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MRI-BASED BRAIN TUMOR IMAGE CLASSIFICATION USING DEEP LEARNING

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ABSTRACT

Modernly speaking, reviewing large numbers of Magnetic Resonance Imaging (MRI) images and manually discovering a brain tumor by a person is a slow and inaccurate process. It may have effects on the correct medical treatment of the patient. Additionally, it could be a slow and laborious task due to the numerous amounts of image datasets involved. Because brain tumors appear similarly to healthy tissue, tumor region segmentation can be difficult. Therefore, there is a need for a high-quality automatic tumor detection system. CNNs are one type of deep learning technique which are often used for image recognition and image classification tasks currently. CNNs are also commonly used to identify Brain Tumors. In our research, we proposed a CNN model for the purpose of classifying images from MRI scans of brains into two classes (Normal or Tumor). Our proposed model was able to achieve a recall of 97.51%, accuracy of 97.889%, F1-score of 97.84%, precision of 98.18%, specificity of 97.62% and an AUC of 97.57%. Our CNN model will help doctors to find brain tumors in MRI images with great efficiency , therefore, greatly increasing the amount of time saved when treating patients.

KEYWORDS

Deep learning (DL), Image Classification, Convolutional Neural Networks (CNNs), Magnetic Resonance Imaging (MRI), Brain Tumors, Tumors.

1. INTRODUCTION

Tumors, also called neoplasms, are the result of aberrant cells proliferating out of control (Swamy, 2020). These aberrant tissue masses are located either inside the brain or in the central spinal canal (D. and H. S., 2020). In contrast to normal cells, which follow their own natural regulatory systems, malignant tumors grow and spread in a rapid and uncontrollable manner. The brain, enclosed in the inflexible skull, is constrained as the tumor grows rapidly within this small area, eventually impairing the brain's natural processes. The development of cancerous tumors from the appearance of malignant cells in the brain can be attributed to various circumstances, including hereditary abnormalities and extended exposure to inorganic pollutants. Brain tumors can be classified as malignant or benign (noncancerous) (Swamy, 2020).

Deep learning is an area where data can be interpreted, learned and understood hierarchically by a computer. The use of an Aartificial neural networks, one of the types of deep learning, as a means to represent the brain's architecture and its function has become popular. (Mohammed, Kareem and Mohammed, 2022). In computer vision, the goal of image classification involves the training of a model to recognize and classify objects in images (Mohamed, Elsamahy and Salem, 2022). CNNs are frequently utilized for images categorization in the setting of brain malignancies (Sahoo, Mishra and Mohanty, 2022). Convolutional Neural Networks are a special form of neural networks designed for handling and processing images. They employ convolutional layers to identify local features in images that can be used to recognize object patterns within an image. The goal of this particular application would be to train the CNN model using a large amount of medical photograph data of the brain so as to discover various types of tumors (Surrisyad and Wahyono, 2020).

CNNs originated back in the 1980s as a Multilayer Perceptron (MLP), but it was a model after how a human brain works. Human brains allow us to see and know what we're seeing by the way things look. Children learn what an item looks like by viewing the same object numerous times (thousands). It allows them to be able to predict an item they've never seen before. The CNN can do this too (Dhankhar et al., 2021).

This paper collectively highlights the significance of CNNs in brain tumor classification, the benefits of data pre-processing, and the implementation of dropout layers to prevent over-fitting, and the importance of thorough performance evaluation using metrics such as confusion matrices and visualizations. The provided code leverages these established methods to build an effective model for brain tumor detection, underscoring its relevance and alignment with contemporary research in this field. our research is organized as follows: a thorough study of the literature, a methodology, an evaluation metrics, an experimental result and a conclusion.

2. RELATED WORK

There are multiple research trends concerning the topic of MRI-based brain tumor image Classification Using Deep Learning, some of these related studies will be explained as follows. The authors of (Chattopadhyay and Maitra, 2022) showed a way to develop hybrid methods that combine CNN with traditional classifiers and deep learning models to separate tumors from the rest of the brain using MRI scans. To test this method they used the SVM algorithm with some others like Softmax, RMSProp and Sigmoid. The authors also made sure to provide many images with different sizes, locations, shape, density etc. to make the model trained well on those images. The system achieved an accuracy rate of 99.74%.

In reference (Khan et al., 2022) The research used two deep neural networks (deep learning) for classification of brain tumors into binary (normal , abnormal) and multi-categories (gliomas, meningiomas and pituitaries). The researches also used two datasets; the Harvard medical dataset and the figshare dataset, which included 3064 and 152 MRIs, respectively. Due to overfitting associated with the limited size of each dataset, the authors initially applied a 23-layer CNN to the first data set. The authors found that the same model had an overfitting problem using the second data set. To solve this challenge, the authors integrated the VGG-16 model with their 23-layer CNN structure, utilizing transfer learning. This hybrid approach significantly improved classification accuracy to 97.8% for dataset 1 and 100% for dataset 2.

The work in (Rahman and Islam, 2023) proposed a parallel deep CNN topology with two parallel stages used to extract features (local, global), using batch normalization and dropout regularize to solve the over-fitting problem. The images are transformed into grayscale in order to minimize the complexity, after which the number of datasets are maximized using data augmentation. Three types of datasets (binary tumor identification, Figshare, Multiclass Kaggle) are used to define the efficiency of the created system. The accuracy of the datasets reached 97.33%, 97.60%, and 98.12%, respectively.

In (Neuroscience, 2023) the researchers proposed CNN-models with (VGG19, InceptionV3, and MobileNetV2) to discover brain tumors from x-ray images. To evaluate the performance of their research, the classification accuracy is used, yielding results for InceptionV3 (91%), VGG19 (88%), and MobileNetV2 (92%).

In (Mahjoubi et al., 2023) the research recommended a CNN model for detecting four classes of brain tumour images (Normal, Pituitary, Meningioma and Glioma). Accuracy (95.44%), f1-score (95.36%) and recall (95 %) have been considered for evaluating the proposed model. The study in (R et al., 2024) analysed the performance of ResNet-177 and Inception-v3 for the prediction of brain tumours. A dataset of 900 images is used to trained this model and then using 180 images. Their study obtained high performance results.

In the study of (Çinar and Yildirim, 2020) a CNN model (Resnet50 model) was proposed to detect brain tumors. They stacked 8 additional layers onto a Resnet50 and dropped the last 5 layers. Their model obtained an accuracy of 97.2%. As for image classification, the brain tumors images are classified using (Alexnet, Densenet201, InceptionV3 and Googlenet) with high performance results.

The proposed system in (Gull, Akbar and Khan, 2021), used a Convolutional Neural Network (FCNN) model using transfer learning to classify brain tumors into two categories. The GoogleNet model was used as the classifier on three public datasets. Average segmentation accuracy was 96.50%, 97.50%, 98.00%, and brain tumor classification accuracy were 96.49%, 97.31%, 98.79% for the BRATS2018, BRATS2019, and BRATS2020 datasets, respectively.

In the following Table 1 illustrates Summary of Related Works.

Table 1.Summary of Related Works

Researchers	Publication year	Dataset	Algorithms	Accuracy
Çinar and Yildirim, 2020	2020	Brain Tumor Detection dataset	Resnet50 Alexnet, Densenet201, InceptionV3 and Googlenet	97.2%.
Gull, Akbar and Khan, 2021	2021	BRATS2018, BRATS2019, and BRATS2020	FCNN model and transfer learning methods	96.49%, 97.31%, and 98.79%
Chattopadhyay and Maitra, 2022	2022	BRATS	CNN &SVM	99.74%
Khan et al., 2022	2022	Harvard Medical Figshare Dataset	23 LAYES CNN & VGG16	97.8% for dataset1 100% for dataset2
Rahman and Islam, 2023	2023	Binary tumor identification, Figshare, Multiclass Kaggle	Parallel deep CNN	97.33% for dataset1, 97.60% for dataset2, and 98.12% for dataset3
Neuroscience, 2023	2023	Brian Tumor Dataset	VGG19, InceptionV3, and MobileNetV2	InceptionV3 is 91%, VGG19 is 88%, and MobileNetV2 is 92%.
Mahjoubi et al., 2023	2023	Figshare1, SARTAJ dataset2, Br35H3.	CNN	95.44%
R et al., 2024	2024	Brain MRI dataset	Resnet 177 Inception v3	94.44% 96.11%
The proposed method	2024	Brain tumor MRI dataset	CNN	97.889%

3. METHODOLOGY

The proposed brain tumor classification system in this work leverages a CNN with three convolutional layers to classify brain tumor images into two categories: normal and tumor. This system follows a structured approach, encompassing several key phases as depicted in the following Fig. 1:

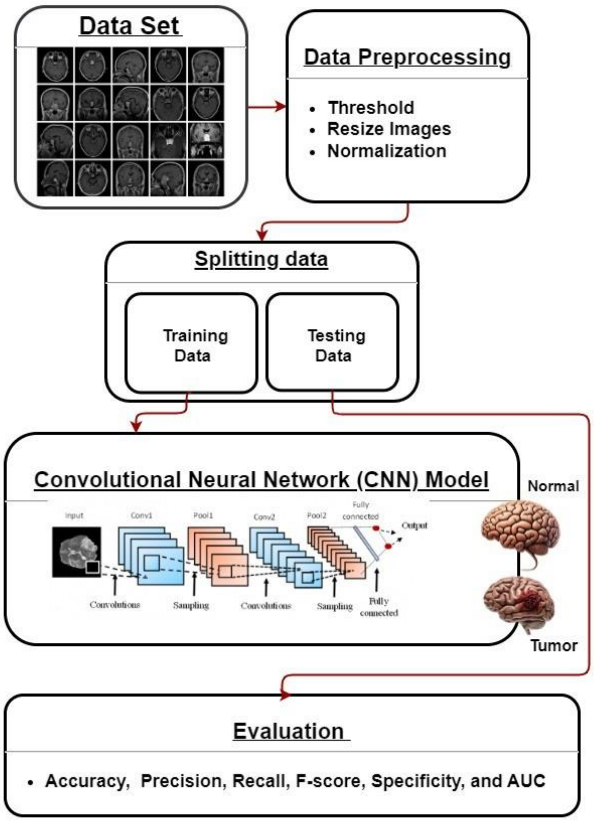

Fig. 1. the proposed CNN model

3.1. Dataset

The Brain Tumor MRI Dataset on Kaggle is a publicly available dataset that is used with brain tumor experiments. This dataset includes a curated set of brain MRI images, which are selected to simplify research into automated brain tumors detection and classification. The data was divided up into training and test datasets using a split ratio of 7/10 for training and 3/10 for testing with a fixed random state for reproducibility

3.2. Preprocessing

Images from two categories, "no tumor" and "yes tumor," are loaded from their respective directories. Each image is checked to ensure it is in JPEG format. The images are the images are scaled down to be 64 x 64 pixels. The scaled images are converted into arrays and appended to the dataset list. Corresponding labels (0 for no tumor, 1 for yes tumor) are appended to the label list. The dataset and labels are converted to arrays. The data was divided up into training and test datasets using a split ratio of 7/10 for training and 3/10 for testing with a fixed random state for reproducibility. The image data is normalized to have values between 0 and 1 by dividing by the maximum pixel value.

3.3. Convolution Neural Network (CNN) Model

One type of artificial neural network is the CNN, which was specifically designed for processing data with a spatial structure, such as images and moving clips. CNN was developed to recognize visual patterns and visual processes, Fig. 2 illustrates the CNN process. The CNN algorithm includes several basic steps that allow the network to learn basic features and information from visual data. These steps include:

1. Input layer: MRI images are provided as input to the network. These images form a two-dimensional matrix, and each pixel in the image expresses the color value.
2. A Sequential model is created.
3. The model consists of three convolutional layers with 32, 32, and 64 filters respectively, each followed by a ReLU activation function and a max pooling layer.
4. After the convolutional layers, the output is flattened.
5. A dense layer with 64 units and ReLU activation is added, followed by a dropout layer with a 0.5 dropout rate to prevent overfitting.
6. The output layer has a single neuron with a sigmoid activation function for binary classification.

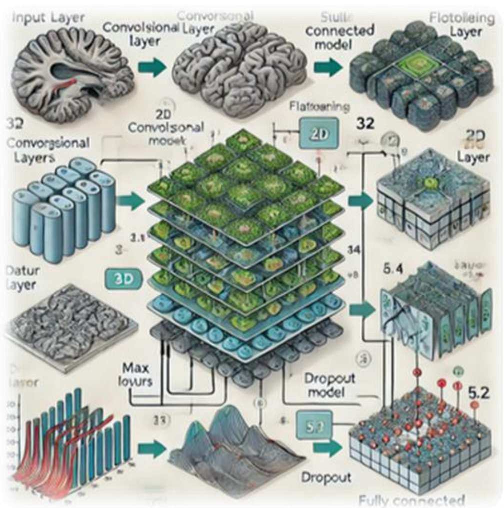

Fig. 2. CNN process

3.4. Evaluation Metrics

To evaluate the performance of the classification mode, the CNN is implemented according to the binary classification (normal, tumor). In this paper, the Accuracy, Precision, Recall, F-score, Specificity, and AUC are used to measure the binary classification.

$$\text{ACCURACY} = \frac{TN+TP}{TN+TP+FN+Fp} \quad (1)$$

$$\text{PRECISION} = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F - score = 2x \ \frac{\textbf{Recall x Precision}}{\textbf{Recall+ Precision}} \quad (4)$$

$$Specificity = \ \mathbf{TN/TN + FP} \quad (5)$$

Where TN: number of True Negative, TP: True Positive, FN: False Negative and FP: False Positive.

4. EXPERIMENTAL RESULTS

In this part of the document, we have utilized a Brain Tumor MRI dataset for training and testing the model with the purpose of developing a system able to classify medical images using high accuracy in making decisions. Similar to other experiments, it has been found that the performance of the model will be influenced by several different variables including; quality of original data provided, how many layers are added to the convolutional neural network to increase complexity (more complex = better), total number of layers and number of coefficient values within those layers, and if enough additional layers were included to extract/produce the required information to train our model.

The data used in this study are (224x224 MRI images with RGB color channels, batch size = 32). The proposed CNN architecture model includes 3 convolutional layers, 3 max pooling layers, 1 flattening layer, and 1 (reLU) activation layer functions. The number of epochs = 100, the model was trained using the Google Colab environment and the GPU that Colab supplied. The model demonstrated high accuracy when tested on a set of MRI images of brain tumors, as shown in Fig. 3, which illustrates the comparison between the model and previous studies in terms of accuracy.

4.1. Training Result

This study used a Brain Tumor MRI Dataset to develop a model to detect tumors in MRI scans. Fig. 4 illustrates evaluation metrics result of training our CNN model using precision, accuracy, recall, specificity, AUC, and F-score values.

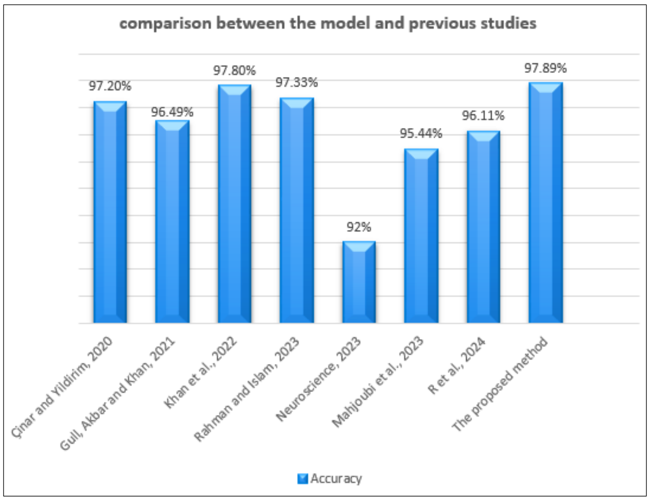

Fig. 3. The accuracy comparison between the model and previous studies

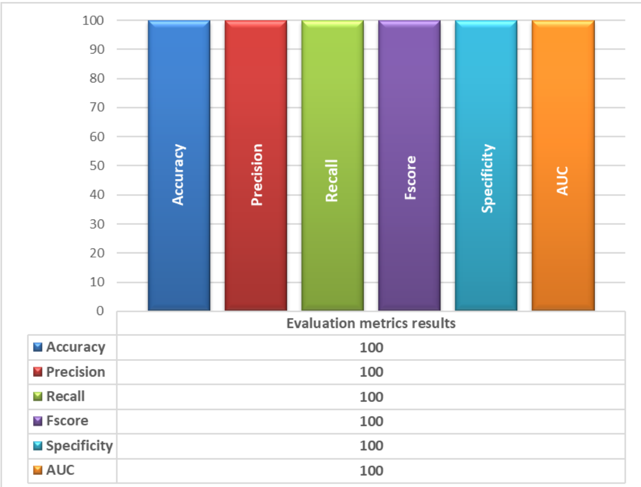

Fig. 4. Evaluation metrics result of training CNN model

4.2. Testing Result

The proposed CNN model successfully detected brain cancers with an outstanding accuracy of 97.889%. Fig. 5 illustrates evaluation metrics result of testing CNN model in terms of the accuracy, Recall, F-score, Precision, AUC, and Specificity during the testing of our model.

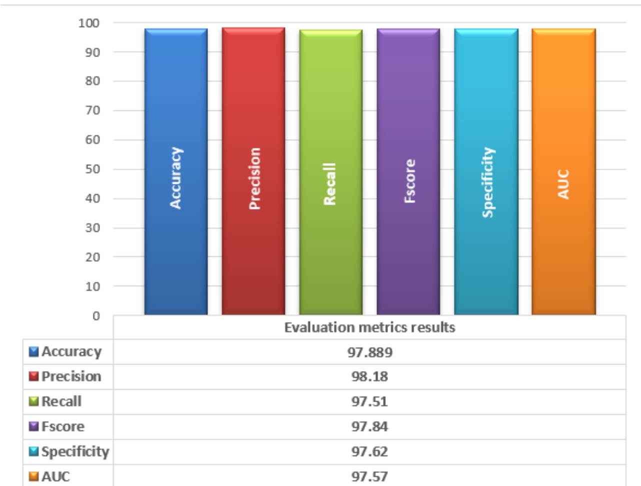

Fig. 5. Evaluation metrics result of testing CNN model

5. CONCLUSIONS

The proposed CNN model used for brain tumor classification from MRI images has shown good potential. The model is expected to enable health care professionals to rapidly and effectively identify brain tumors. The proposed CNN network was able to achieve an accuracy rate greater than many other deep neural networks. Therefore, this research evaluated the performance of the CNN- model using several measures that include accuracy, F-score, Recall, Precision, Specificity and AUC. The proposed CNN Network had a recall of 97.51%, Accuracy of 97.89%, F- Score of 97.84%, Precision of 98.18%, Specificity of 97.62% and AUC of 97.57%.

6. REFERENCES

Chattopadhyay, A. and Maitra, M. (2022) 'MRI-based brain tumour image detection using CNN based deep learning method,' Neuroscience Informatics, 2(4), p. 100060. https://doi.org/10.1016/j.neuri.2022.100060.

Çinar, A. and Yildirim, M. (2020) 'Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture,' Medical Hypotheses, 139, p. 109684. https://doi.org/10.1016/j.mehy.2020.109684.

D., D. and H. S., P. (2020) 'Study of Machine Learning vs Deep Learning Algorithms for Detection of Tumor in Human Brain,' International Journal of Computer Sciences and Engineering, 1–1. https://doi.org/10.26438/ijcse/v8i1.5763.

Dhankhar, A. et al. (2021) 'Kernel parameter tuning to tweak the performance of classifiers for identification of heart diseases,' International Journal of E-Health and Medical Communications, 12(4), pp. 1–16. https://doi.org/10.4018/ijehmc.20210701.oa1.

Gull, S., Akbar, S. and Khan, H.U. (2021) 'Automated Detection of Brain Tumor through Magnetic Resonance Images Using Convolutional Neural Network,' BioMed Research International, 2021, pp. 1–14. https://doi.org/10.1155/2021/3365043

Khan, Md.S.I. et al. (2022) 'Accurate brain tumor detection using deep convolutional neural network,' Computational and Structural Biotechnology Journal, 20, pp. 4733–4745. https://doi.org/10.1016/j.csbj.2022.08.039.

Mahjoubi, M.A. et al. (2023) 'Improved Multiclass Brain Tumor Detection using Convolutional Neural Networks and Magnetic Resonance Imaging,' International Journal of Advanced Computer Science and Applications, 14(3). https://doi.org/10.14569/ijacsa.2023.0140346.

Mohamed, K.A., Elsamahy, E. and Salem, A. (2022) 'COVID-19 Disease Detection based on X-Ray Image Classification using CNN with GEV Activation Function,' International Journal of Advanced Computer Science and Applications, 13(9). https://doi.org/10.14569/ijacsa.2022.01309103.

Mohammed, H.A., Kareem, S.W. and Mohammed, A.S. (2022) 'A COMPARATIVE EVALUATION OF DEEP LEARNING METHODS IN DIGITAL IMAGE CLASSIFICATION,' Kufa Journal of Engineering, 13(4), pp. 53–69. https://doi.org/10.30572/2018/kje/130405.

Neuroscience, C.I.A. (2023) 'Retracted: A robust and novel approach for brain tumor classification using convolutional neural network,' Computational Intelligence and Neuroscience, 2023(1). https://doi.org/10.1155/2023/9760861.

R, M., V. et al. (2024) 'Performance Analysis of Brain Tumor Classification on MRI images using Pretrained Deep Learning Models,' Research Square (Research Square) [Preprint]. https://doi.org/10.21203/rs.3.rs-3998886/v1.

Rahman, T. and Islam, M.S. (2023b) 'MRI brain tumor detection and classification using parallel deep convolutional neural networks,' Measurement Sensors, 26, p. 100694. https://doi.org/10.1016/j.measen.2023.100694.

Sahoo, D.K., Mishra, S. and Mohanty, M.N. (2022) 'Brain Tumor Segmentation and Classification from MRI Images using Improved FLICM Segmentation and SCA Weight Optimized Wavelet-ELM Model,' International Journal of Advanced Computer Science and Applications, 13(7). https://doi.org/10.14569/ijacsa.2022.0130753.

Surrisyad, H. and Wahyono (2020) 'A Fast Military Object Recognition using Extreme Learning Approach on CNN,' International Journal of Advanced Computer Science and Applications, 11(12). https://doi.org/10.14569/ijacsa.2020.0111227.

Swamy, G.B.J. (2020) 'Brain Tumor Detection using Convolutional Neural Network,' International Journal for Research in Applied Science and Engineering Technology, 8(6), pp. 615–620. https://doi.org/10.22214/ijraset.2020.6100.