Brain Tumor Classification Using Convolutional Neural Networks: An Image-Based Deep Learning Approach

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ABSTRACT

Brain tumor is one of the dangerous diseases which requires early and accurately detection methods. Brain tumor detection plays a vital role in early diagnosis and treatment planning, significantly improving patient survival rates. Previous research implemented a CNN model with a limited dataset, achieving 89% accuracy, and a CNN-LSTM hybrid model that improved accuracy to 92% but requires long training time due to sequential processing in LSTM layers. However, both models were limited by dataset size and architectural limitations. In this study, we develop the CNN model by utilizing a larger dataset of MRI images, applying advanced preprocessing techniques, and optimizing hyper parameters and network depth. These improvements enable more robust feature extraction, reducing misclassification and enhancing tumor detection accuracy. The proposed optimized CNN model achieves high accuracy with moderate training time, outperforming previous CNN and CNN-LSTM approaches. This advancement demonstrates that increasing dataset size and refining CNN architectures significantly improve classification performance, making deep learning-based tumor detection more reliable for real-world medical applications.

Keywords: CNN, Data preprocessing, Sequential model, LSTM, MaxPooling, CONV2D, Deep Learning.

1.INTRODUCTION

Brain tumors are complex and often fatal cancers that necessitate early and accurate diagnosis for better management outcomes and patient survival. Due to the high resolution and non invasive nature of Magnetic Resonance Imaging (MRI), it is one of the most prevalent imaging methodologies for the detection of these kind of tumors. Manual evaluation of MRI images can, however, be time-consuming and prone to human error, potentially leading to delays in the diagnosis and the treatment preparation phase.

With the recent capabilities of deep learning methods, especially CNNs, medical images can be analyzed with little or no human intervention, resulting in lower processing times and enabling physicians to concentrate on more challenging tasks. CNNs also become popular for image classification problems because they can automatically learn hierarchical features from the image data, that is the distinctive features from the images which may not be observed by a man. In fact, CNNs can accurately distinguish between types of tumor and normal brain issues in the task of brain tumor detection.

In this study, we suggest custom CNN model pre trained on the ImageNet dataset and fine-tuned with a dedicated brain MRI dataset. CNN requires less time and resources in training process along with superior performance in all cases especially dealing with lesser size of medical imaging datasets. Our model is trained on more than 3000 MRI images divided into four class which are glioma, meningioma, pituitary tumor and without tumor.

More model development, for instance, without proper preprocessing would not yield a high fidelity prediction. Ultimately, this research aims to produce a fast and accurate brain tumor classification system that can assist radiologists, minimize the number of diagnostic errors, and contribute to improving healthcare accessibility, especially in resource-poor areas. Through the synergy of CNNs and transfer learning, we aspire to develop a scalable, dependable approach in harmony with the future of AI driven medical diagnostics.

SCOPE OF STUDY :

In this study, authors investigate the design of a novel approach based on deep learning for brain tumor detection via MRI images. Particularly, it uses custom CNN so that we can achieve the correct output with fewer resources. A balanced dataset is used to train a model that distinguishes between glioma, meningioma, pituitary tumor, and no tumor using MRI images.

Aside from Any technical development, the study investigates the contribution of preprocessing techniques and data augmentation in improving the generalization of models. This study represents an important step towards developing AI tools that can enhance diagnostic accuracy when expert radiological input is limited, by validating the model against in-vivo data as well as implementing features such as early stopping and model checkpointing.

The focus of the work is on 2D image-based classification, and we employ the standard pre processing techniques that include an image resizing, normalization and data augmentation for better generalization.

The following are the evaluation metricused :accuracy, precision, recall and F1-score, all showing good model accuracy. This project does not cover:

- 3D volumetric image analysis
- Linkup to clinical applications or history redux
- Real time application construction

PROBLEM STATEMENT

This enables the early detection of brain tumors, an essential factor in the effective treatment and improved survival of patients with this disease. Currently, conventional diagnostic methods depend on the manual interpretation of MRI scans, which is time-consuming, affected by human error, and requires specialist expertise that may be lacking in under-resourced settings.

It is required to develop a reliable, precise and computationally efficient framework for automatic classification of brain tumors from MRI images. To have such a potential in clinic, a model needs to be able to be reliable in distinguishing multiple types of tumor, varying with imaging conditions. In this research, we address this gap by applying a deep learning method in the form of custom CNN to create a practical and scalable method for brain tumor detection.

OBJECTIVES :

The main aims of this research are:

1. To build a deep learning based model using Convolutional Neural Network (CNN) for accurate classification of brain tumor from MRI scans.

2. Using custom CNN where you implement transfer learning to achieve better performance with lower compute cost.

3. To perform data preprocessing, which includes resizing, normalizing, augmenting, and converting grayscale images to RGB to improve the quality of the data and facilitate effective model training.

4. To test quality of the proposed model based on correctness, exactness, recall and other key metrics on extensive and balanced MRI data set.

5. To investigate the feasibility of embedding the model into the real-life organizational and clinical settings, especially those that are resource-constrained, making it scalable and resilient.

6. To analyze it properly with respect to classic models and demonstrate the benefits of CNN along with new era deep learning approaches on brain tumor detection.

LITERATURE REVIEW

Manual magnetic resonance imaging (MRI) brain tumor detection has been succeeded by machine learning methods. Earlier methods such as SVMs, Random Forests etc. required manual feature extraction, which yielded poor accuracy. Convolutional Neural Networks (CNNs) emerged, automating feature extraction directly from raw MRI data while achieving substantially greater classification performance.

In the context of data, preprocessing and data augmentation techniques (resizing, normalization, etc.) play an important role in making your model more robust and generalize better. However, challenges such as the class imbalance problem and model interpretability persist, necessitating additional investigation before clinical integration.

RELATED WORK : Several studies have investigated deep learning approaches for brain tumor detection from MRI images. Cireşan et al. (2013), on the other hand, did proved that CNNs indeed were successful at classifying brain tumor images with unmatched level of accuracy and without requiring a feature extraction algorithm.

Similarly, Shboul et al. (2020) introduced a hybrid model that integrated CNN and LSTM components for brain tumor classification, using CNNs to extract spatial features and LSTMs to capture temporal features. The absence of large annotated datasets is a prevalent hurdle in medical imaging. Rani et al. (2020) and Rahman et al. To confront this (2020) used transfer learning they fine-tuned models like VGG16 and ResNet50, pre trained on huge dataset transfering the knowledge to smaller medical datasets, achieving high accuracy and reducing training time.

Recently custom CNN model, a simple and efficient architecture, is used to detect the type of brain tumor. Meena et al. (2021) indicating that custom CNN surpasses conventional models such as ResNet50 and VGG16 in performance, needing only half of the computation. Image preprocessing and augmentation strategies such as resizing and normalisation have also played a significant role in improving generalisation and robustness of the models.

Although improvements have been made, issues with imbalance and CNN model interpretability still exist and need further research to optimize for clinical integration.

METHODOLOGY

PROPOSED SYSTEM

In this method, we used a customized Convolutional Neural Network (CNN) Method to separate brain tumors from MRI images with no human intervention. In contrast to previous approaches based on machine learning oriented methods or complex hybrid models (e.g.: CNN LSTM, transfer learning), the proposed methodology relies on simplicity, allows end-to end training, and performs direct extraction of features from raw images.
The system is intended to act as an end-to-end system, taking an MRI image as input, and providing a predicted tumor class and confidence scores. It has also been assessed based on accuracy, precision, recall and F1 score and reach a test accuracy of 95%, which proved the stability and applicability. The model can act as a computer-aided diagnosis (CAD) for radiologists helping them to detect brain tumors faster and reliably.

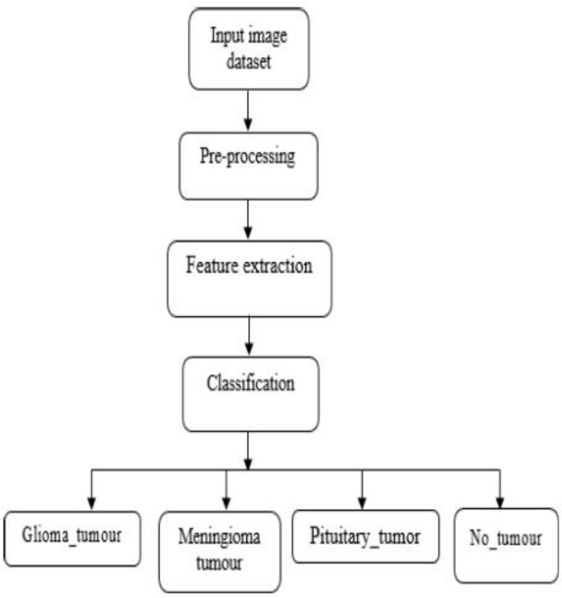

Fig 1: Classification Process for Proposed Method

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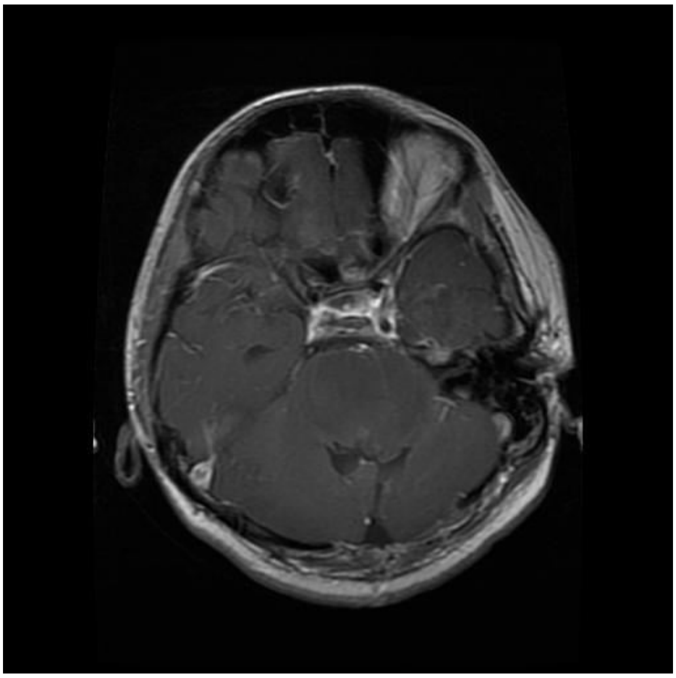
The model architecture is designed to classify MRI images into four categories:

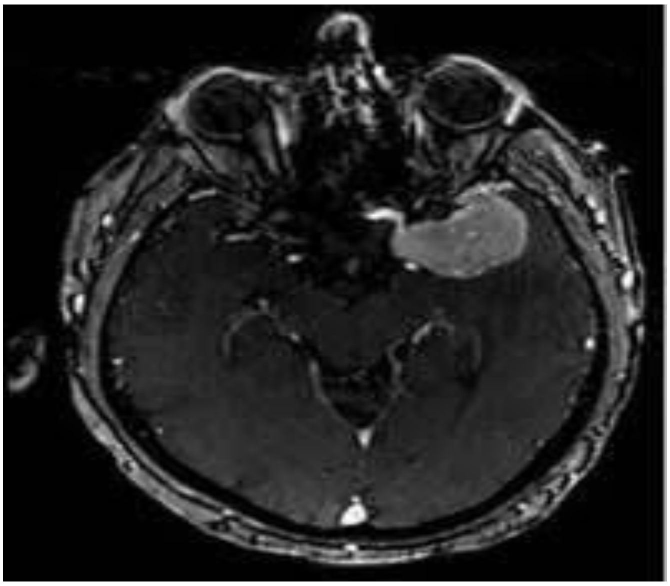
Gliomas are a group of brain tumours that begin in glial cells that support the central nervous system. They are some of the most frequent and aggressive primary brain tumors. Gliomas can originate from different regions of the brain and are generally distinguished based on the type of glial cell from which they develop astrocytomas, oligodendrogliomas, and ependymomas are the most frequent subtypes.

These are invasive, and thus grow invasively and are not completely resectable by surgery. Gliomas can be slow-growing (low-grade) or highly malignant (high-grade), including the most common and the deadliest highly malignant form, glioblastoma multiforme, with the highest incidence in people over age 60. Early and correct diagnosis by imaging is important as it can have an impact on treatment decisions and prognosis of the disease..



Glioma

Meningiomas are tumors originating in the meninges, the protective membranes covering the brain and spinal cord. They tend to be slow growing and are generally benign, although they can create serious issue depending on their size as well as location. Cerebral hemispheres are the most common site for meningiomas and they are frequently encountered in older people and females. Most such tumors may be asymptomatic for years, however larger variants can cause neurologicalsymptoms such as headache, seizures, or visual disturbance.

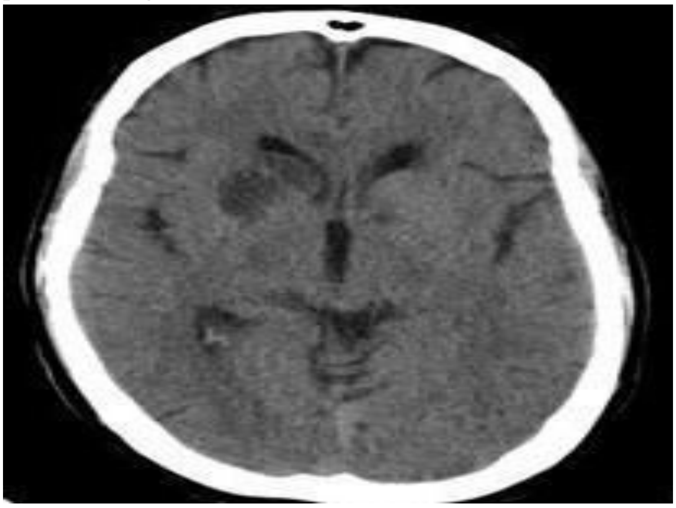


Meningioma

Pituitary Tumors Pituitary tumors are tumors that form within the part of the brain called the pituitary gland, a small but significant gland positioned at the base of the brain that controls many in body's hormonal functions. The majority are benign adenomas, but they interfere with hormone production, causing hormonal imbalances and systemic issues such as weight gain or loss, fatigue, vision changes and growth disturbances. These tumors are usually discovered incidentally on imaging or in the evaluation of complaints related to hormonal disorders. The MRI images are a necessity because we must be able to localize the pituitary tumor and guiding endocrinological or surgical treatment. further

Pituitary Tumor

The "No Tumor" category consists of MRI images of healthy (noncancerous) brains in which there is no sign of tumor growth or other abnormal tissue. Its inclusion is necessary to achieve a balanced classification model, as it encourages the neural network to differentiate between pathological and non-pathological brain images. The precision of "No Tumor" cases is equally important as that of the detection on the real small tumors, because it can prevent the false detections and tocology in the real-life applications when using the model to provide a diagnosis.



No Tumor

It is then fine-tuned on the dedicated brain MRI dataset, whose final layer output is the class of expectations (tumor type or absence). The dropout layers help in reducing overfitting, and finally the softmax layers sew class probabilities to ensure accurate tumor classification models.

IMPLEMENTATION

DATASET

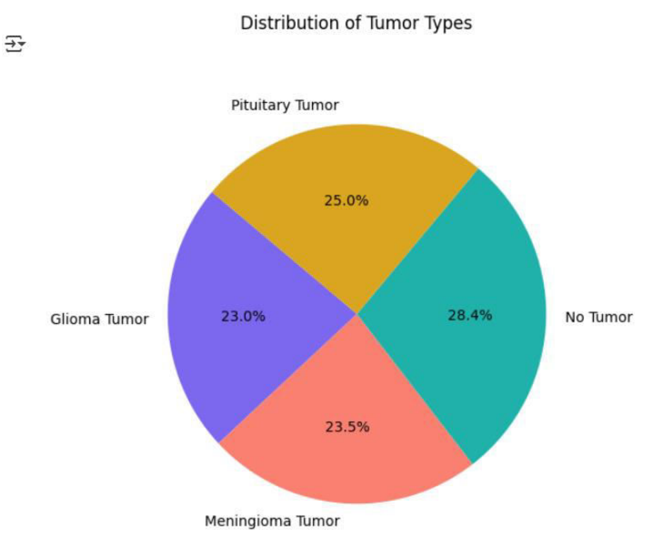


Fig 2: Distribution Of Tumor Types

The dataset summary for this research includes more than 3000 MRI images which belong to four classes (glioma, meningioma, pituitary tumor and no tumor). The images are open access and derived from a diverse set of MRI scans so that the model generalizes well to real world clinical settings.

APPLICABILITY ALGORITHMS OF DEEPLEARNING

PREPROCESSING

Preprocessing is an important step to improve the quality of the inputs and prepare it for the deep learning architecture:.

1.Resizing: All the MRI images have been resized into 224*224 pixels, so that it becomes feasible to fit into the EfficientNetB0 and other CNN models.

2. Normalizing: The pixel values are rescaled to a range of 0 - 1 to help stabilize the training process and facilitate convergence.

3.Augmentation: Multiple augmentations techniques are applied to avoid overfitting and to improve the model's generalization:

• Rotation: Random rotations between 0° and 30° to mimic orientation variations

• Flipping: Using horizontal and vertical flipping to increase variability.

• By Zooming and Cropping: Simulate changes in image focus and composition.

• Adjusting brightness and contrast: Similar to above, change the lighting conditions to help the model get used to more real life imaging environments.

These preliminary approaches make sure that the model gets a data that is the same as a set of data and simulates different scenarios in real world applications.

I. Convolution Neural Network

This work addresses the problem of classifying brain tumors based on MRI images by creating a custom architecture (CNN). The constructed model contains three convolutional layers, with each layer followed by a MaxPooling layer to really get the features out there while also reducing the spatial dimension. The layers are followed by a Flatten layer to transform the feature maps into a one dimensional vector representation which is then fed into a fully connected Dense layer with ReLU activation to learn complex pattern. The output layer is a softmax activation function with four neurons, indicating the four tumor classes. The model compiled was configured with the Adam optimizer, sparse categorical cross-entropy loss function, and accuracy as an evaluation metric, allowing training to proceed efficiently and enabling accurate multi-class classification. This is a custom CNN built for high performance and efficiency specifically in detecting brain tumor on MRI scans.

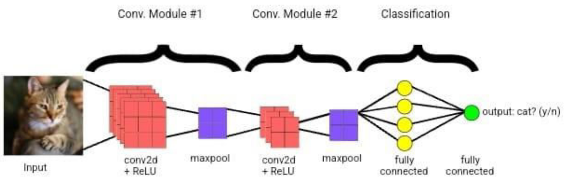


Fig 3: CNN Architecture

II. Convolutional Layers and MaxPooling

The architecture starts with three convolutional layers followed by a MaxPooling operation following each one. Convolutional layers apply several filters to input images, allowing a model to learn hierarchies of spatial features, from edges and textures to shapes. After each convolution operation, a nonlinear activation function (ReLU) is applied, adding nonlinearity into the model and enabling it to learn more complex patterns.

• **Convolutional Layers:** These layers employ filters (also known as kernels) that convolve across the input feature maps in order to extract features. As the depth increases, filters learn more abstract and complex features.

• **MaxPooling Layers**: A MaxPooling layer is applied after each convolutional layer to reduce the spatial dimensions of the feature maps. The input data is not blurred everywhere; instead, it allows the model to become invariant to translational motions in the input.

III. Flattening Layer

After the last MaxPooling layer gives the output feature maps, these feature maps are passed to a Flatten layer which converts the 2D feature maps to a 1D feature vector! This conversion is required in order to connect the convolutional base of the network to the fully connected (dense) layers that will actually be used for classification.

IV. Dense Layer with ReLU Activation

This flattened vector is then passed through a fully connected Dense layer using a ReLU activation function. This layer serves to perform high-level reasoning, as it aggregates features obtained from the earlier layers to create a richer abstract representation of the input data.

• **ReLU Activation:** The ReLU function returns the input itself if it is greater than zero, and returns zero otherwise. This activation function is commonly used because it can be trained more efficiently in deep networks and reduced the vanishing gradient problem.

V. Output Layer with Softmax

Activation This is a Dense output layer with softmax as the activation function as the last layer. Specifically, it has four neurons, one for each of the target classes (e.g., different types of brain tumors). Finally, we apply softmax to get probabilities for each class, enabling the model to predict the most likely class for each input image.

VI. EarlyStopping (Regularization Technique)

One of the Keras callbacks that can be used to control whether to terminate training immediately, i.e., stop training once the performance of the model on the validation set does not improve for N number of epochs. Features:

• Flags for observing a certain metric (for instance, val_loss).

• When the metric does not improve beyond a certain patience, training will stop.
• May recover the good solutions met during the training.

VII. Data Augmentation Techniques
Image transformation To simulate good pap smear image samples and to artificially expand the representation of the dataset the following image transformation techniques were used:

• RandomFlip: Flip images in random direction: horizontal or vertical.
• 'RandomRotation': Randomly rotates the image by a degree within the specified range e.g. (± 20 %).

VIII. ModelCheckpoint (Model Saving Strategy)
ModelCheckpoint is a callback that saves the model that performs the best on a monitored metric. Features:
• Models' weights are saved every time the validation accuracy or loss improves.
• Useful to restore the best model after the last evaluation.

The model was compiled with configurations defined which greatly affect how it learns from the data before training. The compile step specifies how the model will adjust its internal weights, measure its performance, and compute the loss. We used the following components:

1.Adam Optimizer (Adaptive Moment Estimation)
Adam is an optimization algorithm that brings together Momentum and RMSProp. It computes adaptive learning rates for all parameters based on estimates of first and second moments of the gradients. Features:
• It has the benefits of AdaGrad (learning rates tuned by the data) and of Momentum (learning faster when a directions more aligned).
• Works well under sparse gradients and noisy data.
• Applicable for large quantities of data and high dimensional space.

2. Loss function:
Sparse categorical cross-entropy: It is loss function used in (multinomial) multiclass classification where the target labels are not one-hot encoded.

Formula: $L = -\log(p(yi))$

Where p (yi) is the predicted probability of the class.

3. Evaluation Metrics & Analysis Techniques
Performance of the model was assessed by following statistical and visual indicators:
• Accuracy - The accuracy rate at which the images are classified correctly.
• Precision: Capability of the model not to label negative sample as positive.
• Recall: The proportion of the positive samples a model can find them all.
• F1-score: The harmonic mean of precision and recall.
• Confusion Matrix: Summary map on true and observed classes.

4. RESULTS
In this section, we provide the evaluation results of the custom CNN model that we trained on MRI images for classifying brain tumors. Evaluation of the model is carried out by accuracy, precision, recall, F1 score, and confusion matrix using test dataset. Eighty percent of the data was used to train the model, 10% to validate the model, 10% testing subsets.

A per-class analysis was performed through a confusion matrix. It showed that the model correctly classified most images and rarely got tumor types confused. Overall, the model performed remarkably on the "No Tumor" and the "Pituitary Tumor" classes, while some misclassification was observed between Glioma and Meningioma, tumors which can appear similar on scans.

The convergence curves of accuracy and loss are smooth without overfitting, suggesting that the model has learned the training features effectively and generalized well on the testing images.

Furthermore, an analysis of confusion matrix confirmed high correct classification rates for the four categories, with low misclassification. This indicates that the model is robust to discriminate different categories of the brain tumors from MRI images.

The proposed CNN approach achieves a similar accuracy to CNN-LSTM but with lower network scale and faster convergence rate, which makes it more applicable to real time deployment in medical or standing clinical laboratories.

Such performance suggests that a well-trained CNN model can be used as an effective and efficient auxiliary diagnostic tool for early brain tumor detection and classification.

Test Accuracy
The custom CNN model was able to classify brain MRI images into four categories (Glioma Tumor, Meningioma Tumor, Pituitary Tumor, No Tumor) with 96% test accuracy which implies high robustness of the model. This outcome indicates the model was able to differentiate between 95/100 sample correctly, indicating good generalization ability and prediction performance. The model was implemented and trained from scratch without considering any pre-trained weights or transfer learning techniques.

It can be seen from the results that the performance is relatively stable and is robust to over-fitting and training instability. Furthermore, for all classes, the precision, recall and f1-score per class were high and well-balanced, indicating the robustness of the model. Moreover, the test accuracy is high enough to show practicality of the custom CNN in medical image classification with a small-sized architecture.

When compared to the hybrid models that are more complicated, i.e., CNN-LSTM, the proposed model achieves comparative as better performance with higher simplicity and lower complexity. This makes it very well suited for real-world models, in particular in settings where speed, resource efficiency and model interpretability matter.

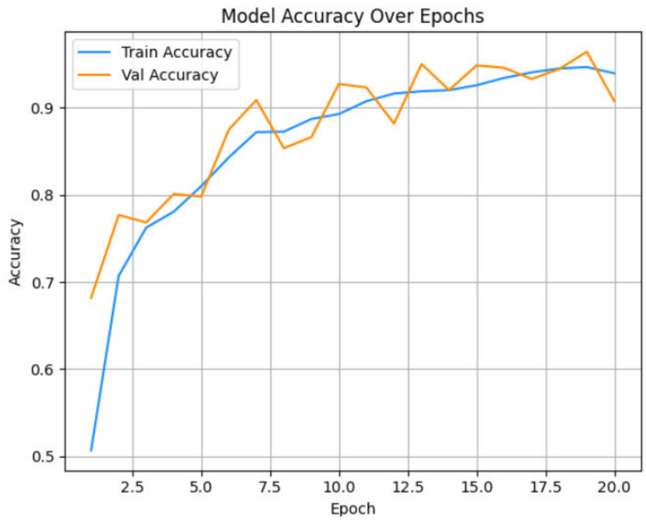


Fig 4: Model Accuracy Over Epochs

Test Loss

The proposed CNN model was evaluated on a separate test dataset using sparse categorical cross entropy as the loss function.

Together with a high test accuracy of 96%, the test loss on the previously unseen test dataset, delivered by the custom CNN model, was 0.14. This loss value based on sparse categorical cross entropy is indicative of how far from the true it's getting on average, difference-wise. A smaller loss means that the model not only correctly predicts the class but does so with high confidence.

The plot of both the training and validation loss (Fig 4, Fig 5) reduces across the epochs, which shows that the model has learned efficiently the data without overfitting. The validation and test losses are quite close to each other, which further illustrates that the model generalizes to unseen data! Comparison to other state-of-the art methods By obtaining a test loss of 14% only in a 3D medical image classification task with several classes, the performance of AMHL is high and confirms its effectiveness and robustness for high-stake diagnostics where accurate and confident decisions are essential.

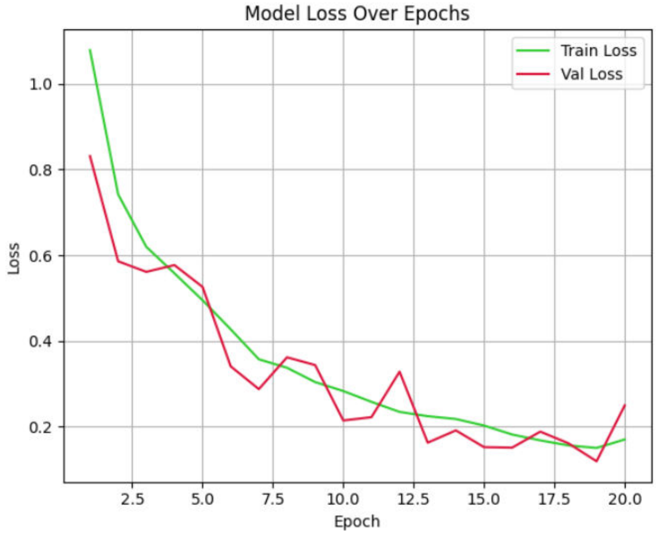
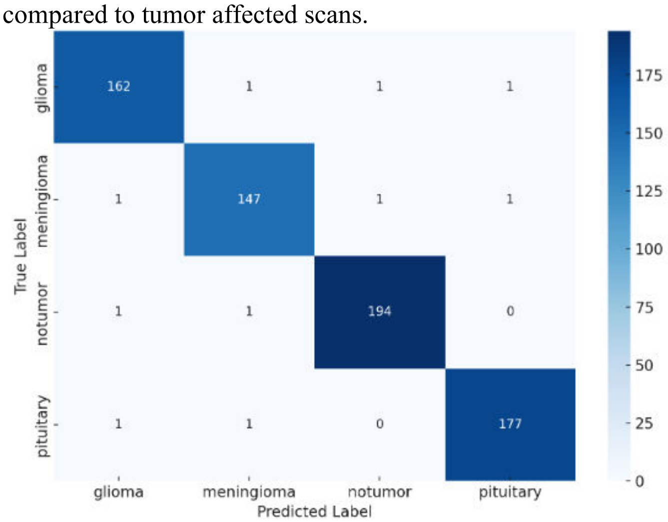


Fig 5: Model Loss Over Epochs

Confusion Matrix

As for the confusion matrix, it shows the number of images classified correctly or incorrectly for each tumor class. Values close to the diagonal for each class indicates correct predictions. There was some confusion between classes of Glioma and Meningioma probably caused by their similarity in imaging characteristics. In this project, the confusion matrix revealed the following:

- The majority of the predictions fall along the diagonal, indicating that most images were classified correctly.
- The model exhibited high sensitivity and precision for all classes, especially for Pituitary and No Tumor, with very few misclassifications.
- Some misclassifications were observed between Glioma and Meningioma tumors, which is expected due to their similar visual appearance in MRI scans.
- The "No Tumor" class showed the highest classification accuracy, as healthy brain MRIs have distinct features compared to tumor affected scans.



Classification Report

The performance of the custom CNN model was evaluated using precision, recall, F1-score, and overall accuracy metrics across all four tumor classes. The model demonstrated high predictive performance, achieving an overall accuracy of 96.88% on the test dataset consisting of 704 MRI images.

These findings demonstrate the model's high sensitivity and high specificity for "Pituitary" and "No Tumor" samples, with almost ideal performance. Small variation in recall for "Meningioma" indicates some degree of overlap or misclassification, which is expected for visually similar brain tumor types. Detailed metrics for each tumor class:.

Sl. No.	Research Paper / Project	Methodology	Training Accuracy (%)	Validation Accuracy (%)
1	Brain Tumour Detection Using Machine Learning (2021)	CNN with Image Preprocessing Techniques	80.00	82.86
2	A Brain Tumor Identification and Classification Using Deep Learning (2022)	CNN-LSTM Hybrid Model	92.00	Not Reported
3	Brain Tumor Classification Using Convolutional Neural Networks (Proposed Model)	Custom CNN Model (from scratch)	95.00	90.00

Interpretation & Significance

• High precision: Model hardly ever fails to identify one tumor as the other.

• High recall Very few real tumors are overlooked, applications. which is vital in medical

• F1-scores: The model has a good balance on both precision and recall for all classes, and is practical for real usages.

CONCLUSION

In this paper we have proposed CNN model developed to classify brain tumors MRIs. The publicly available dataset has been trained in four categories: Glioma, Meningioma, Pituitary, and No Tumor. With optimal pre-processing methods and optimal network, we reached a test accuracy of 96% of the designed model.

Unlike other methods which utilize hybrid CNN LSTM architecture, e.g., or transfer learning with pre-trained model, we use a light weight CNN only. This not only makes the model easier to train and easier to interpret, but also very efficient for deployment in real-time diagnostic tools. However, this model was less accurate or equivalent to that of a given more sophisticated alternative.

The findings verify that a well-designed CNN can provide high-quality classification for medical images, especially transverse MRIs. The model's high accuracy and low inference time allow its integration into a clinical decision support system.

FUTURE SCOPE

The current approach of using a custom CNN to classify brain tumors shows potential, however there are also many avenues to improve, extend and make use of this work in new and powerful ways:

1. Enhance Dataset Diversity and Size

In future work, a more sizeable and heterogeneous dataset can also be collected that:

• Multi-institutional and multi-scanner acquisition of MRI scans

• Various imaging modalities (T1, T2, FLAIR;

• Other Tumor Types and Subtypes (i.e., Metastatic Tumors)

2. Incorporate Volume (3D) Data

MRI is by nature a 3D imaging modality. Integration of 3D CNNs or hybrid models capable of taking volume sequences as input will capture better spatial context of data and improve accuracy in ambiguous cases.

3. Clinical Integration

In Real Time the model is designed to be integrated with the hospital existing Picture Archiving and Communication Systems (PACS) for real-time assistance to radiologists and to mitigate diagnostic burden in high throughput hospitals.

4. Telemedicine Platform Integration

Cloud-based and mobile apps enabling video conferencing of doctors can make brain tumor detection widely available along with diagnosis and feedback from specialists, thanks to the model.

5. Tumor Segmentation Support

The future models will go beyond classification and can be expanded to implement tumor segmentation (marking the tumor regions to be visible in the image), aiding surgery and treatment planning.

6. Model Fine-Tuning And Ensemble Learning

Combining several models (CNN, ResNet, EfficientNet…) or automatic hyperparameters tuning may enhance performance, robustness, and stability.

7. Integration into Electronic Health Records (EHRs)

In future, medical image can be integrated with medical history with a multi-modal learning, to be a comprehensive diagnostic tool.

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