a "ragged" surface (primitiveBrain degradation), a tumor (geographic Brain destruction), or holes (a moth-eaten pattern of Brain deterioration). Treatment of Braintumors requires accurate grading[1] of the illness and the determination of the underlying pattern of Brain deterioration. Braintumors' stage and grade are indicators of the disease's seriousness. Determining how quickly a tumor is spreading or how well a treatment plan is likely to work requires an accurate assessment of the pattern of destruction in a Brain that has been damaged by the illness. Medical professionals will benefit from the computerized categorization of Brain-tumor stage[1], grade[2], and destruction pattern to plot out a treatment strategy. Researchers have suggested many methods for detecting Braintumors[11] in recent years. For the identification of the tumor area in X-ray and MRI1 images, traditional image processing methods have been applied. These methods include thresholding, region growth, classifiers, and the Markov random field model. Brain-tumor segmentation using multi-scale analysis of MRI perfusion images has been performed by Frangi et al.. To differentiate between viable and non-viable tumors, they presented a two-stage cascaded classifier for the hierarchical categorization of healthy and malignant tissues. Ping et al. have suggested a method for the identification and categorization of Braintumors from clinical X-ray pictures that make use of intensity analysis and graph description. To pinpoint the likely tumor region, the approach examines a graph representation. It may also categorize benign and malignant tumors based on the number of pixels culled from the study of brightness values. In addition, CT scans of Brains have been frequently utilized to spot breaks and diagnose diseases. It is suggested that malignant areas in a Brain scan may be located by fusing data from CT2 and SPECT3. The identification of lytic Brain metastases may now be done automatically thanks to the work of Yao et al.. For the segmentation of the spine area, the method makes use of adaptive thresholding, morphology, and regional growth. For the identification of lytic Brain lesions, we use a watershed-based method; for feature classification and diagnosis, we employ a support vector machine (SVM) classifier[8][17]. Huang et al. presented an automated method for detecting secondary Braintumors using a computed tomography (CT) scan of the vertebrae. In their methodology, texture-based classifiers and an ANN are employed to spot anomalies. Furthermore, a variational model and a fuzzy-possibility classification[6][20] are used for multimodal Braintumor diagnosis using CT and MRI data. Many studies have employed CT or MRI to locate tumors or tumorous areas in the Brains. Currently, there is no recognized automated approach for identifying the pattern of destruction produced by a Braintumor and classifying the disease at its various stages and grades. In this study, we present a computer-assisted diagnostic approach that uses artificial intelligence to automatically analyze X-rays of Brains and locate the tumorous tissue. You may use our approach to pinpoint the damage pattern and evaluate the disease's severity according to its stage and grade. The remaining parts of the paper are structured as follows. Methods detail the steps of the proposed procedure and the characteristics used in the diagnosis of Braintumors. In "Localization of Tumor-Affected Region," the method for pinpointing the area hit by the tumor is laid forth. Methods for staging and grading tumors are laid forth in "Tumor Severity Analysis." The performance of the suggested approach[29] is evaluated and the results of the test cases are provided in "Identification of Brain-Destruction Pattern." The sections under "Results" and "Discussion" provide analyses of the tests and final thoughts, respectively.

II.RELATED WORK

"Brain damage detection in digital X-ray images based on digital-geometric[13] techniques."

Computer-assisted telemedicine systems rely heavily on automated fracture identification. In this study, we present a unified method for analyzing digital X-ray images of Brains to identify and grade orthopedic fractures. Moreover, we have created a software application that is easy for EMTs and specialists to use. The suggested method first separates the Brain area from the surrounding flesh region in an input digital X-ray picture and then uses an adaptive thresholding technique to construct the Brain-contour. Afterward, it carries out unsupervised rectification of Brain-contour discontinuities that may have been produced as a result of segmentation mistakes, and lastly, it can identify the existence of fracture in the Brain. The approach can pinpoint the fracture's line of break, determine the fracture's orientation, and evaluate the Brain damage. Correction of contour flaws and detection of fracture sites and types make use of many ideas from digital geometry, such as relaxed straightness and concavity index. Experimental findings using a database of digitized X-ray pictures of Brains are encouraging.

"Automatic segmentation of Brains in X-ray images based on entropy measure."

In this study, we provide a practical technique for extracting the skeletal structure from an X-ray picture while preserving the surrounding soft tissues. Because of its low contrast with the surrounding tissue, automated segmentation of the Brain portion in a digital X-ray[3][4] picture is a difficult task. Further complicating the segmentation is the existence of noise and false edges. Existing approaches often either have trouble detecting contours in the absence of noise or need training samples and human adjustment of threshold values. Using a variation of the entropy measure of the picture, we offer a completely automated segmentation approach[12]. The system is effective for the rapid and efficient processing of a large variety of human X-ray pictures, including those of the skull, chest, pelvic region, and ortho-dental zones. To measure segmentation accuracy, we propose a novel metric based on the local characteristics of the contour pixels, which we refer to as the average contour distortion index (ACDI). Experimental findings on several X-ray pictures show promising outcomes compared to previous methods, as measured by the ACDI metric. We also redo a quality check on numerous segmented Brain images using segmentation entropy[25] quantitative assessment (SEQA) and a precision-recall profile based on boundary conditions. All three indicators show that the suggested method outperforms existing alternatives.

III.METHODOLOGY

The mechanism of a brain tumor may be better understood after its detection and classification. Magnetic Resonance Imaging (MRI) is a novel kind of diagnostic imaging that aids the radiologist[7]suppor in locating the tumor. Manually testing the MRI pictures, however, takes time and skill. With the development of CAD, machine learning[15], and deep learning in particular, radiologists can now more accurately detect brain tumors. Conventional machine-learning approaches to this issue need a manually generated feature for categorization. In contrast, deep learning approaches may be tailored such that correct categorization is achieved without the need for human intervention in the form of feature extraction. In this study, we present two deep-learning models for differentiating between normal and malignant brain tumors, as well as between meningioma, glioma, and the pituitary gland. We employ two open-source collections, totaling 3064 and 152 MRI pictures, respectively. Since there are so many MRI pictures to use for training, we begin by applying a 23-layers convolution neural network (CNN) to our initial dataset. However, our suggested "23-layer CNN" design runs into an overfitting issue when working with little amounts of data, as is the case in the second dataset. To solve this problem, we use transfer learning and combine the VGG16 architecture[5] with the reflection of our suggested "23 layers CNN" design. In the end, we contrast the results of our suggested models with those found in the published literature. Our experimental findings show that our models outperform the state-of-the-art by a wide margin, with accuracy levels of up to 97.8% and 100%, respectively, on the datasets we used.

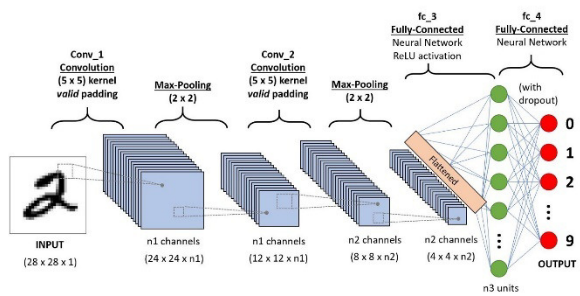

Fig 1 : Neural networks

IV. IMPLEMENTATION

The algorithm used in our project is :

- CNN algorithm

CNN is a deep-learning algorithm that can analyze the image[3]. CNN is very useful as it minimizes human effort by automatically detecting the features. For example, for apples and mangoes, it would automatically detect the distinct features of each class on its own.

CNNs are a class of Deep Neural Networks[12] that can recognize and classify particular features from images and are widely used for analyzing visual images. Their applications range from image and video recognition[10], image classification, medical image analysis[23], computer vision, and natural language processing.The term 'Convolution" in CNN denotes the mathematical function of convolution which is a special kind of linear operation wherein two functions are multiplied to produce a third function which expresses how the shape of one function is modified by the other. In simple terms, two images that can be represented as matrices are multiplied to give an output that is used to extract features from the image.

V. RESULT AND DISCUSSION

In this project, we are implementing deep learning Convolution Neural Network (CNN) to predict Braintumors, and to train this algorithm we have used Brain images with and without tumors.

By uploading individual images we can predict whether the image is having a tumor or not.

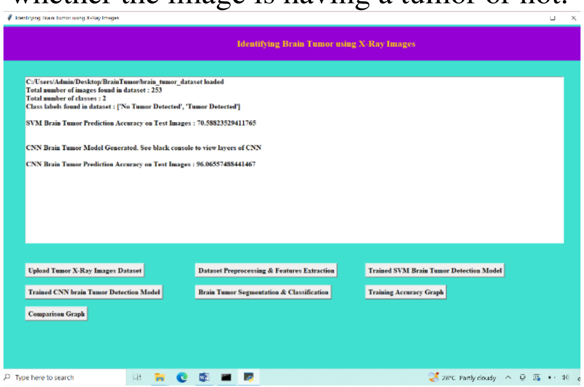

Fig 2 : CNN accuracy percent

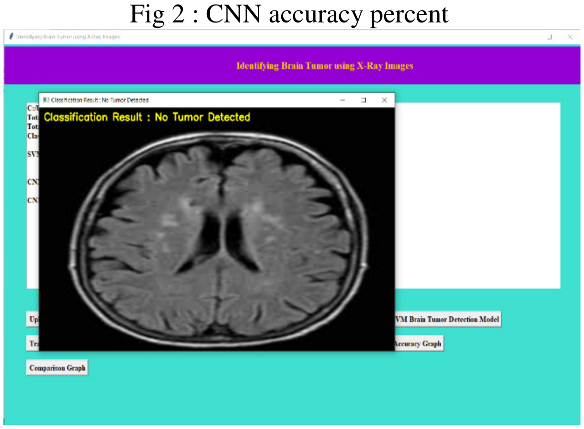

Fig 3 : classification result

The above image is one of example predicting the tumor.

VI. CONCLUSION

We provide the first method for automated - Braintumor detection based purely on the processing of an input X-ray picture in this study. The suggested technique incorporates several diverse ideas, including a statistical runs-test[14][19], digital-geometric analysis, SVM classification, and a decision tree[9]. For straightforward analysis and diagnosis, as well as for categorizing the degree of damage done by the tumor, the concept of the ortho-convex cover of a cluster of indicated pixels is applied. Utilizing digital-geometrical tools allows for a quick calculation of ROI area since the computation requires just integer-domain operations. The suggested technique is fairly accurate, as shown by an AUC for Braintumor identification of more than 0.85 in experimental findings on a medical database of healthy and tumor-affected X-ray pictures[26]. In addition, the automated technology accurately predicts the pattern of Brain degradation, tumor stage, and tumor grade in 85% of instances as determined by physicians and medical specialists.

There are two main parts to a CNN architecture

- A convolution tool that separates and identifies the various features of the image for analysis in a process called Feature Extraction.
- The network of feature extraction consists of many pairs of convolutional or pooling layers.
- A fully connected layer that utilizes the output from the convolution process and predicts the class of the image based on the features extracted in previous stages.
- This CNN model of feature extraction aims to reduce the number of features present in a dataset. It creates new features which summarise the existing features contained in an original set of features. There are many CNN layers as shown in the CNN architecture diagram.

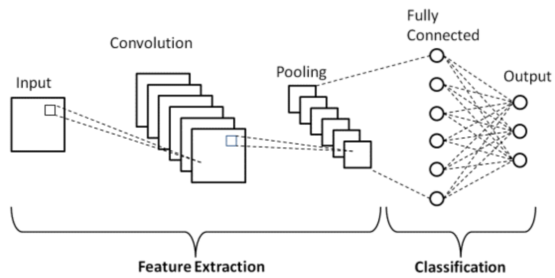

Fig 4: CNN architecture diagram

REFERENCES

[1] American Joint Committee on Tumor (AJCC) AJCC tumor staging manual vol 17(6). Springer-Verlag (2010)

[2] Alelyani S, Tang J, Liu H: Feature selection for clustering: a review. In: Data clustering: Algorithms and applications, vol 29, pp 110–121. CRC Press, 2013

[3] Bandyopadhyay O, Biswas A, Bhattacharya BB: - Brain fracture detection in digital X-ray images based on digital-geometric techniques. Comput Methods Programs Biomed 123:2–14, 2016 [PubMed]

[4] Bandyopadhyay O, Chanda B, Bhattacharya BB: Automatic segmentation of Brains in X-ray images based on entropy measure. Int J Image Graph 16(1):1650,001–32, 2016

[5] Bennett JR, Donald JSM: On the measurement of curvature in a quantized environment. IEEE Trans Comput 24(8):803–820, 1975

[6] Bourouis S, Chennoufi I, Hamrouni K: Multimodal Braintumor detection using fuzzy classification and variational model. In: Proceedings, IAPR, vol LNCS 8258, pp 174–181, 2013

[7] Brant WE, Helms CA. *Fundamentals of diagnostic radiology*. Philadelphia: Wolters Kluwer; 2007. [Google Scholar]

[8] Burges CJC: A tutorial on support vector machines for pattern recognition. Data Min Knowl Disc 2:121–167, 1998

[9] Criminisiand A, Shotton J. *Decision forests for computer vision and medical image analysis*. London: Springer; 2013. [Google Scholar]

[10] Dillencourt MB, Samet H: A general approach to connected component labeling for arbitrary image representations. J ACM 39:253–280, 1992

[11] Ehara S: MR Imaging in the staging of Brain tumors. J Tumor Imaging 6:158–162, 2006 [PMC free article] [PubMed]

[12] Frangi A, Egmont-Petersen M, Niessen W, Reiber J, Viergever M: Segmentation of Brain tumor in MR perfusion images using neural networks and multiscale pharmacokinetic features. Image Vis Comput 19:679–690, 2001

[13] Freeman H: On the encoding of arbitrary geometric configurations. IRE Trans Electron Comput 10:260–268, 1961

[14] Hastie T, Tibshirani R, Friedman J. *The elements of statistical learning*. London: Springer; 2009. [Google Scholar]

[15] Heidl W, Thumfart S, Lughofer E, Eitzinger C, Klement EP: Machine learning based analysis of gender differences in visual inspection decision making. Inf Sci 224:62–76, 2013

[16] Comparative analysis of 3D-SVM and 4D-SVM for five-phase voltage source inverter
Ramasamy, P., Balasubramanian, K., Mahammad, F.S.
International Transactions on Electrical Energy Systems, 2021, 31(12), e13138

[17] Hsu C, Chang C, Lin C (2003) Practical guide to support vector classification. http://www.csie.ntu.edu.tw/cjlin/papers.html

[18] Huang S, Chiang K: Automatic detection of Brain metastasis in vertebrae by using CT images. In: Proceedings, world congress on Engineering, vol 2, pp 1166–1171, 2012

[19] Tammineni Sreelatha, MV Subramanyam, MN Giri Prasad: Shape and color feature-based melanoma diagnosis using dermoscopic images, 2021/5

[20] Maulik U, Chakraborty D: Fuzzy preference-based feature selection and semisupervised SVM for tumor classification. IEEE Trans NanoBiosciences 13(2):152–160, 2014 [PubMed]

[21] Nandy SC, Mukhopadhyay K, Bhattacharya BB: Recognition of largest empty ortho convex polygon in a point set. Inf Process Lett 110(17):746–752, 2010

[22] Nisthula P, Yadhu RB: A novel method to detect Braintumor using image fusion and edge detection. Int J Eng Comput Sci 2(6):2012–2018, 2013

[23] Ping YY, Yin CW, Kok LP: Computer-aidedBrain tumor detection and classification using X-ray images. In: Proceedings, the international federation for Medical and biological engineering, pp 544–557, 2008

[24] Popovic A, Fuente MDL, Engelhardt M, Radermacher K: Statistical validation metric for accuracy assessment in medical image segmentation. International Journal of

[25]T Sreelatha, MV Subramanyam, MNG Prasad Journal of medical systems 43 (7), 190: Early detection of skin cancer using melanoma segmentation technique,2019/7

[26]R Sumalatha, MV Subramanyam International Journal of Scientific & Engineering Research 2 (9), 1-4: Medical image compression using multiwavelets for telemedicine applications,2011/9

[27] R Sumalatha, MV Subramanyam International Conference on Electrical, Electronics, Signals, Communication and Optimization (EESCO),2015

[28] Leven RI, Rubin DS, Rastogi S, Siddiqui MS. *Statistics for management.* India: Pearson; 2012. [Google Scholar]

[29] Performance analysis of data compression algorithms for heterogeneous architecture through parallel approach
Mahammad, F.S., Viswanatham, V.M.
Journal of Supercomputingthis link is disabled, 2020, 76(4), pp. 2275–2288

[30]Heymann D. *Brain tumor.* Cambridge: Academic Press; 2015. [Google Scholar]

[31] Advanced implementation patterns of internet of things with MQTT providers in the cutting edge communication. R.Balaji, A.V.R. Mayuri, N.Ramadevi, R.Anirudh Reddy. 2020,ISSN number – 2214-7853Materials Today : Proceedings

[32] Advertisement Conversion Predition in instagram Employing Ensemble Machine Learning. M.Veeresha, Journal of algebraic satistics,2022,ISSN number - 1309-3452

