IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⪤ Impact Factor 7.918 ⪤ Vol. 12, Issue 2, February 2023

DOI: 10.17148/IJARCCE.2023.12251

LITERATURE SURVEY OF WORKS ON DETECTION OF CANCER CELLS IN BRAIN TUMOUR USING DEEP LEARNING AND CNN

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Abstract: Brain tumours are mostly produced by aberrant brain cell development, which can harm the brain's structure and eventually progress to dangerous brain cancer. The proper detection of various disorders in the gorgeous MRI pictures is one of the primary obstacles in providing an early opinion to allow decisive therapy utilising a computer-backed opinion (CAD) system. In this study, a novel Deep Convolutional Neural Network (DCNN) framework for accurate diagnosis of glioma, meningioma, and pituitary tumours is suggested together with a three-step preprocessing methodto improve the quality of MRI images. For quicktraining with a high literacy rate and simple initialization of the sub caste weights, the armature employs batch normalisation. The suggested armature is a lightweight computational model with a few convolutional, maximum-- pooling layers and training duplications.

Keywords: Brain tumors, deep convolutional neural network, image processing, MRI images.

I. INTRODUCTION

The majority of human behaviours, including memory, speech, thought, and leg and arm motions, are controlled by the brain, making it the mostsignificant organ in the body [1]. The primary cause of brain cancer and other brain diseases is the brain cells. Brain anatomy is directly harmed by abnormal growth.[2].Globally,The World Health Organization (WHO)[3] predicts that 9.6 million people died of cancer in 2018. There is a significant mortality rate from brain cancer.A prompt and accurate diagnosis isalso necessary due to the complicated anatomy of thebrain.The MRI pictures provide for a more pronounced contrast and spatial definition[4]. In order to detect any discrepancies in the MRI images,the technique of detecting brain abnormalities is crucial.

Since 2012, deep convolutional neural networks (DCNNs) have seen considerable use by academics, who have had great success categorising pictures using them[6]. Recently, DCNNs classifiedmedical pictures successfully as well[7]–[11]. As a first step, a recommended three-step pre-processing approach The pre-processing technique improves the MRI images' quality and broadens their histogram, enhancing their contrast. At the pre-processing stage, a Blind Referenceless Image Spatial Quality Evaluator (BRISQUE) is utilised to evaluate the finalimage's quality. A diagnostic model that uses DCNN to separate meningioma, pituitary, or glioma from normal MRI images. It uses batch normalisation,accelerates model training, boosts learning rate, andmakes initialising layer weights straightforward. The suggested architecture is compared to well-known systems such and more modern ones in an analytically rigorous comparison of meningioma, glioma and pituitary detection approaches like CNN-SVM.

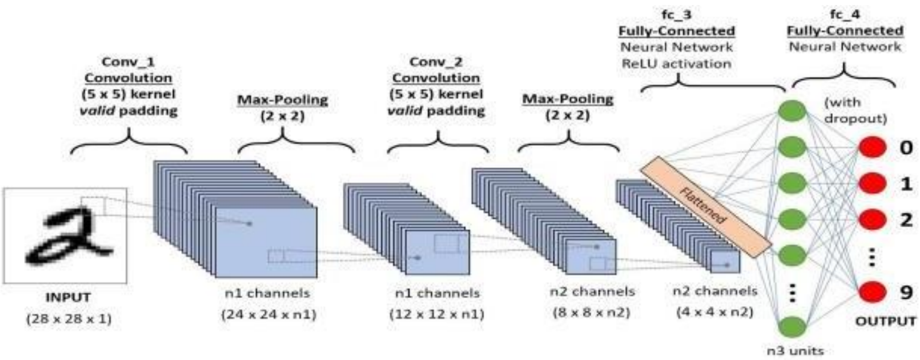

Figure 1: CNN Layers

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II. LITERATURE REVIEW

Recently, a range of imaging modalities, notably those gathered using MRI, have been utilised to identify and assess brain cancers using machine learning (ML) and deep learning (DL) algorithms. This section presents recent research on the subject as well as studies that are pertinent to the paper's theme. Mohsen, Heba, et al.[8] introduced a system that combines Deep Learning (DL) techniques with Discrete Wavelet Transform (DWT) characteristics.The brain tumor was segmented using the fuzzy c-mean approach, and the DWT was used to extract the features for each lesion that was found.In order to reduce the feature dimension, the featureswere then sent to the PCA before being transmitted to deep neural networks (DNN).

They may achieve 97.0% accuracy and 96.97% sensitivity, according to the data. Convolutional neural networks (CNN) and features based on the Gray Level Co-occurrence Matrix were used to create a brain tumour classification system by Widhiarso, Wijang, Yohannes Yohannes, and Cendy Prakarsah [10]. (GLCM). Using two sets of features—contrast with homogeneity and contrastwith correlation—the Gl-Pt dataset yielded the greatest accuracy, 82.27%. They tested their techniques on 4 different datasets (Mg-Gl, Mg-Pt, Gl-Pt, and Mg-Gl-Pt), and the outcomes were encouraging.

Seetha, J., and S. S. Raja [12] suggested a deep CNN based method for automatically identifying and evaluating brain tumours. Fuzzy C-means is used by the algorithm to segment the brain (FCM). Texture and shape data were gathered from these divided regions and supplied into SVM and DNN classifiersas features. The results showed that the approach hada 97.5% accuracy rate. The efficacy of the brain tumour classification process was increased by Cheng, Jun, et al. [13] by using fine ring-form partition and region of interest (ROI) augmentation. These enhancements were applied to the bag-of- words (BoW), the GLCM, and other feature extraction methods.

These feature vectors are then supplied to a classifier. According to the experimental findings, the GLCM, intensity histogram, and BoW accuracy increased from 83.54% to 87.54%, 71.39% to 78.18%, and 89.72% to 91.28%, respectively. M.

Sasikala and N. Kumaravel suggested using a genetic algorithm feature selection approach to reduce the dimension of wavelet features. The technique relies on choosing the optimum feature vector that may be used to feed the chosen classifier, such as an artificial neural network (ANN). The results show that only 4 out of a total of 29 features were selected by the genetic algorithm and that using only those features, it was able to achieve a 98% accuracy rate. Khawaldeh, Saed, et al. developed a technique using a modified version of AlexNet CNN for non-invasively classifying glioma brain tumours.

III. METHODOLOGIES

A.THE PRE-PROCESSING APPROACHPROPOSED

The secret to correctly identifying the brain tumour detection problem for MRI pictures is finding the appropriate pattern. MRI image classification models confront a number of issues that could cause mislearning and poor classification accuracy ratings. As an outcome, we put forward a three-stage pre- processing approach.

1) EXCLUSION OF THE COMPLICATEDOBJECTS

Conflicting elements such as text and dark regions onthe right and left of the image have been removed by deleting 100 pixels from each side of the image to disclose the specific brain item in figure1.

2) ANALYSIS OF MRI IMAGES

The non-local mean algorithm (NLM) effectively handles noisy MRI images [12]. Unwanted patterns are learned as a result of the noise in these photographs, decreasing the classification accuracy. According to the Blind Reference less Image Spatial Evaluator (BRISQUE) [15], the NLM perspective substantially enhances the quality of MRI images when compared to the Gaussian [13] and Median [14]algorithms.

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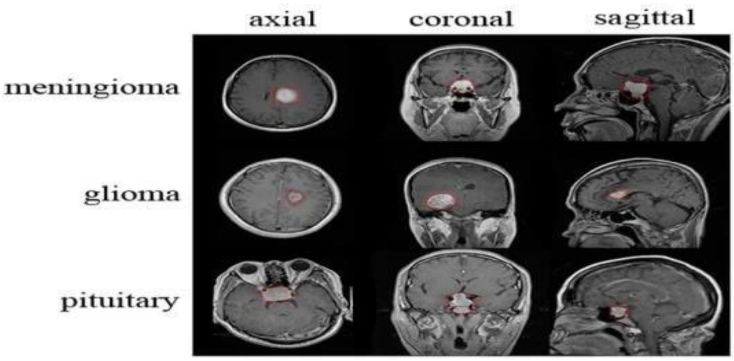

Figure 2. Portraying various tumour kinds in variousplanes using normalised magnetic resonanceimaging (MRI) scans.

1) HISTOGRAM EQUALISATION

In the MRI scans, histogram equalisation greatly enhances contrast [32]. Besides that, it makes it easier to see fine details by lowering contrast where it is necessary. This process is carried out by conducting a split to the most common intensity levels. Also, it getsrid of the interference that the most common Brain mripatterns produce.

B. DATASET

The Navoneel brain tumour dataset [17] and theSartaj brain MRI imaging dataset [16] were the sources of the datasets used in the tests and investigations. Two different MRI types are included in the dataset [18]. T1- and T2- weighted images. T1-weighted images are created with short time to echo(TE) and repetition time (RT) restrictions of 14 and 500 milliseconds, respectively. T2- weighted images are created with increased TE and RT limitations of 90 and 4000 milliseconds, respectively. The dataset was split into 3 files using subfolders for each class (GLIOMA, MENINGIOMA, NO-TUMOR, and PITUITARY) (Training, Testing, and Validating). Overall, 3394 MRI scans were done, with the categories GLIOMA (934), MENINGIOMA (945), NO-TUMOR (606), and PITUITARY being the mostconvenient (909).

C. PROCESSING STRATEGY

We can state that our model is problem-based because we applied a brand-new training method.To generate a considerable number of MRI images for the training procedure, an image data generator [33] was applied..The models only picked up on the desirable qualities because the data generated during the generation phase came from the same domain as the dataset thatwas used. The training technique has 60 epochs, a batch size of 16 and 385 stepper epochs. When using a batch size of 16, 16 samples are delivered to the trained model at once until the training data for a single epoch has been supplied to completion.

D.THE APPROPRIATE MODEL

A Deep Convolutional Neural Network (DCNN) model is outlined in this research. Reduced clustering [43], slow learning rates, and an inadequate training accuracy due to batch normalisation operation are justa few of the initiatives taken by the proposed model.Aconvolutional component and a classifier componentmake up the suggested model. The convolutional part consists of 5 batch normalisation layers, 10 convolutional layers, and 4 max-pooling layers. The classifier component consists of 2 dropout layers and 3 dense layers.

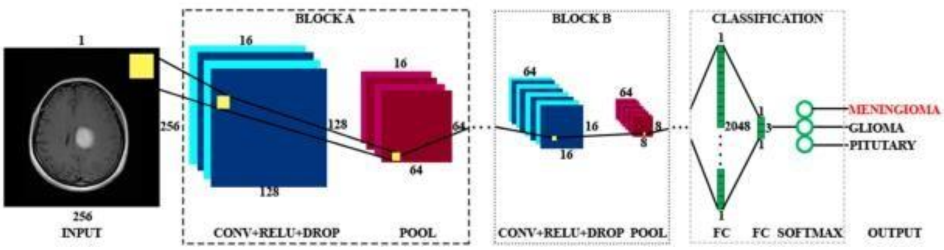

Figure 3. The input layer of a convolutional neural network (CNN) is depicted crudely in this image.

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IV. CONCLUSION

It is advised to use a deep convolution neural network design to quickly achieve high classification accuracy for the diagnosis of gliomas, meningiomas, and pituitary brain diseases. First, a relevant brain tumour dataset for rapid training and testing. Second, a three-step pre-processing technique is utilized to eliminate the ambiguous regions, denoise the MRI images, and improve their contrast. This scheme had a beneficial and substantial impact on all of the models studied.Lastly, as part of a training mode, we teach our model the desired patterns from start. Finally, we used our model to easily and accurately analyze the Pixels based on their properties.We put the proposed model to the test using 396 MRI images from the dataset. The proposed model had an overall accuracy of 97.72%, 98.26% meningioma detection accuracy, 99% glioma detection accuracy, 95.95% pituitary detection accuracy, and 97.14% normal image detection accuracy.In practice, the proposed framework can serve as an automated computer- aided detection tool for robustly and briskly spottingbrain abnormalities in MRI data.

REFERENCES

[1] N. B. Bahadure, A. K. Ray, and H. P. Thethi, ''Image analysis for MRI based brain tumor detection and Feature extraction using biologically inspired BWT and SVM,'' Int. J. Biomed. Imag., vol. 2017, pp. 1–12, Mar. 2017, doi: 10.1155/2017/9749108.

[2] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, ''Brain tumor segmentation using convolutional neural networks in MRI images,'' IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1240–1251, May 2016, doi: 10.1109/TMI.2016.2538465.

[3] World Health Organization. Accessed: Jun. 10, 2021. [Online]. Available: https://www.who.int [4] E. El-Dahshan, H. Mohsen, K. Revett, and A. Salem, ''Computer- aided diagnosis of human brain tumor through MRI: A survey and a new algorithm,'' Expert Syst. Appl., vol. 41, no. 11, pp. 5526–5545, 2014, doi: 10.1016/j.eswa.2014.01.021.

[5] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei, ''ImageNet large scale visual recognition challenge,'' Int. J. Comput. Vis., vol. 115, no. 3, pp. 211–252, Dec. 2015, doi: 10.1007/s11263- 015-0816-y.

[6] W. Liu, Z. Wang, X. Liu, N. Zeng, Y. Liu, and F. E. Alsaadi, ''A survey of deep neural network architectures and their applications,'' Neurocomputing, vol. 234, pp. 11–26, Apr. 2017, doi: 10.1016/j.neucom.2016.12.038.

[7] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. W. M. van der Laak, B. van Ginneken, and C. I. Sánchez, ''A survey on deep learning in medical image analysis,'' Med. Image Anal., vol. 42, pp. 60– 88, Dec. 2017, doi: 10.1016/j.media.2017.07.005.

[8] P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, T. Duan, D. Ding, A. Bagul, C.Langlotz, K. Shpanskaya, M. P. Lungren, and A. Y. Ng, ''CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning,'' 2017, arXiv:1711.05225.

[9] D. Shen, G. Wu, and H.-I. Suk, ''Deep learning in medical image analysis,'' Annu. Rev. Biomed. Eng., vol. 19, pp. 221–248, Jun. 2017, doi: 10.1146/annurev-bioeng-071516-044442.

[10] J. H. Chen and S. M. Asch, ''Machine learning and prediction in medicine—Beyond the peak of inflated expectations,'' New England J. Med., vol. 376, no. 26, pp. 2507–2509, Jun. 2017, doi: 10.1056/NEJMp1702071.

[11] G. Deng and L. W. Cahill, ''An adaptive Gaussian filter for noise reduction and edge detection,'' in Proc. IEEE Conf. Rec. Nucl. Sci. Symp. Med. Imag. Conf., vol. 3, Nov. 1993, pp. 1615–1619,doi: 10.1109/NSSMIC.1993.373563.

[12] Pitas and A. N. Venetsanopoulos, ''Median filters,'' in Nonlinear Digital Filters: Principles and Applications. Boston, MA, USA: Springer, 1990, pp. 63–116, doi: 10.1007/978-1-4757-6017-0_4.

[13] A. Mittal, A. K. Moorthy, and A. C. Bovik, ''No reference image quality assessment in the spatial domain,'' IEEE Trans. Image Process., vol. 21, no. 12, pp. 4695–4708, Dec. 2012, doi: 10.1109/TIP.2012.2214050.

[14] Sartaj. Brain Tumor Classification (MRI) Dataset. Accessed: Jun. 10, 2021. [Online].Available:https://www.kaggle.com/ sartajbhuvaji/brain-tumor-classification-mri.