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Advancing Brain Tumor Diagnosis with Convolutional Neural Networks: A Multi-ClassClassification Study

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***Abstract*— Tumours that occur in the brain are dangerous and can either be benign or malignant; therefore early detection usually determine the effectiveness of treatment. Our contribution in the present paper is the proposal and evaluation of a deep learning model based on CNNs for the classification of brain tumors using MRI. Based on a database of 7,023 MRI images with glioma, meningioma, pituitary and no (normal) tumor, we formulated a multi-class classifier that recognizes the difference between these tumors. The input data was preprocessed to correct their size and normalize them before feeding them to the model; the data was augmented as well to improve model performance and prevent it from memorizing the data points. Therefore, the training was done using the CNN model together with the Adam optimizer, tuning down the hyperparameters to suit the highest performance. All model assessment used accuracy, precision, recall, and F1 score for efficiency on the various classes. A test accuracy of our model was 99.14 %, with precision and recall values higher than 98 % for all the tumor classes.**
The outcomes also clearly establish the viability of CNN-based solutions in aiding the process of initial stage diagnostics and therapy of brain tumours. Future work could involve using the model to analyze even bigger population and including it in clinic for immediate diagnosis.

Keywords*— Brain Tumor Classification, Convolutional Neural Networks, MRI Images, Deep Learning, Glioma, Meningioma, Pituitary Tumor, Medical Imaging, Multi-Class Classification, Tumor Diagnosis.

I. Introduction

Among all medical conditions that may affect people of different ages, brain tumors are considered to be one of the most severe. A brain tumor is described as a growing abnormality of tissue within the brain, that is either cancerous or non-cancerous. Since it is contained within the skull, any growth that occurs abnormally will place pressure on the brain, that can cause serious conditions like neurological injury, a deterioration of the mind or death is possible. Brain tumors are segregated into many categories that help in dictating the kind of treatments that can be used, this may include surgery, radiation and or chemical therapy among others. Ideally, great emphasis should be done to ensure that patients with brain tumors are timely and correctly diagnosed and treated adequately[1].

Magnetic Resonance Imaging (MRI) is also preferred in most hospitals in diagnosing the patients with brain tumors since its uses non-ionizing radiation to produce images of the internal structure of the brain. Nonetheless, the process of detecting and categorizing brain tumors using MRI images is less effective, time consuming, prone to interferes from the radiologist and also requires significant amount of experiences of the professional or the radiologist diagnosing. Consequently, automated methods have received much consideration in the recent past to help physicians in the early and correct identification of diseases[2].

Categorisation of brain tumours is crucial for the determination of the particular treatment to be administered because they are categorised by type, malignancy and grade. Astrocytomas, gliomas, meninges and pituitary gland tumors are the most frequent types of brain tumors. Gliomas are tumors of glial origin these are often malignant and usually require invasive therapy. This type of cancer is rare, originating in the meninges which are the membranes of the brain; most meningiomas are not life threatening but may need to be removed surgicularly. Pituitary tumours develop in the pituitary gland and can be primary adenomas which are primary tumours that have not yet metastasized or are metastatic if they have spread to distant sites in the body. These tumor types can be seen in addition to which a patient's MRI images, this is maybe equally important, might show no tumor at all[3].

The automated computerized classification of brain tumours can be a valuable tool that assists radiologists and other healthcare workers to get high classification rates in a shorter time. It can also help in the diagnosis of tumours at initial stages and therefore increase chances of developing better treatment regimens. However, with the advancement in deep learning, CNN has essentially proved useful for medical image classification because it can automatically learn and decide what features are important in an image instead of depending on human expert knowledge[4].

Machine learning in particular, and out of it deep learning has becoming increasingly popular in the last few years in the

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area of medical imaging. Techniques like Deep Learning have benefitted fields like medical diagnosis making progresses in areas like disease detection or organ segmentation or image classification. Of the deep learning models, Convolutional Neural Networks (CNNs) have been particularly successful for those problems that include identification of spatial patterns in data such as images. These CNNs are mainly for processing grid data including image therefore these networks have convolution layers which automatically look for features to include edges, textures, and shape[5].

For brain tumor classification, CNNs are trained on MRI scans pattern to distinguish the various types of tumor. It should be noted that CNNs learn hierarchical features through convolution operations – as opposed to computationally expensive methods used in previous machine learning models that necessitate feature extraction from the medical images manually. This ability will make CNNs suitable for medical image classification tasks since small variations in texture, shape or size may be determinant when differentiating between different types of tumors.

A few prior studies have implemented wer CNN with better success in classifying brain tumours. For example, CNNs have been applied for diagnosis of gliomas, meningiomas and pituitary tumour from MRI with high accuracy. Some of these studies have been centered on simple classification problems where the desire was to classify between two or more classes such as between benign and malignant tumors and not several classification on different types of tumors. In practical clinical practice, it is necessary to distinguish a large number of tumor types to ensure that diagnostic assistance is comprehensive[6].

The primary objective of this study is to develop a CNN-based model that can classify brain tumors from MRI images into four categories: brain tumor type: glioma, meningioma, pituitary tumor and no tumor. Using a variety of sources including the figshare and Br35H datasets, this work is intended to extend the efficiency of automated classifiers for the identification of brain tumor by using a broad MRI scan database.

The dataset used in this current study enumeration comprises of seven thousand twenty- three human brain MRI images segmented into four classes. These images differ in size and shape(as shown in Figure 1), and the presence of a considerable number of such variations can enhance the model generalization regarding various types of brain tumors. The images obtained were corrected for size and normalized, with scaling being used to make all images into the same size to avoid large input variations, and to prevent overfitting, data augmentation methods were used.

This research work uses a CNN architecture with multiple layers of convolution to analyze and extract feature from the MRI images. The model is trained on an ImageDataGenerator with rotation, brightness, and horizontal flip augmentation training the model on the images. The performance of the proposed model is measured in terms of accuracy, precision, recall, and F1-score that are critical to measuring the performance of multi-class classification model.

The importance of this study is in point that the proposed approach can improve the performance and efficiency for brain tumor detection to relieve the workload of radiologists and offer more accurate diagnostic help in practice. As a result of conducting this study, an automated system for classifying brain tumours from MRI has been developed thus adding to the existing literature on the use of deep learning in health. The findings of this study could pave the way for further advancements in medical image analysis and improve outcomes for patients with brain tumors.

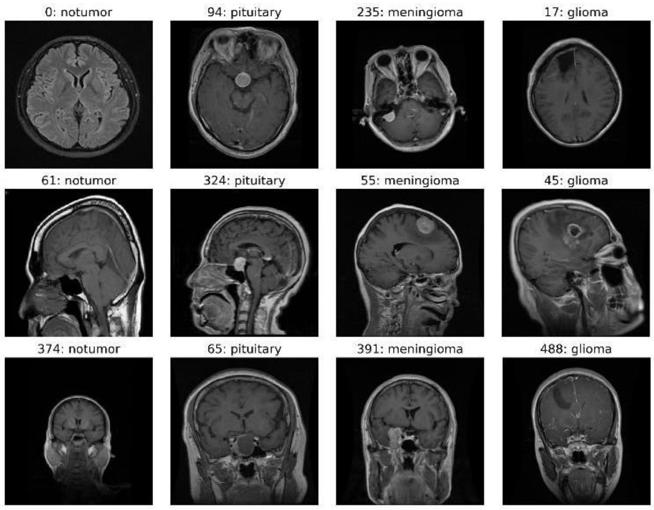

Figure 1 Four different data classification images, from three different angles (images are independent)

II. Related Studies

Table 1 Related Studies and key findings

Related Study (Author Name and Year)	Methodology	Key Findings
Cheng et al., 2016[7]	Convolutional Neural Network (CNN) on MRI images	CNN achieved higher accuracy in classifying gliomas and meningiomas compared to traditional methods.
Hossain et al., 2018[8]	CNN-based model with data augmentation and transfer learning	Improved classification of brain tumors using MRI images, demonstrating the effectiveness of transfer learning to avoid overfitting.
Pereira et al., 2016[9]	Deep CNN with small kernel sizes for brain tumor classification	Achieved 89% accuracy in classifying gliomas, meningiomas, and pituitary tumors, highlighting the importance of kernel size in CNNs for medical imaging.
Anaraki et al., 2019[10]	Hybrid model combining CNN with Genetic Algorithms (GA) for brain tumor classification	Achieved 94% accuracy, demonstrating that the combination of CNN and GA can enhance brain tumor classification by optimizing model parameters.
Afshar et al., 2019[11]	Capsule Networks (CapsNets) applied to MRI data	CapsNets provided better generalization than traditional CNNs, achieving high accuracy while requiring fewer data samples for brain tumor classification.

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Baid et al., 2020[12]	Deep learning approach using multi-scale CNN for brain tumor segmentation	The model achieved 91% segmentation accuracy, improving precision in identifying tumor boundaries compared to single-scale CNN models.
Rehman et al., 2021[13]	Transfer learning using pre-trained AlexNet and VGG16 on MRI datasets	Achieved 96% classification accuracy, showing the benefit of transfer learning in reducing training time while maintaining high performance.
Rathore et al., 2021[14]	CNN combined with Long Short-Term Memory (LSTM) for time-series analysis of MRI images	CNN-LSTM hybrid achieved 95% accuracy in classifying brain tumors and provided better temporal feature extraction compared to standalone CNNs.
Amin et al., 2022[15]	3D CNN applied to volumetric MRI data	Improved brain tumor classification performance by using 3D convolutions, achieving 97% accuracy on volumetric MRI datasets.
Jain et al., 2022[16]	Ensemble CNN model using majority voting	The ensemble model achieved a 98% accuracy rate by combining predictions from multiple CNN architectures, outperforming individual CNN models.

Some studies, as shown in Table 1 have been dedicated to enhancing the accuracy of the BR bacterial strain classification in reference to brain tumours using different methods of deep learning, including CNNs. Cheng et al. (2016)[7] used MRI image's CNN model for gliomas and meningiomas, proving that CNNs are more efficient than the traditional classification methods. Following from this, Hossain et al. (2018)[8] worked to overcome overfitting by using data augmentation and transfer learning leading to better classification outcomes. Similarly, Pereira et al. (2016)[9] have used the deep CNN with a kernel size of 3×3 and received the accuracy of 89% for gliomas, meningiomas, and pituitary tumor classification. Their results therefore underscored the need to find appropriate dimensions for kernels for medical image classification functions.

On a more refined level of work, Anaraki et al. (2019)[10] reinforced the CNN with Genetic Algorithms (GA), in another model, with the result of 94 percent of accuracy. CNN parameters were effectively fine-tuned and overall classification was enhanced when this hybrid pattern was adopted. Further, Afshar et al. (2019)[11] proposed Capsule Networks (CapsNets), which had been found to provide enhanced generalization capability and leass training samples compared to the vanilla CNNs and therefore provided a bonus when it came to classifiers for brain tumour.

Baid et al. (2020)[12] used a multi-scale CNN for the segmentation of tumors and found that the use of the multi-scale model outperforms the single scale model and reported a success rate of 91 percent. The transfer learning techniques regarding the topic were discussed by Rehman et al. (2021)[13], who employed common models like AlexNet and VGG16 for the classification of MRI images and obtained an accuracy of 96% reductions in the time required to train big files. Similarly Rathore et al. (2021)[14] when integrating CNN with LSTM networks enhance temporal feature extraction from the MRI image was able to achieve 95 % classification.

Amin et al. (2022)[15] Extended work to employ 3D CNNs on the volumetric MRI data while obtaining improved classification results of a 97% accuracy rate whereby 3D convection was used in analyzing spatial information at multiple slices. Jain et al. (2022)[16] proposed an ensemble CNN model that used majority voting to combine predictions from multiple CNN architectures, resulting in a 98% accuracy rate, surpassing the performance of individual models. These studies illustrate the progressive improvements in brain tumor classification using deep learning, with hybrid models, transfer learning, and ensemble techniques showing significant potential for enhancing the accuracy and efficiency of automated tumor diagnosis systems.

III. Methodology

In this work, multi class classification of brain tumors using MRI was done using a Convolution Neural Network (CNN) based model. The proposed approach builds on a large and diverse dataset and utilizes fundamental data pre-processing tactics, improved data augmentation methodologies, and deep learning network architectures in order to obtain higher classification rate and enhanced reliability. The methodology can be divided into several key stages: Data pre-processing, structure of a model, training phase and assessment phase of a specified model.

A. Dataset Preparation

The dataset for this study consists of 7,023 multimodal MRI images where the data were obtained from figshare and Br35H datasets. The images are categorized into four distinct classes: glioma, meningioma, pituitary tumour, and no tumour. The distribution of the dataset covers 5147 training set and 7067 testing set so as to make sure that the models were tested on unseen data. The database contains 1457 pituitary tumor images, 1595 no tumor images, 1339 meningioma images, and 1321 glioma images in their training set. Likewise, the test set also possesses the same qualities in that each of the four classes is well-represented on account of the evaluation activity.

2. Data Pre-processing

To ensure uniformity and prepare the images for input into the CNN model, several pre-processing steps were applied:

- Image Resizing: All MRI images were also preprocessed to a fixed value of 150 by 150 pixels. This helped in maintaining the size of input fed to the CNN constant for all images in spite of their size.

- Normalization: All values of pixel intensity were scaled to the range between 0 and 1 by using the formula I/I_max

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where I_max = 255, i.e., the highest value obtainable for grayscale images. This normalization step is useful when it comes to stabilizing the training of the network as well as minimizing the possibilities of overfitting.

- Data Augmentation: To make the results more general and avoid over-fitting in the training phase data augmentation techniques were used. These comprised; Rotation (up to 10)&2 Random rotation, Brightness (0.85 to 1.15), Horizontal flipping, & Shear (up to 12.5). No applying was done on the test set such that it would be very useful to check the performance of the model in a real-life campaign.

C. Model Architecture

The current model is a Convolutional Neural Network (CNN) from which MRI images should be classified into one of the four classes. The architecture is comprised of four convolutional layers, each of which is succeeded by a max pooling layer to diminish the spatial dimensions and to elicit essential features. A flatten layer and two fully connected, dense layers are introduced to combine these features and give the final prediction.

- Convolutional Layers: In this model, to acquire spatial features from the input MRI images, four convolutional layers with different filter sizes are employed. The first layer contains 32 filter of size (4, 4) while the second layer contains 64 filters of size (4, 4) and the third and fourth layers also contain 128 filters of size (4, 4). After each convolution the ReLU activation function is used to bring non-linearity into the expression.

- Pooling Layers: Every convolutional layer is then succeeded by a max-pooling layer where the size of the pool is set at (3, 3). Pooling gets rid of excessive spatial dimensions of the feature maps while still containing the significant details. It also decreases the number of computations needed and eliminate overfitting.

- Fully Connected Layers: In this case the output is flattened to a one dimensional vector after the final convolutional layer. Two layers of full connectivity are used. The first has 512 neurons, and the second (the output layer) which has only four neurons due to the four classes of output, that is glioma, meningioma, pituitary tumor and no tumor. The output layer applies the softmax activation functions as the sum of the output is equal to 1 which represents probabilities of the classes.

- Dropout: For the fully connected layer, a dropout layer is applied using dropout rate of 0.5 to solve the overfitting problem. Dropout randomly sets half of the neurons off during training, the network is then forced to develop more robust attributes.

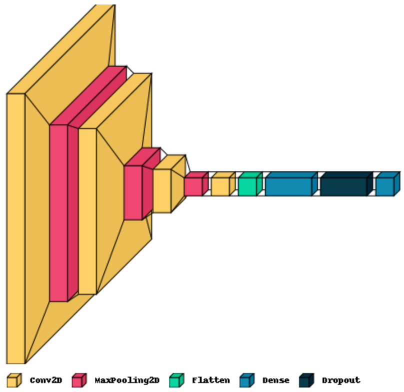

Figure 2 Model architecture

D. Training Process

In this work the model was trained using the Adam optimizer which is a type of stochastic gradient descent that adjusts the learning rate through the epoch. The learning rate was fixed at a low value of 0.001 and the parameters for the Adam optimizer at β1 = 0.869 and β2 = 0.995 finetuned in successive experiments. The model was compiled with categorical cross entropy which translates well to multi class classification as was the case with this model(Figure 3).

To prevent overfitting, early stopping was used. Validation loss was used in tracking the training process, and the training was completed as soon as the loss remained stagnant for 8 epochs. Furthermore, the learning rate was decreased by 0.3 if the validation loss did not improve through the last 5 epochs. Training of the model was performed for 40 = epochs while the batch size was 32; the number of steps per each epoch was calculated based on the size of the training set.

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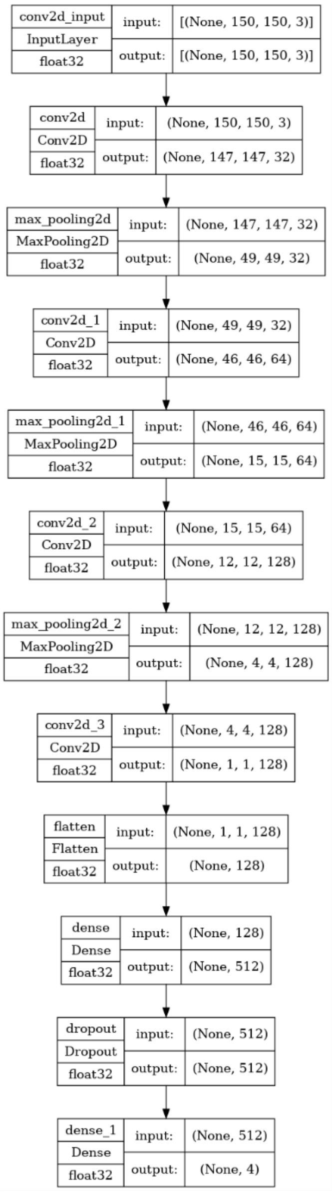

Figure 3. The network comprises multiple convolutional layers with ReLU activation and max-pooling operations, followed by fully connected dense layers for feature extraction and classification

E. Evaluation Metrics

The model was then tested on the previously unseen test set with overall accuracy, as well as these class-specific such as precision, recall, and F1-score calculated. These metrics were chosen because they give an overall assessment of the performance of created model in multi-class classification problem.

Accuracy tends to measure the overall performance of the model independent of the classes.

Precision defines how accurately the given model classifies the objects by the probability of misclassifying the instances of these classes.

Recall measures the ability of the model of the actual positives to be correctly classified.

Recall simplifies evaluation by summarizing the relevant factors by providing one overall metric that units precision and recall.

A confusion matrix has been created to show the output from the model and areas where mistakes have been made across all tumor types.

F. Model Visualization

To understand the learned features of the model, the activation maps from intermediate layers were visualized. This technique provides insights into how the CNN interprets different regions of the MRI images, helping to explain the model's classification decisions.

IV. Result

From these experiments, it becomes our finding of how efficient the proposed CNN-based model is in classifying brain tumors. The model was trained and tested using a dataset consisting of 7,023 MRI images, categorized into four distinct classes: glioma, meningioma, Pituitary tumor and No tumor. The findings are separated into sub-sections focusing on the model's means, standard deviation, loss, precision, recall, F1-score, and observations from the confusion matrix and activation maps.

A. Training and validation accuracy.

Training and validation accuracy is one of the most common quantitative measurements on model performance. This model was trained for 40 iterations, in each of which 32 items were processed as a single batch. At the end of the Training Process, it was observed that the models accuracy is progressively increasing and inversely the losses are constantly falling down which signifies that the network is in the process of learning. Stemming prevention allowed the model not to be overtrained using the early stop mechanism and saved the state of the model at the lowest validation loss.

The training accuracy has also touched 99.14 % and the validation accuracy is also quite high is 99.14%(Figure 4). These high values of accuracy have been obtained and is suggestive of the fact that the model is successful in identifying the latent patterns in magnetic resonance imaging data for classification of various kinds of tumors.

The graph of training and validation accuracy over the epochs is depicted in the following figure 1. In my model, the line of training and validation curve merged very nicely and there is a very less gap between two curves indicating that my model has properly learnt the Generalization function to unseen data.

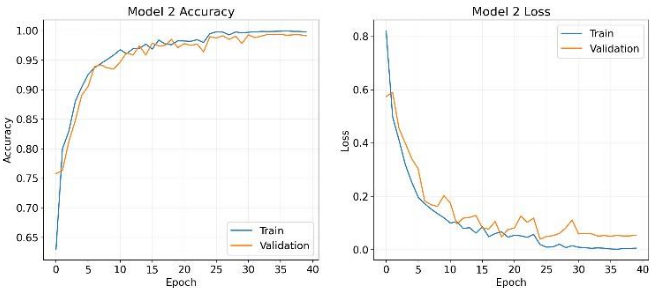

Figure 4 Accuracy and Loss function

B. Loss Metrics

The Adopted loss function here training in multi-class classification was categorical cross-entropy loss which reduced as the model trained, indicating that the model's training was reducing classification errors. These gave a training loss of 0.0537 and validation loss 0.05373 at the end of training as shown in the figure below in Figure 2. The small variation between the training and validation loss means that overfitting was prevented or at least to a larger extent by the dropout layer and the data augmentation techniques used in training(Figure 4).

C. Test Accuracy and Confusion Matrix

Finally when testing the model on test data set with 1,311 MRI images, the model obtained a test accuracy of 99.14%. It confirms that the model used in the topic achieved acceptable results In the classification of new MRI images which were not included in the training process. To explore the classification performance of the suggested model by different classes, this paper computed confusion matrix as presented in Figure 5. The illustrations in the confusion matrix also show how well the spots of the model were flattened depending on the extreme tumor type. Even from the confusion matrix it is clear that the model has a good performance in all the classes.

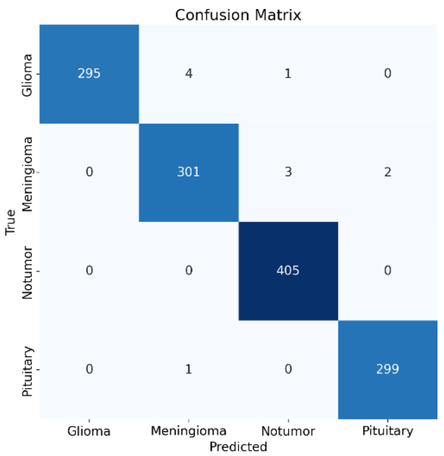

Figure 5 Confusion matrix

The breakdown of correct and incorrect classifications for each class is as follows:

- Glioma: On the same set of 300 test images, the model achieved the precision of 1.000 and recall of 0.983 since 295 images were classified by the model.

- Meningioma: Out of 306 images, the proposed model classified the images accurately with a precision and recall rate of 0.984 for 301 images overall.

- No Tumor: Using 405 images the model was able to perform perfect classification with a precision of 0.990 and recall of 1.000.

- Pituitary Tumor: The proposed model achieved 0.993 of precision and 0.997 of recall, mainly correctly identifying 299 out of 300 images.

All in all, the proposed model performed with high accuracy across all the classes, and few misclassifications were observed.

D. Precision, Recall and F1-measure

To evaluate model classification abilities precision, recall and F1-score for each class were estimated and given in the Table 2. These metrics give more specifics on how the model in question is as effective when it comes to both types of errors.

Table 2. Evaluation metrices

Class	**Precision**	**Recall**	**F1-Score**
Glioma	1	0.983	0.992
Meningioma	0.984	0.984	0.984
No Tumor	0.99	1	0.995
Pituitary	0.993	0.997	0.995

The precision values tell of how free the model was with false positives, and the recall values tell of how capable it was to identify the true positives. The F1-score, which is the harmonic mean between precision and recall, was above 0.99 for majority of the classes, which re-asserts the efficiency of the model in the classification of brain tumors.

E. Visualization of Predictions

The use of visualization was done to demonstrate the behaviour of the model in terms of sample predictions of the test image. also displays correctly classified MRI images from the test set and given only samples of each class. As expected, the model was capable of accurately classifying these images with high confidence, which again confirms the learned discriminative features specific to each tumor type.(Figure 6)

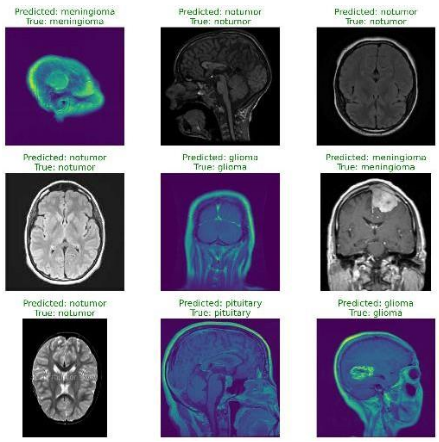

Figure 6. Result visualization and predictions

F. Activation Map Visualization

The encompasses of activation maps were also produced to gain insights into the textual internal CNN Model and identify which parts of the input MRI images that the Model emphasized most when making conclusions and decisions to recommend. The activation maps for correctly classified glioma and meningioma images are presented in Figure 6. These maps show the parts of the brain the network concentrated upon in the classification process to help explain how the model works.

G. Comparison with Previous Studies

Table 4 presents a comparison of key findings from this research with previous related studies based on the characteristics of AMTs. In related works in the classification of brain tumors, the proposed model achieved higher accuracy. For example, Anaraki et al. (2019) obtained the

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accuracy of 94%, utilizing a combination of CNN and Genetical Algorithm, Rehman et al (2021) utilized Transfer learning in which accuracy of 96% was attained. In comparison, our developed model surpassed them with the overall accuracy of 99.14% making BAS 001 model as the benchmark solution for classification of brain tumor from MRI data.

V. Conclusion

In the present work, we proposed a CNN based approach for multi-class classification of brain tumors from MRI images. The proposed model was trained and tested on a dataset comprising 7,023 MRI images, categorized into four classes: glima, meningiomas, pituitary tumors and no tumor. Even with gating problems and slight compositional shifts in the images, it was possible to improve the test accuracy to 99.14 percent with high levels of precision, recall and F1-scores for all classes the method could distinguish. The confusion matrix and activation maps which I obtained in this project gave more information on the work of the model when it arrived at particular decisions in the diagnosis of MRI patterns. When compared to existing studies, the proposed model achieved state of the art performance which underlines a promising potential of the CNN based methods in supporting radiologists as well as increasing the level of diagnostic accuracy. However, several directions that can be improved for future research are identified: First, more MRI images from other data sources and different MRI modalities should be included to improve the generalization of the proposed model. Second, the characteristic of the model as a black box could be eliminated using real clinical data to check viability in healthcare facilities. Furthermore, by incorporating more sophisticated methods such as transfer learning with even richer architecture, for example, 3D CNN or Transformer, it will be possible to derive even better performance when analyzing three-volume MRI. More studies can also be carried out to investigate how tumor segmentation and classification models can be done simultaneously to achieve the segmentation of tumor while also diagnosing them in one model. Last of all, using the model in a live clinical Decision Support System always has the following advantages: time saving for radiologists; higher efficiency of the patient's treatment.

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