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Brain Tumor Classification Using CNN on MRI Data: A PyTorch Implementation

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Abstract:- The early detection of brain tumors and correct diagnosis are key factors capable of influencing the success of treatment and more importantly patient outcome. In this study, we hypothesize that MRI data set of brain tumors can be classified and detected using a deep learning method of Convolutional Neural Network (CNN) built on PyTorch. It utilized a sufficiently large Dataset obtained from Kaggle and incorporated various techniques of data augmentation in the training procedure to enhance its robust and generalization capability. The architecture of the CNN comprises of several convolutional layers, which allows the model to recognize complex features present in the MRI data set. With the network architecture trained using the Adam optimizer, the model could successfully differentiate between tumor and non-tumor images. Model validation metrics such as confusion matrices, accuracy, precision, recall ratio, F1 and other metrics were used to validate the model. The findings indicated that the tumor and healthy images classification is achieved with a high degree of accuracy with an adequate ability to generalize to the validation dataset.

Keywords:- *CNN, Brain Tumor Detection, Deep Learning, Pytorch, Tumor Segmentation.*

I. INTRODUCTION

In the field of neuro-oncology, one of the most dangerous pathologies is brain tumors, where correct and timely diagnosis is essential in saving a patient's life. However, the inspection of MRI scans manually is quite tedious, and so human error often creeps in, which makes it difficult for radiologists to provide accurate diagnosis consistently. New technologies such as CNN contribute significantly to medical imaging in different fields that did not exist before deep learning came in. Such models have the capabilities of learning nontrivial patterns and features from images which comes in handy in differentiating brain tumor types.

The present research paper discusses the application of a CNN designed in PyTorch for identification and classification of brain tumors based on MRI data set. The intention of obtaining this model is to train it in a dataset of labeled brain tumors images to improve the diagnosis in the health sectors. The system is able to detect gliomas, meningiomas and pituitary tumors with high F1 score of all the tested subtypes assisting the practical clinical applications. In the end, this aim of this research work is to provide effective assistance to clinician in regards to brain tumors diagnosis containing an outline of the diagnostic process.

Diagnostic imaging and classification of brain tumors are vital operations in the realm of neuro-oncology and inform the patient's outcome. Existing practices regarding the analysis of MRIs are performed through human intervention usually causing bias, time, and error in the outcome. New technologies have emerged however, with deep learning proven to be an ability that can substitute and improve the processes for better diagnosis. This study presents a finer, faster, and more accurate brain tumor identification and typing application based on CNN and PyTorch platform. In this direction, the research intends to harness deep learning to improve the manner in which the diagnosis is performed which will aid health organizations in formulating appropriate treatment for patients in a timely manner.

II. METHODOLOGY

This subsection explains the procedures that have been undertaken in constructing and assessing the brain tumor detection model. It explains the process followed in the course of the model development which includes data collection, data preprocessing, and dataset partitioning for training and validation. Several methods are used to augment the images in order to improve the performance of the model by making it robust to variations in the input data. The most important aspect of the methodology is that of the tumor classifier; a type of CNN that utilizes the processed MRI data set to classify the tumor types. The last stage is model training where the classifier is trained on a learning schedule in order to optimize performance without overfitting. Every step explains how the model is capable of performing in real life without compromising reliability.

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A. Brain Tumor Dataset Acquisition and Preprocessing Strategies

The data set for brain tumor detection was downloaded from the internet it consists of MRI scans marked as 'Brain Tumor' and 'Healthy'. The data was arranged in folders and brought into the system for use. The data was then categorized as training and validation data, where it was split 80% into training and 20% into validation. A constant image size was adopted for all images and pixel wise scaling was done to count take care of variance. Additionally, all images were resized to a uniform dimension, and pixel-wise normalization was applied to mitigate the effects of varying brightness and contrast across the MRI scans. Image preprocessing also involved converting the images into grayscale to reduce complexity while preserving essential features for tumor detection.

B. Methods of Data Augmentation

Data augmentation helps in the increase of the variability of the training dataset through the use of different changes on videos/images. Important methods include performing standardization mean-variance, where subject's video images sizes upon capture are made the same. To add variability in terms of the orientation of images, random horizontal and vertical flips (or both) are done while random rotation allows adjustment of images using different angles. In addition to random horizontal and vertical flips, random rotations are applied at varying angles to enhance the model's robustness to orientation changes. Techniques such as brightness adjustment and zoom are also incorporated, further simulating real-world variability. These augmentations contribute to improved generalization by training the model to perform under diverse and unseen conditions. Average Normalization shifts the pixel values with its mean and divides the result with a factor equal to the standard deviation for this reason; it is used to improve the learning process. Such changes are beneficial for the model to be able to perform effectively as if those conditions exist. This technique helps in enhancing the model's performance and stability towards new and rare data.

C. Data Preparation and Splitting

To improve model learning where paradigms with computerized models are used and to tighten the evaluation of the model performance, the dataset is split into training and testing datasets. For the model building, the division made sure that 80% of the data is given so that salient features are captured by the model. The remaining 20% is saved for validation purposes and this serves as a way of controlling how models perform as path is trained. This division also minimizes overfitting in that the model is able to perform well on data it has not seen before. The use of cross-validation procedures can also improve on this as they test the model with various portions thus increasing the reliability of the model in use. The purpose of stratified sampling when splitting the dataset is to ensure that both classes—tumor and healthy—are present and in appropriate proportion to their occurrence. This greatly improves the learning of the model as every class is better represented, and in turn helps augment the performance of the model to training and evaluation tasks. This means that the learning and validation aspects of the model are well taken care off such that development of a configuration that describes a model that suffers from overfitting is avoided. This strategy allows one to attribute the model performance on a more clinical level and ensures that when deployed the model will be highly accurate.

D. Tumor Classifier

Regarding this research, the design of the tumor classifier is based on the images gathered from this study, which is a CNN – Deep Learn model, and is mended in image segmentation. For this study too, the tumor classifier is more or less modeled in a CNN in which the emphasis is more about MRI imagery feature extraction. The architecture comprises of four convolutional layers with filters of successively larger dimensions in order to extract more complex structural elements from the images. Consequences of this additive procedure is that the model could identify such things as complex patterns of tumor associations.

Features maps extraction occurs after every convolution operation and this is referred to saturation pooling. It reduces the burden of processing demands but on the same hand makes sure that the most important elements remain thus increasing the efficiency of the network. Following the processes of convolution and pooling, there are what are called fully connected layers which are used for classification of the features formed. The features that are gotten out must belong some class type which in this case belongs to a tumor or a healthy.

ReLU (Rectified Linear Unit) or some of its variants are introduced in order to capture the nonlinear characteristic of the model. This option guarantees that some level of interactions among features is captured without the limitation of linearity. In addition, dropout regularization is also included as deployed to improve the generalization performance of the model.

E. CNN Architecture Description

The architecture of the visualized CNN model is aimed at classification from MRI scans of brain tumors. This includes four layers of convolution in order to ensure spatial and hierarchical features are progressively extracted from the input image as part of the layers' structure. On every layer, the convolution increases on the number of filters used that ranges from 8 to 64, followed by ReLU activation to introduce non-linearity, and MaxPooling layers to reduce dimensionality while keeping the essential patterns captured. The MaxPooling operation helps in down sampling and keeps the essential features.

Following the convolution layers is the shift in architecture to fully connected layers. The first fully connected layer had 100 neurons, and the second had 2 neurons, which are for the output of the binary classification as either healthy or tumor-affected. The last layer used softmax activation to convert raw output scores into probabilities, hence letting the model perform binary classification. Backpropagation through the Adam optimizer is used to get the weights in the architecture to converge faster.

This model's structure is optimized to capture those very faint differences in brain tumor images, and it captures textures and edges within shapes based on the specifics of the MRI scans, the fully connected layer which is used classifying those features. The use of data augmentation during training helps the model generalize better to unseen data and the evaluation metrics like confusion matrices ensure that a classifier has been validated for accuracy and reliability in distinguishing normal cases and tumor cases. The architecture signifies a balance drawn between depth, feature extraction and computational efficiency which makes it particularly well-suited for medical image analysis, especially for neuro-oncological diagnoses.

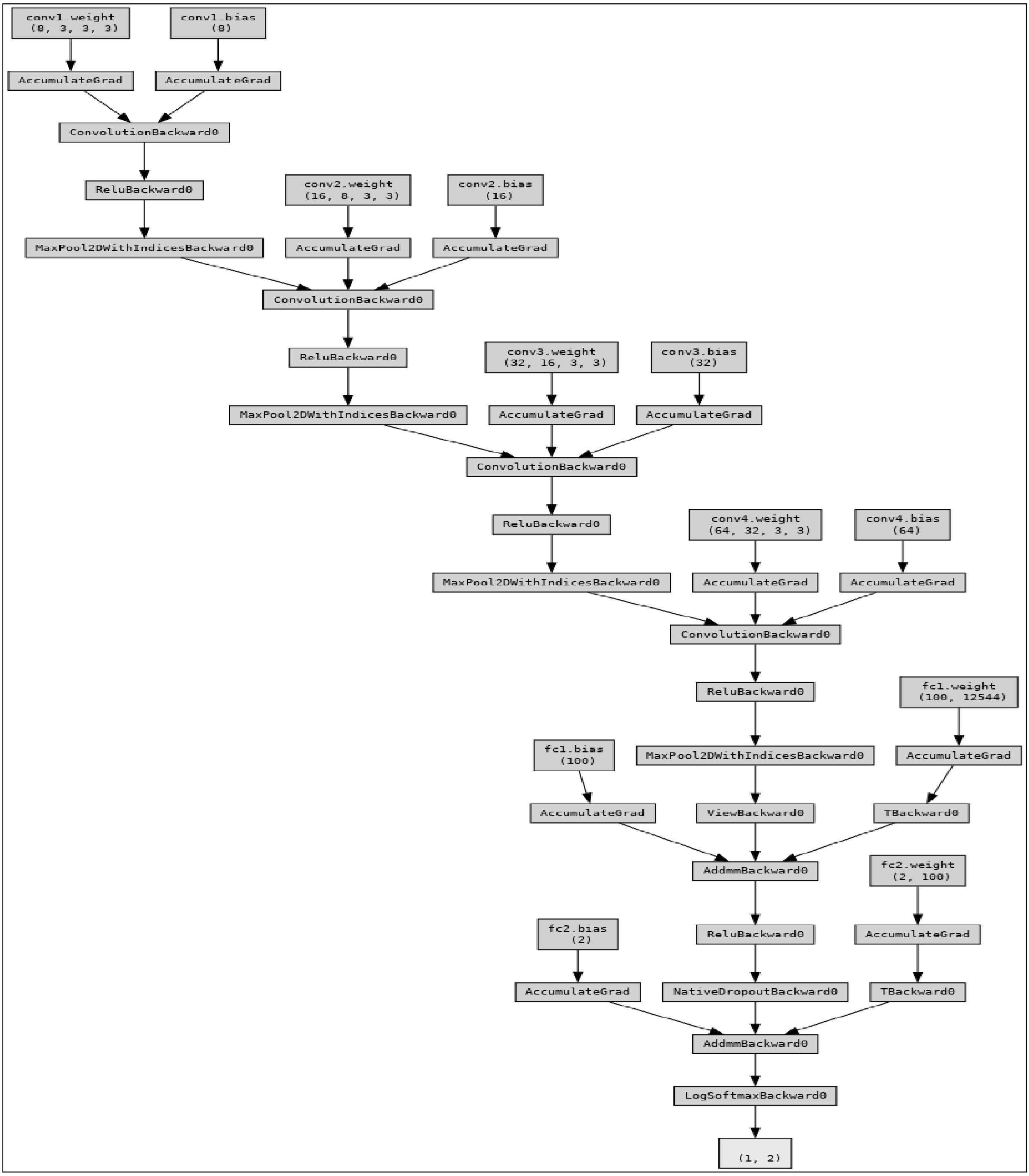

Fig. 1. CNN Model

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F. Model Training

The model was trained based on an adaptive learning rate strategy, which dynamically changes based on trends observed in validation losses during optimization of parameters. This is critical since it can fine-tune the weights of the model to minimize classification errors over the training data. A learning rate is decreased once validation performance becomes plateaued; this allows more tuning and enhances the ability of the model to converge toward optimal solutions.

The loss function selected is such that it penalizes a lot for the wrong prediction as compared to a correct one, hence tending to drive the network more toward improving its predictive accuracy. It involves several epochs consisting of rounds where the model is subjected to exposure to the training dataset followed by evaluation against the validation set based on its performance. Throughout the training process, key metrics such as accuracy and loss determine improvements in performance and are used to detect overfitting.

The training framework also enforces saving the best parameters of the model in validation. This will be saved because it is through that the practical deployment of the trained model can be ensured and that this classifier will still perform well in real applications. The iterative nature of this training along with careful monitoring and adjustment of parameters are what contributes to the overall robustness and reliability of the brain tumor detection model. From Figure 2, we can observe that both training and validation losses decrease over time, showing that the model learns from the data. It is seen that the loss stabilizes, indicating convergence. From Figure 3, it is seen that the accuracy increases steadily for both training and validation, reaching above 95%, showing effective learning and generalization of the model. The close alignment between training and validation suggests minimal overfitting.

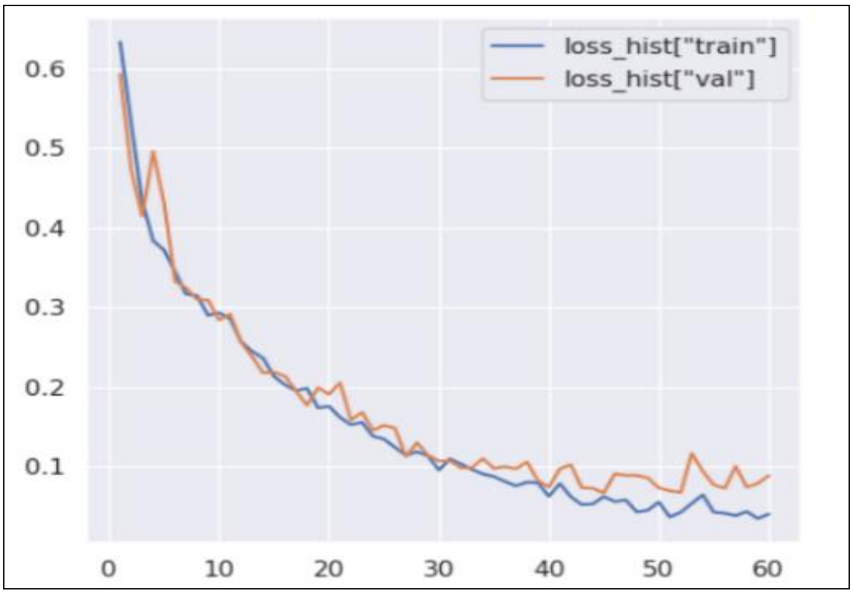

Fig. 2. Loss Graph - Number of epochs (0-60) vs. Loss value (0-0.6)

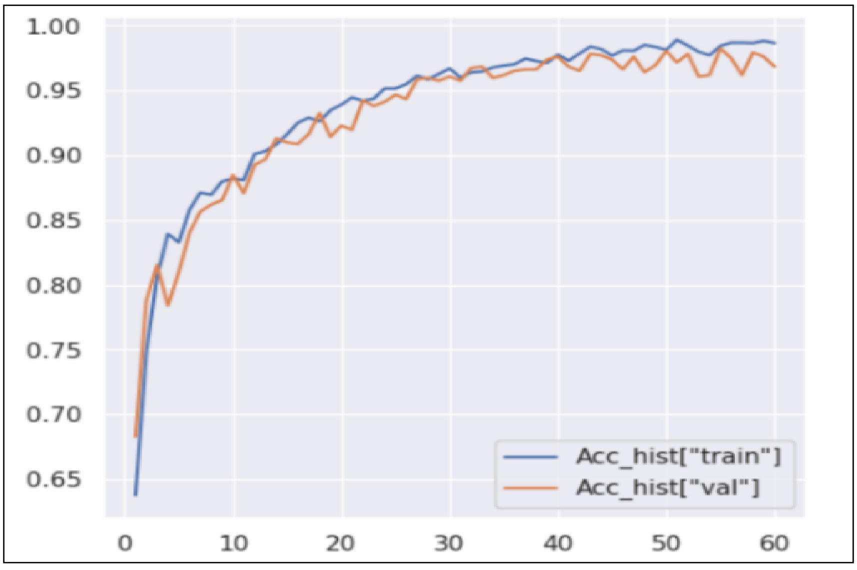

Fig. 3. Accuracy Graph - Number of epochs (0-60) vs. Accuracy values (0.65-1.00)

III. EVALUATION AND RESULTS

A. *Confusion Matrix*

A confusion matrix was constructed as shown in (Figure 4), exhibiting a good performance. There are a total of 489 true positives (correctly identified brain tumors) and 405 true negatives (correctly identified healthy cases) derived from the data set, as shown in confusion matrix. This is evidence of a model that is not overfit, and generalization has been done to new data.

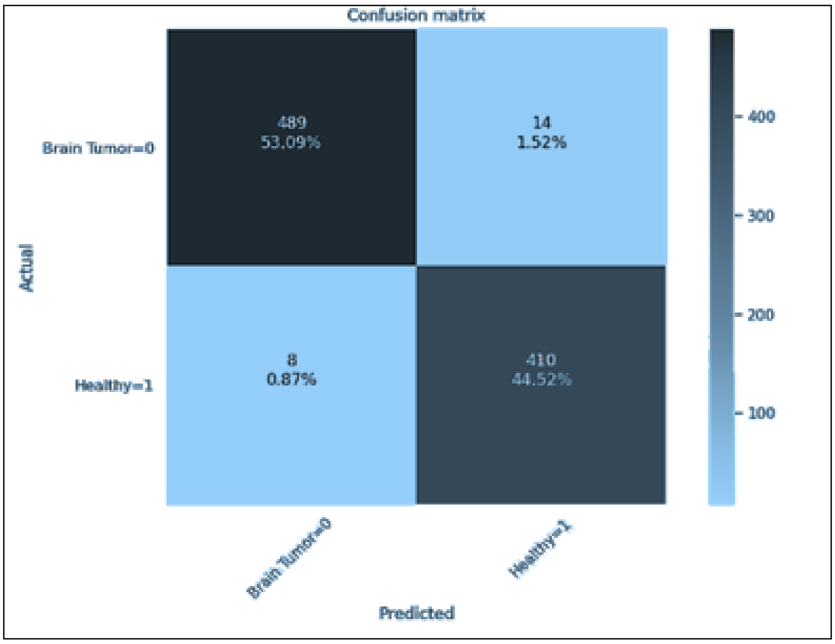

Fig. 4. Confusion Matrix

B. *Performance Analysis*

A number of metrics including precision, recall, F1-score, and overall accuracy were computed to evaluate the performance of the classifier. Learning curves show that there is an upward trend that both training and validation accuracies are going up to a point of nearly 99% within 60 epochs (Figure 3). The precision, recall, accuracy and F1-Scores for both classes are calculated as described further.

- *Precision:*

Precision is defined as the ratio of true positive predictions to all the positive predictions by the model. In case of the detection of brain tumors, high precision would mean that whenever the model predicts something as being a tumor, in most of the cases, it is supposed to be a tumor. In other words, precision is very essential for ensuring minimal false positives that may create unnecessary anxiety and subsequent medical procedures for patients. Precision can be calculated as follows:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

- *Recall:*

Also called as sensitivity, recall may also be evaluated in terms of the ability of the model to correctly identify all the actual positive cases. In the context of our study, a high recall indicates that the model is able to evaluate most of the tumors present in the MRI data set. This is quite important because a failure to diagnose a tumor can adversely affect the management and treatment of the patient. The recall is computed as follows –

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

- *F1-Score:*

Fu and Vijaya (2015) observed that F1 score is the ratio of twice the product of precision and recall to the addition of precision and recall. F1 encompasses all this by assuming the harmonic mean of both precision and recall thus enabling the over reliance on one metric to be partially overcome. In our study, it is especially important in the situation, where there are more healthy samples than tumor samples. Higher scores simply imply the score toward the F1 score is near to the value of the model for both detection of the tumor and avoidance of false alarm. The score calculation is as follows –

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + \mathrm{Recall}}$$

- *Accuracy:*

This depicts the absolute performance level of the model, describing the ratio of correct prediction instances to actual instances-prediction of true positives as well as true negatives. In our model for brain tumor detection, high accuracy means that the system identifies healthy vs. tumor-affected MRIs precisely, which would serve as a significant

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basis for practical application in clinical situations. Accuracy can be calculated thus –

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Samples}$$

Table 1 Performance metrics

Class	Precision	Recall	F1-Score
0.0 (Healthy)	0.98	0.97	0.98
1.0 (Tumor)	0.97	0.98	0.97
Accuracy	-	-	0.98

Hence, with the calculation methods as specified for the parameters under study – Precision, Recall, F1-Score, Accuracy, it is observed that the accuracy is recorded at 97%. The precision, recall and F1 scores for both classes are at nearly 0.97 which is a good indicator in evaluating the performance distribution among the classes.

IV. CONCLUSION

The present study introduces a vast methodology in the development of a machine learning-based brain tumor detection system using CNN. Thus, the approach begins with the selection of the appropriate labeled MRI dataset followed by splitting the same into training and validation sets to ensure reliability in the proposed model. The model is trained for generalization well through various conditions prevailing in images using different types of image augmentation techniques like resizing, flipping, and normalization.

The CNN showed good performance on the F1 score as 0.9784, meaning it has been accurate for the brain tumors with the least number of false positives and false negatives. This is an important thing concerning the clinical setting, as a misdiagnosis made will have a devastating effect on patient care. Thus, the results reflect not only the ability of the proposed system to be accurate but also to help in achieving early diagnosis-an essential factor in improving the patient outcome.

This study goes beyond mere classification; it hints at the possibility of inducting artificial intelligence in medical diagnostics. Further studies shall continue to look at ways of improving the size of the dataset and the architecture of the model. Then, there should be validation studies through clinical trials attesting that the system is functional. In a nutshell, this effort provides a basis for application of advanced AI techniques in oncology towards a venue for diagnostic accuracy and better patient management into the context of brain tumors.

REFERENCES

[1]. Mahmoud Khaled Abd-Ellah, Ali Ismail Awad, Ashraf A. M. Khalaf and Hesham F. A. Hamed, "Two-phase multi-model automatic brain tumour diagnosis system from magnetic resonance images using convolutional neural networks", in Eurasip Journal on Image and Video Processing, 2018.

[2]. Kevin P. Murphy. 2012. Machine Learning: A Probabilistic Perspective. The MIT Press.

[3]. S. Shanjida, M. S. Islam and M. Mohiuddin, "Hybrid model-based Brain Tumor Detection and Classification using Deep CNN-SVM," 2024 6th International Conference on Electrical Engineering and Information & Communication Technology (ICEEICT), Dhaka, Bangladesh, 2024, pp. 1467-1472, doi: 10.1109/ICEEICT62016.2024.10534376.

[4]. A. Pashaei, H. Sajedi and N. Jazayeri, "Brain Tumor Classification via Convolutional Neural Network and Extreme Learning Machines", Proceedings of the 2018 8th International Conference on Computer and Knowledge Engineering (ICCKE), pp. 314-319, 25–26 October 2018.Prokop, Emily. 2018. The Story Behind. Mango Publishing Group. Florida, USA.

[5]. H. Mohsen, E.-S.A. El-Dahshan, E.-S.M. El-Horbaty and A.-B.M. Salem, "Classification using deep learning neural networks for brain tumors", Future Comput. Inform. J, vol. 3, pp. 68-71, 2018.Brian K. Reid. 1980. A high-level approach to computer document formatting. In Proceedings of the 7th Annual Symposium on Principles of Programming Languages. ACM, New York, 24–31. https://doi.org/10.1145/567446.567449

[6]. GeÌ ron, A. (2019). Hands-on machine learning with Scikit-Learn, Keras and TensorFlow: concepts, tools, and techniques to build intelligent systems (2nd ed.). O'Reilly.

[7]. Russell, Stuart J. (Stuart Jonathan), 1962-. Artificial Intelligence: a Modern Approach. Upper Saddle River, N.J. :Prentice Hall, 2010.

[8]. Andrew Trask. 2019. Grokking Deep Learning (1st. ed.). Manning Publications Co., USA.

[9]. A. Wulandari, R. Sigit and M. M. Bachtiar, "Brain Tumor Segmentation to Calculate Percentage Tumor Using MRI," 2018 International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC), Bali, Indonesia, 2018, pp. 292-296, doi: 10.1109/KCIC.2018.8628591. keywords: {Tumors;Brain;Magnetic resonance imaging;Image segmentation;Filtering;Image color analysis;Bones;Thresholding;Segmentation;Brain Tumors;MRI Image},

[10]. Abd El Kader Isselmou, Guizhi Xu, Shuai Zhang, Sani Saminu, and Imran Javaid. 2019. Deep Learning Algorithm for Brain Tumor Detection and Analysis Using MR Brain Images. In Proceedings of the 2019 International Conference on Intelligent Medicine and Health (ICIMH 2019). Association for Computing Machinery, New York, NY, USA, 28–32. https://doi.org/10.1145/3348416.3348421

[11]. T. P. Pries, R. Jahan and P. Suman, "Review of Brain Tumor Segmentation, Detection and Classification Algorithms in fMRI Images," 2018 International Conference on Computational and Characterization Techniques in Engineering & Sciences (CCTES), Lucknow, India, 2018, pp. 300-303, doi: 10.1109/CCTES.2018.8674150. keywords: {Tumors;Feature extraction;Image segmentation;Classification algorithms;Functional magnetic resonance imaging;Support vector machines;Clustering algorithms;fMRI;brain tumor;machine learning},

[12]. Mahmoud Al-Ayyoub, Ghaith Husari, Omar Darwish, and Ahmad Alabed-alaziz. 2012. Machine learning approach for brain tumor detection. In Proceedings of the 3rd International Conference on Information and Communication Systems (ICICS '12). Association for Computing Machinery, New York, NY, USA, Article 23, 1–4. https://doi.org/10.1145/2222444.2222467

[13]. A. Goswami and M. Dixit, "An Analysis of Image Segmentation Methods for Brain Tumour Detection on MRI Images," 2020 IEEE 9th International Conference on Communication Systems and Network Technologies (CSNT), Gwalior, India, 2020, pp. 318-322, doi: 10.1109/CSNT48778.2020.9115791. keywords: {Image processing;MRI images;Brain Tumour;Image Segmentation;Image Segmentation Techniques;Brain Tumour Detection},