Automated Brain Tumor Classification System using Convolutional Neural Networks from MRI Images

6 authors, including:

Diponkor Bala
Islamic University (Bangladesh)
21 PUBLICATIONS   55 CITATIONS

SEE PROFILE

Mohammad Anwarul Islam
Georgia Southern University
10 PUBLICATIONS   16 CITATIONS

SEE PROFILE

Mohammad Iqbal Hossain
North Carolina Agricultural and Technical State University
4 PUBLICATIONS   8 CITATIONS

SEE PROFILE

Mohammed Mynuddin
North Carolina Agricultural and Technical State University
31 PUBLICATIONS   157 CITATIONS

SEE PROFILE

Some of the authors of this publication are also working on these related projects:

Project   PhD thesis View project

Automated Brain Tumor Classification System using Convolutional Neural Networks from MRI Images

Diponkor Bala
Dept. of Computer Science and Engg.
Islamic University
Kushtia-7003, Bangladesh
diponkor.b@gmail.com

Mohammad Anwarul Islam
Department of Mathematical Sciences
Georgia Southern University
Georgia, USA
mislam@georgiasouthern.edu

Mohammad Iqbal Hossain
Dept. of Electrical and Computer Engg.
North Carolina A&T State University
North Carolina, USA
mohammad.iqbl.hossain@gmail.com

Mohammed Mynuddin
Dept. of Electrical and Computer Engg.
Georgia Southern University
Georgia, USA
mm40771@georgiasouthern.edu

Mohammad Alamgir Hossain
Dept. of Computer Science and Engg.
Islamic University
Kushtia-7003, Bangladesh
alamgir@cse.iu.ac.bd

Md. Shamim Hossain
School of Computer Science and Tech.
Uni. of Science and Technology of China
Hefei, China
shamim2@mail.ustc.edu.cn

Abstract—**Recent advances in machine learning have employed deep learning to do several tasks. Deep learning has been used in the health sector to solve complex problems that require human intelligence. Without timely medical attention, the prognosis for patients with brain tumors is dismal. Radiologists are responsible for classifying tumors in radiographic images, which is a complex and time-consuming process that relies solely on their expertise. Modern radiology diagnosis, such as magnetic resonance (MR) scans, is largely subjective, putting patients at risk of damage. Use of Artificial Intelligence (AI) technology in order to avoid making mistakes when diagnosing is important to success. An automated approach for classifying different brain tumor classes in patients using magnetic resonance imaging (MRI) was suggested in this research, which focused on merging deep learning and radionics. We performed our work on three unique datasets with several classes. The proposed technique makes use of a convolutional neural network (CNN) as our deep learning model with the K-fold cross-validation concept in order to perform both binary and multiclass classification on our magnetic resonance imaging (MR) data. We took advantage of the power of CNN architecture in medical imaging. The model was trained and tested on random folded images from the dataset and was able to get an accuracy rate of 100%, 99.86%, and 100% in the corresponding dataset respectively, those are utterly remarkable, to put it mildly.**

Index Terms—**Brain Tumor, MRI Images, Classification, Deep Learning, CNN;**

I. Introduction

A number of sectors that attempt to improve the quality of health care facilities have been revolutionized by AI systems, along with diagnosis of diseases, robotic surgery, and remote surgical excellence. As a result, the health industry for AI systems will be grown rapidly over the upcoming years. In 2022, the estimated value of AI in healthcare is $13.82 billion, and in 2029, it will be $164.10 billion as expected [1]. Still, MRI scans, CT scans, mammograms, nuclear medicine scans, Positron Emission Tomography (PET) techniques, and many more are some of the most well-known ways that AI technology is being used to improve medical care [2]. There is absolutely no shadow of a doubt that the numerous forms of medical imaging that are currently available have contributed significantly to the improvement in the accuracy with various diseases, including malignancies of the bone, ovary, and brain, may be diagnosed.

Brain cancer was formerly difficult to identify, and the medical industry struggled until the introduction of artificial intelligence (AI). The abnormal proliferation of cells in the brain can lead to the development of a brain tumor. Primary brain tumors develop in normal brain tissue while secondary brain tumors move from another section of the body to the brain by a process called metastasis. Primary brain tumors are the most frequent and fatal type of brain tumor [3]. The rate at which a brain tumor develops affects how much it can disrupt the neurological system. Experts believe the initial brain tumor was caused by ionizing radiation and a family history of brain cancer. The subsequent brain tumor's origin is uncertain. Brain tumors are a serious health issue, with an estimated 350,000 new cases worldwide each year. Children below the age of seven are most vulnerable to the effects of this disease, which include death or stunted brain development. As reported by the NCI, 30,500 people will be diagnosed with brain tumors in 2026, including 17,125 men and 13,375 women. 13,775 of these diagnoses will result in death [4].

Deep learning, a subset of machine learning, has shown superiority in diagnosing brain tumors using MRI, which improved diagnosis speed and accuracy. Since the beginning, it has been very effective in medical imaging, proving to be a reliable and time-saving method. First, though, let's define our terms so we can talk intelligently about AI and ML. AI is a large sub-field of computer science that focuses on making computers that can do tasks that used to require intelligent behavior on their own [5]. AI is the exploration and creation of autonomously learning and improving computer systems, whereas machine learning is a sub-field within AI that tries to make robots behave like humans. There are actually relatively few different kinds of A.I. IBM Watson, Brain Miner, and Visit

A.I. are examples of medical imaging startups that are using artificial intelligence technologies to diagnose brain tumors and other disorders [6]. Furthermore, a significant amount of research has been conducted regarding the implementation of AI in medical care; a significant amount of money has been invested in it because adopting this technology in the medical field may undoubtedly help us save a significant amount of time and money.

Using the convolutional neural network model, this research proposes a novel and robust method for separating several types of brain tumors flourished on images obtained from MRI scans. The suggested model that we have developed has been incorporated with lower computational complexity than the pre-trained frameworks that we utilized to undertake binary and multi-class categorization of brain tumors on our brain MIR scan image database. These classifications were performed in order to forecast whether or not each of those images contained several categories of tumor. The output is a set of predetermined categories based on our predictions. The categorized output accurately displays both healthy and several harmful examples.

Here's how the rest of the article is laid out: The second section discusses related literature. There is a brief summary of the original dataset in Section III. In Section IV, we provide a brief overview of the suggested strategy; in Section V, we provide the outcomes and discuss them; and in Section VI, we make the conclusions based on this study.

II. Related Works

Many researchers worldwide are interested in malignant tumors. Every year, many studies on brain tumors and early detection approaches come out. Most of this research advises using image processing approaches like segmentation. Many use artificial intelligence to conduct similar work. Other investigations used a variety of detection methods to identify suspects. A study [6] demonstrated their work on using CNN to identify brain tumors using MRI images. They developed a CNN model and used a cross-validation technique and obtained an accuracy of 96.56%. J. D. Bodapati *et al.* [7] proposed a DNN architecture with two channels. MRI brain tumors are classified using a technique that uses different feature extraction techniques like pre-trained CNN block and attention mechanism. The classifier's 98.04% accuracy was higher than that of other classifiers used in the same type of studies. A. Rehman *et al.* [8] made a framework by putting together the transfer learning techniques of three CNN architectures that had already been trained, and the VGG16 model was able to provide 98.69% accuracy. S. Deepak *et al.* [9] suggested a multi-label classification method to identify malignancies in patients by analyzing MRI data from the brain. Initially, the author used transfer learning concepts and later used a GoogleNet pre-trained model to extract the features and obtained an average accuracy of 98%.

R. L. Kumar *et al.* [10] used the ResNet50 deep learning model to classify three types of tumors from MRI images. They performed their study on non-augmented and augmented datasets and obtained 97.48% and 97.08% accuracy. H. H. Sultan *et al.* [11] proposed a deep learning model with a CNN model that performed the classification on three types of 3064 brain tumor images and the subtype of galioma tumor and provided 96.13% and 98.7% accuracy, respectively. N. Abiwinanda *et al.* [12] implemented a CNN model that perform on an openly attainable dataset that consists of 3064 MRI images and performed with train and validation accuracy of 98.51% and 84.19% respectively. A. K. Anaraki *et al.* [13] used two methods that are based on CNN and GA concepts and were able to classify the three different grades of glioma tumors. They also used the ensemble technique to reduce the number of errors predicted, resulting in a 90.90% accuracy in determining the grade of glioma tumor. M. F. I. Soumik *et al.* [14] suggested a pre-trained deep learning model based framework that was developed based on the concept of transfer learning method and cross validation and was able to classify three types of brain tumors with an accuracy of 99.45%.

Most recent advances in automated brain tumor diagnosis using computers have been achieved through the application of deep learning techniques. While deep learning application to the evaluation of clinical data for certain diseases has grown dramatically, it hasn't yet been utilized to analyze medical imaging of other disorders. When it comes to detecting brain tumors, we haven't heard of any applications using deep learning. Deep learning has many advantages over previous methods. Deep learning is a good tool for making models from start to finish because it can find a lot of features in images.

III. Dataset Descriptions

One of the keys and critical components of every investigation is data collection. Data that is relevant as well as satisfying the parameters for the study must be collected. The data must include readings reproducing all the possibilities, even severe situations. This serves to make more precise and specific observations. Acquiring data is the basis of any research and should be carefully collected. For data collection, we have used three datasets, both of which were collected from Kaggle datasets. The first is a collection of 4600 MRI scans of the brain, 2513 of which were determined to be damaged by tumors, while the remaining images were determined to be healthy. All of these scans are in 2D, as was our intention [15]. The second dataset contains three classes of brain tumors, and the entire dataset consists of 3064 brain MRI images with different types of brain tumors. The recent datasets are focusing on 3D segmentation of brain tumors and so we did not use them as they do not align with our objective. We used this dataset to distinguish between unhealthy and healthy brains [16]. The third dataset was also obtained from Kaggle. It contains 3264 images classified into 3 classes of tumors contains 2764 and 1 class of non-tumors contains 500 images [17]. We used all of the tumor classes as tumor examples and the non-tumor class as non-tumor examples. Both of the datasets are heavily biased towards positive examples meaning the tumor dataset which was handled inside the

implementation of our paper for better results with image augmentation and imbalance handling.

IV. METHODOLOGY

This section discusses the steps involved in data preprocessing, including feature scaling, data splitting, augmentation, and model creation, model training and testing, and then brain tumor recognition, as shown in Fig. 1. The data is prepared here for the CNN model. Data cleaning removes undesired anomalies and inconsistencies from the data, making it ready to be input into our various models for further processing. The data is then separated into training and test sets. After the model has been trained with the training sets, the test sets are used to see how well it can predict. The data has independent features that must be standardized. This is the data normalization procedure. Scaling of features After normalization, the data is ready to be fed into our suggested CNN model. The preprocessed data is used to train the model. During training, we use cross-validation. The trained model is now ready to be tested on the test dataset.
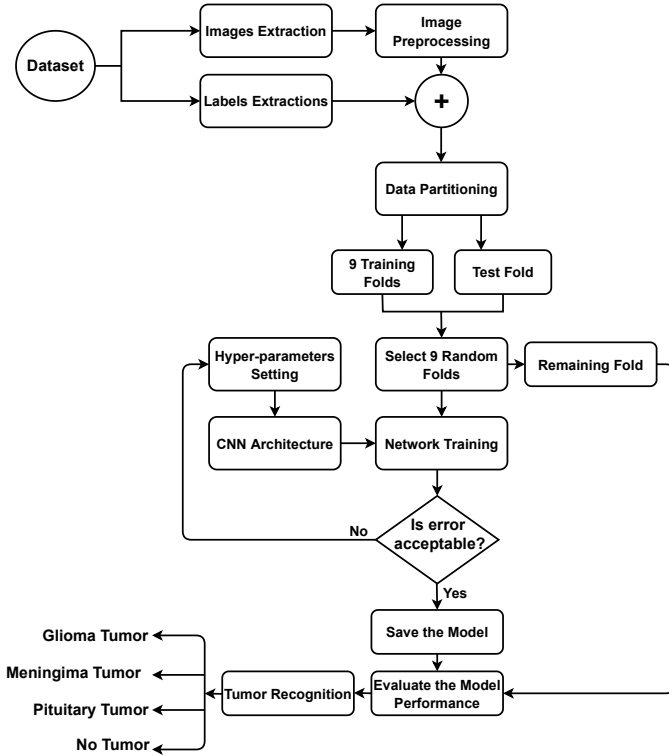

Fig. 1: Flowchart of the Proposed Methodology

A. Data Preprocessing:

Feature Scaling: We began by preparing the dataset for our proposed CNN model to correctly predict the brain tumor class from MRI data. In this step, we resize our datasets into 128x128 resolutions with RGB formatted images. In addition to this, we generate a randomly selected image for the purpose of target class confirmation and preserve the labels of each image in a list. We used normalization to minimize the

influence of lighting variations [18]. Also, when given data between [0, 1], the CNN converges more quickly than when given data between [0, 255]. After normalization, we split the dataset into 10 folders so that each folder had the same number of images for the K-fold cross-validation method. If the normalized value is represented by x' then

$$x' = \frac{x - min(x)}{max(x) - min(x)} \quad (1)$$

where x is the actual intensity of the image.

Data Augmentation: The term "augmentation" refers to increasing the size of the training dataset. Data augmentation creates additional images from a single image. That's why it's used to boost the quantity of training samples and perhaps boost the amount of variation in our dataset, which helps keep us from over-fitting [19]. The Keras image preprocessing package was used to achieve this. Our data augmentation includes:

- Randomly rotated by 30 degrees
- Randomly shifted in width by 10%
- Randomly shifted in height by 10%
- Randomly zooming by 30%
- Randomly flip inputs horizontally

B. Model Creation:

Proposed CNN model: Convolutional neural networks are commonly utilized in image processing and classification. Convolutional layers and max pooling layers with shared weights modify the input features and offer to make it a shift-invariant or space-invariant neural network. Contrary to popular assumption, many convolutional neural network topologies are only suitable for image processing. In deep learning, the convolutional neural network is utilized for image and video identification, recommendation system services and financial time series. We suggested a deep neural network (CNN) design for brain tumor identification that included four convolutional layers, four pooling layers, two dropout layers, and a fully connected layer. The proposed CNN model architecture is shown in Fig. 2. The description of the suggested deep CNN model is illustrated below:

- The hidden and output layers can communicate with one another through the input layer. During this investigation, the input layer's image format is (128, 128, 3).
- Our CNN model uses a mathematical approach called convolution. For each layer of convolutional processing, we used a 2D convolution. Locally, the features of the previous layers are compared to see if there are any similarities. If there are, those similarities are added to the extracted features as appearances [20] [21]. For the input image (X) and kernel k, the 2D convolutional operator is defined as:

$$(X * K)(i, j) = \sum_m \sum_n K(m, n)X(i - m, j - n) \quad (2)$$

where $*$ represents mathematical representation of convolution operation, the k matrix moves over the input data matrix with stride parameter.
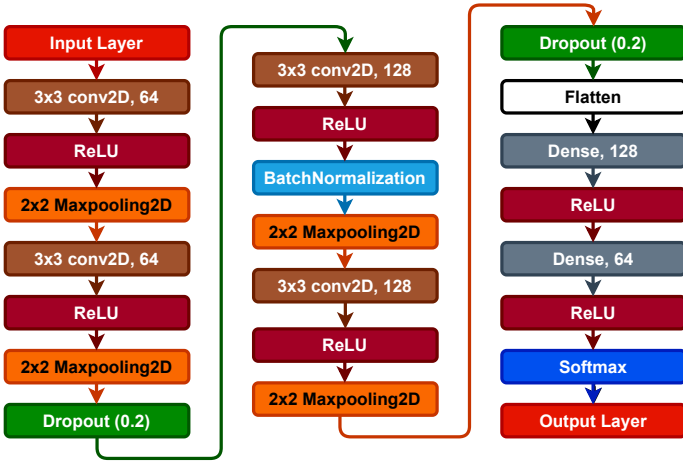
Fig. 2: Proposed CNN Model Architecture

- This study recommends employing padding to ensure that the output feature maps have the exact pixel size as the source features once an image has undergone a convolutional process. In this study, we used padding to supplement the input feature maps with extra pixels in both the vertical and horizontal planes. It ensures that the original image's data is preserved after executing kernel filters [21].

- Rectified linear units are a deep neural network design that combines non-linearity and rectification layers. By combining non-linearity and rectification layers, a deep neural network is created, which is referred to as a rectified linear unit. It is present throughout every convolution layer in our design to prevent the disappearing gradient. That is, it maintains the weights of our network current throughout back propagation. In a nutshell, weight updates among both epochs or iterations are prevented by the diminishing gradient. "ReLU" helps make forward propagation weights so that features from the input nodes can be sent to the hidden layer [21]. The following is an example of an equation that may be written to represent the ReLU function:

$$ReLU(x) = \begin{cases} max(0, x) & \text{for x>0} \\ 0 & \text{for x}\leq 0 \end{cases} \quad (3)$$

to which x refers to the value received by the neuron.

- Max-pooling is the most reliable pooling technique on a CNN. As a result, a feature pooling layer receives the same collection of feature maps but with lower dimensions. To do so, it applies a pooling filter on top of the convolutional layer's convolved feature and then places the highest pixel value from each stride in the associated output matrix. The ReLU activation function updates the pooling filters during back-propagation [21].

- Dropout ignores randomly picked neurons or CNN filters throughout training. Their activation contribution is momentarily eliminated on the forward pass, and weight

upgrades are not performed in the backward direction. In our work, we have adopted the above technique on the convolutional layer. Dropout could easily destabilize the training procedure if some of the input filters in the first convolutional layer are temporally removed. For this reason, the first convolutional layer includes all the main information about the source images, because dropping out some of these filters could provide bad information through the next layers. It is necessary to use the dropout layer after the convolution layer in order to prevent over-fitting during the processing process [22]. In the proposed CNN, we implemented two dropout layers with dropout rates of 20% in both.

- Higher learning rates can be used with batch normalization, resulting in a significant acceleration of the learning process. Because of vanishing gradients, it is possible to train deep neural networks with sigmoid activation, which had previously been believed impossible[21].

- The flatten layer turns images into a one-dimensional array, allowing each pixel to be connected to the next layer. It combines all the features retrieved from the layers. Then we add and transmit data through layers [21].

- The dense layers function is responsible for determining the relationship between all of the characteristics that have been provided to it without the use of any more input parameters than convoluted layers [21].

- The Softmax activation function was employed to create the suggested CNN architecture. Softmax takes data that is entered in a linear way and turns it into a list of possible future events. It then compares the probability of future events with the output that was seen [21]. To calculate the softmax function, the following formula should be used:

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \; for \; i = 0, 1, \ldots, K \quad (4)$$

This method provides a K-dimensional vector of values ranging from 0 to 1 that add to 1.

C. Model Training and Testing:

We employed sparse categorical cross-entropy to label targets. It assesses how far our model diverges from the gradient slope, which shows us all how inaccurate our model is in discovering the actual and projected features. Ultimately, we build our network and use the Adam optimization process to reduce model loss throughout training by upgrading it based on our loss function. This optimizing algorithm's hyper-parameters are straightforward and demand little or no modification. It's computationally more efficient and memory-light [23]. It was decided that the learning rate would be 0.00001, the batch size would be 64, and the number of epochs would be 100.

The considered dataset was analyzed in this study did not have independent train and test sets. This study divided each dataset into $K = 10$ folds using a random number generator. $K...1$ of these folds served as training data for the model, and the remaining fold served as a performance test for the model. The training procedure was performed ten times, and the

accuracy of the model was determined by calculating the mean of all of the accuracy rate and reporting it as the prediction accuracy [24]. All of the work for this investigation was done on a single computer. The hardware and software were both recorded. The computer had a 2.40GHz Intel Core i5-9300H processor and NVIDIA GeForce RTX 2060 graphics built into Windows 10 Home 64-bit. We looked at its test accuracy to see how well the model did overall.

V. RESULTS AND DISCUSSION

The research reported in this study demonstrates the effectiveness of our model both before and after training, as well as the findings are displayed both graphically and numerically. To evaluate the efficacy of the suggested model, we have examined its operation on three different sets of data. The model has been trained using a very strong network with millions of parameters, as was previously indicated. This is why we fed the model 4600, 3046, and 3264 examples of brain MR images. Our model's training and validation accuracy reports serve as the foundation for the categorization outcomes. Using a cross-validation strategy, we were able to assess the model's genuine performance after feeding it with a dataset. Ultimately, the model's performance was really good.
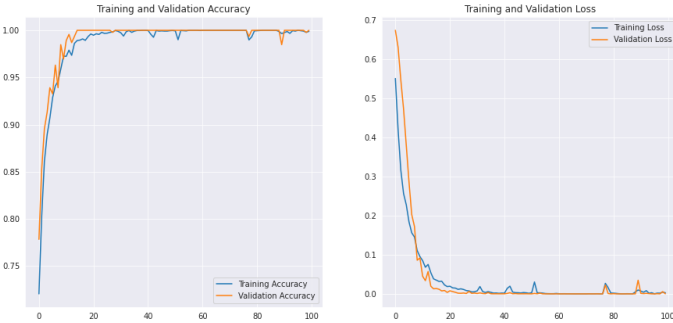

Fig. 3: Accuracy and Loss Curve on 2 Classes Dataset

Fig. 4: Accuracy and Loss Curve on 3 Classes Dataset

After we were done, the model could accurately label nearly all of the input image in the training dataset. Our proposed model has been obtained 100%, 99.86%, and 100% accuracy on the 4600, 3046, and 3264 images dataset respectively. Standard procedure calls for looking at the accuracy and loss plot of a deep learning model to determine its efficacy. The
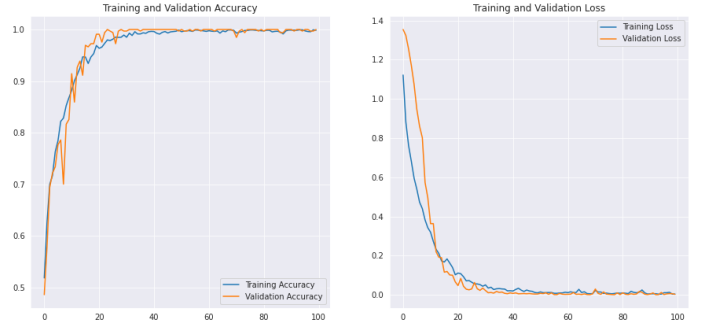

Fig. 5: Accuracy and Loss Curve on 4 Classes Dataset

accuracy statistics are given in two ways: for training and for validation. The loss statistics are also given in two ways: for training and for validation. The performance of our proposed model on different dataset shown in Figures 3, 4, and 5. Table I shows the performance of our proposed mode according to 10-fold cross validation process.

TABLE I: Proposed Model Performances

Validation Set	Validation Accuracy		
	Dataset (2 Class)	*Dataset (3 Class)*	*Dataset (4 Class)*
1	100%	100%	100%
2	100%	99.64%	100%
3	100%	100%	100%
4	100%	100%	100%
5	100%	100%	100%
6	100%	99.91%	100%
7	100%	100%	100%
8	100%	100%	100%
9	100%	100%	100%
10	100%	100%	100%
Average	**100%**	**99.86%**	**100%**

According to the above plots, the model obtained 72.04%, 59.04%, and 51.87% training accuracy at the beginning of the epochs and, when they were in the process of training, this correctness kept growing, and by the end of the training phase, the model had achieved a perfect score of 100% in 2, 3, and 4 class datasset. Inquiring into the correctness of the validation, the model attained 77.83%, 39.35%, and 48.62% accuracy at the first epoch and training continued to improve accuracy, with some epochs sharing gains, until finished the epoch, at which point the model achieved a validation accuracy of 100% in each class datasets. To be sure, the training loss reached 0.5510, 0.8757, and 1.1219 in the initial epoch, but it steadily decreased as the model learned, and by the last epoch it was just 0.0029, 0.0031, and 0.0037, or nearly at the optimum on the gradient curve. In terms of validation loss, the model was excellent. It can be observed in the preceding figures that the training and validation performance curves both converge to 100% at epoch 100. As a result, the model achieves convergence fairly quickly.

Our methods, however, are being compared to other, more recently proposed methods by various scholars (a selection of which are summarized in Table II). According to the findings

TABLE II: Comparision with Previous Works

Authors	Methods	Accuracy(%)
N. Abiwinanda *et al.* [12]	CNN and GA	84.19%
A. K. Anaraki *et al.* [13]	Ensemble Learning	90.90%
M. M. Badza *et al.* [6]	CNN	96.56%
R. L. Kumar *et al.* [10]	Deep Learning (ResNet50)	97.48%
A. Rehman *et al.* [8]	Transfer Learning	98.69%
M. F. I. Soumik *et al.* [14]	Transfer Learning	99.45%
Proposed	**CNN + Cross-Validation**	**100%**

of this study, categorization brain tumors perform exceptionally well with high confidence in a variety of class sizes than all the previous works. The performance was analyzed and evaluated in accordance with many standards that were necessary to make an accurate prediction. We did this study because we were worried about the high rate of incorrect diagnoses in the health care field, which leads to many people dying because they rely on their own intelligence.

VI. CONCLUSION

Due to the high inter-class variation among images, it is very tough to recognize the corresponding image classes for clinicians. After the medical image analysis, the classification of brain tumor is a critical undertaking because it often determines whether or not a patient will survive their malignancy. To solve this problem, AI is a reliable way, and we recommend this approach. For our research, we used three different datasets with 2D MRI images of brain tumors and implemented a framework based on the CNN model with a cross-validation concept for correctly diagnosing tumor types. Our proposed framework provides 100%, 99.86%, and 100% accuracy in the corresponding datasets.

In the future, we will upgrade this work. We have planned to implement instance segmentation and semantic segmentation of 3D brain MRI in the future to correctly identify cancerous tissues and other lesions besides brain tumors to perform better diagnosis for disease and abnormalities from brain MRI, ensuring better results in terms of early prevention of brain-related diseases. If we can implement a more accurate model for that with better precision and specificity, it could be a great step towards early detection and reduction of brain tumor-related diseases.

ACKNOWLEDGMENT

REFERENCES

[1] F. B. Insights, "Healthcare IT," *[Online]. Available: https://www.fortunebusinessinsights.com/industry-reports/artificial-intelligence-in-healthcare-market-100534*.

[2] P. Afshar, K. N. Plataniotis, and A. Mohammadi, "Capsule networks for brain tumor classification based on mri images and coarse tumor boundaries," in *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2019, pp. 1368–1372.

[3] P. Nagaraj, V. Muneeswaran, L. V. Reddy, P. Upendra, and M. V. V. Reddy, "Programmed multi-classification of brain tumor images using deep neural network," in *2020 4th international conference on intelligent computing and control systems (ICICCS)*. IEEE, 2020, pp. 865–870.

[4] N. I. of Health (NIH), "National cancer institute (nci)," *[Online]. Available: https://www.nih.gov/about-nih/what-we-do/nih-almanac/national-cancer-institute-nci*.

[5] M. A. Islam, "Reduced dataset neural network model for manuscript character recognition," 2020.

[6] M. M. Badža and M. Č. Barjaktarović, "Classification of brain tumors from mri images using a convolutional neural network," *Applied Sciences*, vol. 10, no. 6, p. 1999, 2020.

[7] J. D. Bodapati, N. S. Shaik, V. Naralasetti, and N. B. Mundukur, "Joint training of two-channel deep neural network for brain tumor classification," *Signal, Image and Video Processing*, vol. 15, no. 4, pp. 753–760, 2021.

[8] A. Rehman, S. Naz, M. I. Razzak, F. Akram, and M. Imran, "A deep learning-based framework for automatic brain tumors classification using transfer learning," *Circuits, Systems, and Signal Processing*, vol. 39, no. 2, pp. 757–775, 2020.

[9] S. Deepak and P. Ameer, "Brain tumor classification using deep cnn features via transfer learning," *Computers in biology and medicine*, vol. 111, p. 103345, 2019.

[10] R. L. Kumar, J. Kakarla, B. V. Isunuri, and M. Singh, "Multi-class brain tumor classification using residual network and global average pooling," *Multimedia Tools and Applications*, vol. 80, no. 9, pp. 13 429–13 438, 2021.

[11] H. H. Sultan, N. M. Salem, and W. Al-Atabany, "Multi-classification of brain tumor images using deep neural network," *IEEE access*, vol. 7, pp. 69 215–69 225, 2019.

[12] N. Abiwinanda, M. Hanif, S. T. Hesaputra, A. Handayani, and T. R. Mengko, "Brain tumor classification using convolutional neural network," in *World congress on medical physics and biomedical engineering 2018*. Springer, 2019, pp. 183–189.

[13] A. K. Anaraki, M. Ayati, and F. Kazemi, "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms," *biocybernetics and biomedical engineering*, vol. 39, no. 1, pp. 63–74, 2019.

[14] M. F. I. Soumik and M. A. Hossain, "Brain tumor classification with inception network based deep learning model using transfer learning," in *2020 IEEE Region 10 Symposium (TENSYMP)*. IEEE, 2020, pp. 1018–1021.

[15] P. VIRADIYA, "Brian tumor dataset," *[Online]. Available: https://www.kaggle.com/preetviradiya/briantumor- dataset*.

[16] J. Cheng, "brain tumor dataset," *[Online]. Available: https://figshare.com/articles/brain_tumor_dataset/1512427*, 2017.

[17] SARTAJ, "Brain tumor classification (mri)," *[Online]. Available: https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri*.

[18] H. Zhao, Z. Xu, G. Han, and D. Xie, "The fast image recognition based on grayscale features," in *2012 IEEE International Conference on Computer Science and Automation Engineering (CSAE)*, vol. 3. IEEE, 2012, pp. 730–734.

[19] A. Mikołajczyk and M. Grochowski, "Data augmentation for improving deep learning in image classification problem," in *2018 international interdisciplinary PhD workshop (IIPhDW)*. IEEE, 2018, pp. 117–122.

[20] M. S. Islam, M. M. Hasan, M. A. Rahim, A. M. Hasan, M. Mynuddin, I. Khandokar, and M. J. Islam, "Machine learning-based music genre classification with pre-processed feature analysis," *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI)*, vol. 7, no. 3, pp. 491–502, 2021.

[21] D. Bala, "Childhood pneumonia recognition using convolutional neural network from chest x-ray images," *Journal of Electrical Engineering, Electronics, Control and Computer Science*, vol. 7, no. 4, pp. 33–40, 2021.

[22] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfitting," *The journal of machine learning research*, vol. 15, no. 1, pp. 1929–1958, 2014.

[23] D. Bala, B. Sarkar, M. I. Abdullah, and M. A. Hossain, "American sign language alphabets recognition using convolutional neural network."

[24] C. Alippi and M. Roveri, "Virtual k-fold cross validation: An effective method for accuracy assessment," in *The 2010 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2010, pp. 1–6.