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Brain Tumor MRI Classification

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***Abstract*—Due to its complex and time consuming nature, magnetic resonance imaging (MRI) can be an accurate method for classifying and independently detecting brain cancers, but it can also cause difficulties and errors. A thorough examination including several modules is required, which is the main reason for the intricacy of the brain tumor detection process. An apparent answer to this problem has been made possible by the development of deep learning (DL), which has enabled auto-mated medical image processing and diagnosis systems to occur. An important approach in visual learning and picture classification is the use of convolutional neural networks (CNNs).The suggested model is combined witha unique methodology presented in this paper, which combines two picture enhancing techniques: Adaptive Histogram Equalization (CLAHE) and Gaussian-blur-based sharpening. Withthis method, various types of brain tumors are intended to be accurately classified.**

***Index Terms*— deep learning, neural networks, pre- trained models, brain tumors, magnetic resonance imaging, and classification.**

I. INTRODUCTION

An aberrant multiplication of cells in- side the brain tissues can lead to the formation of a brain tumor [1]. The World Health Organization (WHO) has determined that tumors are the second largest cause of death worldwide. Benign and malignant are the two basic categories of brain tumors [2]. Benign tumors are often not thought to pose a serious harm to a person's health. It is mostly because they do not have the same development rate as malignant tumors, cannot invade nearby tissues or cells, and do not spread [3, 4].Their recurrence is generally uncommon after the surgical removal of benign tumors. [5] Malignant tumors are more likely than benign tumors to spread to other tissues and organs, and if they are not treated quickly and efficiently, they can cause serious physiological malfunction [6]. Optimizing the survival percentage of patients with brain malignancies requires early detection [7]. The three most common forms of brain tumors that are diagnosed are pituitary tumors, meningiomas, and gliomas [8]. A neoplasm called glioma arises from the glial cells that envelop and sustain neurons.

The cellular composition of these structures includes astrocytes, oligodendrocytes, and ependymal cells [9, 10]. The pituitary gland be- comes home to a pituitary tumor [11]. The meninges, the three layers of tis- sue that lie between the skull and the brain, are the site of a meningioma, which is a tumor [12]. The referenced source states that it has been demonstrated that gliomas are classed as malignant tumors and meningiomas as benign tumors [13]. Furthermore, benign pituitary tumors have been observed [14]. The dissimilarity above represents the most notable differentiation among these three cancer variants [15].

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II. LITERATURE REVIEW

It is challenging to distinguish between various varieties of brain tumors[16]. The authors examined the clinical applica- tions of DL in radiography and outlined the processes necessary for a DL project in this disci- pline[17]. They also discussed the potential clinical applications of DL in various medical disci- plines[18]. In a few radiology applications, DL has demonstrated promising results, but the technology is not yet developed enough to replace the diagnostic occupation of a radiologist. To improve the efficacy and efficiency of diagnosis, radiologists and DL algorithms may work to- gether[19,20]. Using a range of re- search techniques, several studies have examined the potential of MRI to detect and categorize brain cancers[21]. To boost effort, out- perform prior methods, and obtain a 90.89% classification rate, Afsharet al. adapted the CapsNet architec-ture to classify the primary brain tumor consisting of 3064 pictures utilizing tumor borders as extra in- puts[22]. A approach for classify- ing brain tumors utilizing hybrid feature extraction methods and RELM was proposed by Gumaei etal[20].The authors preprocessed brain images using min–max nor-malization, extracted features using the hybrid method, classified them using RELM, and achieved amaximum accuracy of 94.23%[14].

III. IMPLICATIONS FOR FUTURE RESEARCH AND PRACTICE

Improved Classification Algorithms: Develop more advanced machine learning and deep learning algorithms to improve the accuracy and efficiency of brain tumor classification [06]. This could involve exploring novel architectures, incorporating multimodal imaging data, and leveraging transfer learning technique [14].Enhanced Feature Extraction: Focus on extracting more informative features from MRI images, including texture, shape, and spatial features, to better capture the characteristics of different tumor types and subtype [19].
Integration of Multi-omics Data: Integrate MRI imaging data with other omics data (such as genomics, proteomics, and metabolomics) to create comprehensive models for tumor classification, providing a more holistic understanding of tumor biology [17].

IV. REFERRING TO BRAIN TUMOR MRI CLASSIFICATION

Brain tumor MRI classification involves the use of machine learning and deep learning techniques to analyze MRI images of the brain and classify tumors into different categories, such as benign or malignant, and different tumor types [06]. This classification is important for accurate diagnosis, treatment planning, and monitoring of brain tumors [15]. Here are some key aspects of brain tumor MRI classification:
Data Acquisition: High-quality MRI images of the brain are acquired using specialized imaging protocols to capture detailed information about the tumor's location, size, shape, and other characteristics [02].
Image Preprocessing: Preprocessing techniques such as skull stripping, intensity normalization, and image registration are applied to the MRI images to enhance their quality and prepare them for analysis [10].
Feature Extraction: Features such as texture, shape, and intensity statistics are extracted from the preprocessed MRI images. These features help characterize the tumor and differentiate between different types of tumors [18].
Classification Algorithms: Machine learning algorithms, such as support vector machines (SVM), random forests, and convolutional neural networks (CNNs), are trained on the extracted features to classify the tumors. CNNs, in particular, have shown promising results due to their ability to learn hierarchical features directly from the images [11].

V. METHODOLOGY

The suggested approach is described in this section. It has two main parts: model training and picture preprocessing. Figure I displays the flowchart for the recommended system [21]. The preprocessing stage used CLAHE- based Adaptive Histogram Equalization and Gaussian-blur-based sharpening to improve the image quality [22]. The annotated photos were then separated into three groups (Figure II) and downsized while preserving the aspect ratio. In addition, the model was trained via 5-fold cross-validation with the Adam optimizer, and ReduceLROnPlateau callbacks were used to dynamically adjust the learning rate during training [16]. Metrics including ac- curacy, precision, recall, and F1-score were used to assess the efficacy of the suggested model [07].
This study used the Msoud MRI dataset, which is available to the public and was downloaded from the Kaggle repository. This dataset integrates Figshare, SARTAJ, and BR35H, three publicly available datasets [16]. It is made up of 7023 grayscale and jpeg images of human brain MRIs [15]. The principal forms of brain cancers included in the collection are pituitary tumors, meningiomas, gliomas, and picturesdevoid of tumors [17].

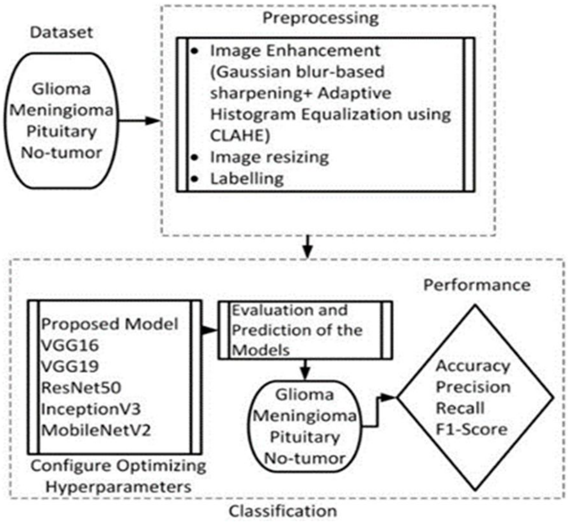


Figure 1.

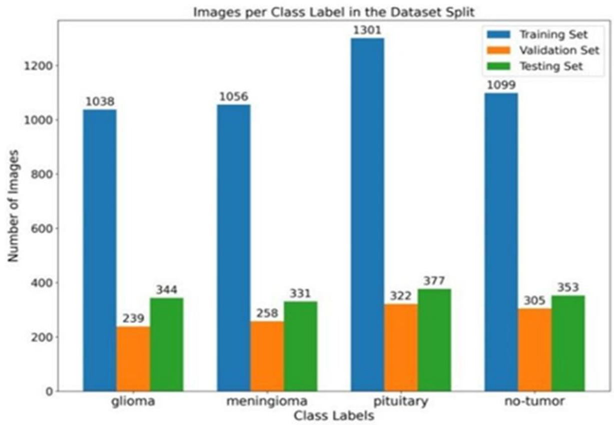


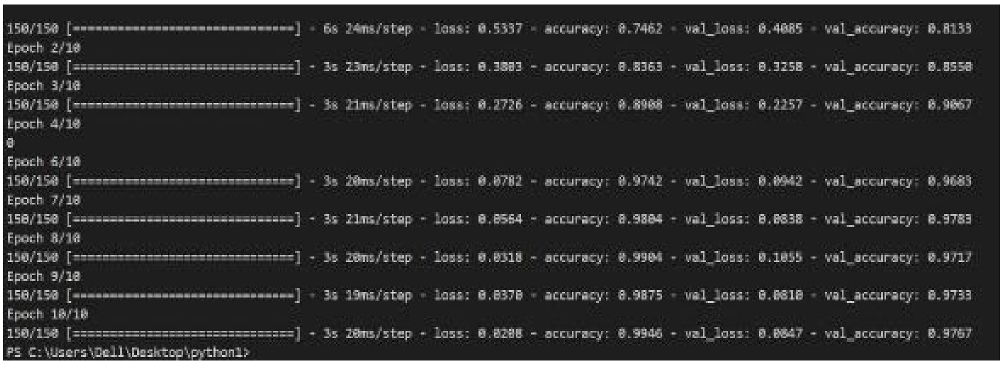
Figure 2.

VI. Results

The suggested model was utilized in this work to classify a large MRI dataset of 7023 pictures [10]. Gliomas, meningiomas, pituitary cases, and tumor free cases were all included in the dataset [06]. To improve the feature extraction, a preprocessing step was first included [14]. During this phase, image enhancement methods such as CLAHE and Gaussian blur were used to raise the image quality [14]. Three subsets of the dataset were created: training, validation, and testing [07]. The technique for training and evaluating is shown in Algorithm 1[08]. In addition, libraries like Numpy, Pandas, Matplotlib, Keras, SKLearn and Tensor Flow, were used by the platform to improve the effectiveness of data processing and model building [11]. The calculation was carried out using an Intel Core i7-7800 CPU running at 3.5 GHz [07]. GPU management for the model training and tweaking was done with an NVIDIA GeForce GTX 1080 Ti [12]. Python 3.7 was chosen as the main programming language for this research because to its extensive toolkit for data analysis, visualization, and manipulation. The platform's huge 32 GB RAM capacity allowed it to successfully maintain the data used in this investigation [19].

VII. Coding

There are some codes we use as a TensorFlow / Keras implementationfor training a convolutional neuralnetwork (CNN) for binary classification (binary_crossentropy loss function) of MRI images (assumed to be located in 'train_dir' and 'validation_dir')[6]. The CNN architecture consists of several convolutional layers followed by max pooling layers, aflattening layer, and dense layers with dropout for regularization [7].When you run this code, it will train the model on the provided MRI image dataset using the specified data augmentation and preprocessing



```
150/150 [==============================] - 6s 24ms/step - loss: 0.5337 - accuracy: 0.7462 - val_loss: 0.4085 - val_accuracy: 0.8133
Epoch 2/10
150/150 [==============================] - 3s 23ms/step - loss: 0.3883 - accuracy: 0.8363 - val_loss: 0.3258 - val_accuracy: 0.8558
Epoch 3/10
150/150 [==============================] - 3s 21ms/step - loss: 0.2726 - accuracy: 0.8908 - val_loss: 0.2257 - val_accuracy: 0.9067
Epoch 4/10
0
Epoch 6/10
150/150 [==============================] - 3s 20ms/step - loss: 0.0782 - accuracy: 0.9742 - val_loss: 0.0942 - val_accuracy: 0.9683
Epoch 7/10
150/150 [==============================] - 3s 21ms/step - loss: 0.0564 - accuracy: 0.9804 - val_loss: 0.0838 - val_accuracy: 0.9783
Epoch 8/10
150/150 [==============================] - 3s 20ms/step - loss: 0.0318 - accuracy: 0.9904 - val_loss: 0.1055 - val_accuracy: 0.9717
Epoch 9/10
150/150 [==============================] - 3s 19ms/step - loss: 0.0370 - accuracy: 0.9875 - val_loss: 0.0810 - val_accuracy: 0.9733
Epoch 10/10
150/150 [==============================] - 3s 20ms/step - loss: 0.0288 - accuracy: 0.9946 - val_loss: 0.0847 - val_accuracy: 0.9767
PS C:\Users\Dell\Desktop\python1>
```

Accuracy: 97%

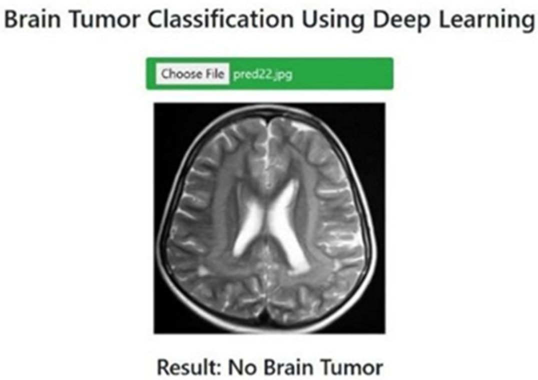


Figure 3. Result that the person having no brain tumor

settings[10]. After training, the model will be saved as 'brain_tumor_classifier.h5'[56].The output of this code will include the training and validation accuracy and loss val- ues for each epoch, as well as other metrics if specified [16]. These metrics can be used to evaluate the performance of the model and make any necessary adjustments to improve its accuracy [22].

VIII. Discussion

This investigation introduces a novel methodology for categorizing the Msoud dataset, which consists of a varied assortment of 7023 brain images [11]. The efficacy of the proposed system is demonstrated by its capacity to attain highly precise prediction outcomes, surpassing prior research endeavors with comparable aims [12]. Moreover, this study proposes a method that does not rely on segmenting brain tumor images for classification purposes. The primary advantage of our approach resides in its capacity to substantially diminish the requirement for manual procedures, such as feature extraction and tumor localization [14]. In addition to taking a lot of time, these procedures can be inaccurate [13]. The quality of the brain pictures is significantly improved by using a variety of enhancement techniques, such as Contrast-Limited Adaptive Histogram Equalization (CLAHE) and sharpening using Gaussian blur [14]. The process of enhancement is essential for sharpening edges and enhancing overall picture quality, as well as for lowering the amount of manual labor required for feature extraction [16].

IX. Conclusion

A new method for classifying several types of brain tumors—primary, meningioma, pituitary, and cases in which there is no tumor—was presented in this study [8]. This is accomplished by fusing a suggested convolutional neural network with two image enhancing techniques: Contrast-Limited Adaptive Histogram Equalization (CLAHE) and Gaussian-blur-based sharpening. Our study's results show an impressive degree of accuracy—97.84%—which was attained by carefully assessing how successful the recommended frame- work was [8]. The study's conclusion demonstrates the model's strong generalization ability, making it an invaluable and trustworthy resource for the medical industry [4]. It is clear that this approach can help medical practitioners make decisions about brain tumor diagnosis more quickly and accurately. In order to improve patient care [6].

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