Brain Tumour Prediction Using CNN Algorithm

MSc Research Project
MSc in Data Analytics

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MSc Project Submission Sheet

School of Computing

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Brain Tumour Prediction Using CNN Algorithm

Susanth Kumar Athanti Gurunathan

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Abstract

Diagnosis of brain tumor is a crucial problem in modern neurology because the timely and correct diagnosis of a brain tumor would make a substantial contribution to the survival of a patient and his/her medical rehabilitation. Manual MRI analysis is slow, has human error and a problem with inter-observer variation, and thus automated diagnostic solutions have an acute demand. The research question of this study is: How do Architecture and preprocessing techniques combination relating to CNNs provide the best solution to the accurate classification of brain tumors based on MRI images?

This evaluated four different CNN models based on Brain Tumor Classification MRI Kaggle database (6,056 scans of MRI with three different tumors: glioma, meningioma and pituitary tumors). The framework of our tests pitted a simple CNN model, a slightly modified CNN version through the use of the batch normalization technique, a ResNet50 transfer learning solution, and a new custom CNN-based solution inspired by the YoloV8 architecture. The preprocessing of each model involved systematic operations such as scaling of the images, normalization of the pixel values and data augmentation methods.

The CNN model based on YOLOv8 produced expected results since it had high test accuracy of 97.75%, which was a marked improvement compared to the basic CNN (88.50%), the improved CNN with batch normalization (95.42%), and the ResNet50 transfer learning model (74.33%). The Residual connection, SiLU activators, and bottle neck blocks have facilitated the use of multi-scale features extraction and sturdy classification. All this proves that specialized CNNs architectures have the potential to offer consistent, automatic brain tumor recognition, which can be of great assistance to clinical decision-making and seem to enhance medical practice diagnoses.

1 Introduction

Diagnosis of brain tumors is a major problem in contemporary neurology because proper and timely diagnosis significantly increases the chances of survival and successful treatment. Brain tumors are abnormal growths of cells within the brain and can vary in size, shape and location, thus interpretation of medical images by eye can be complex and time consuming and is also subject to the interpersonal differences between radiologists. Magnetic Resonance Imaging (MRI) is the gold standard in the detection and is a non-invasive study and has high soft tissue contrast which is non-invasive and has no Radiation exposure. The shortcomings of traditional manual MRI analysis are that it takes time, it is prone to error of the humans, variability between observers, and the shortage of radiologists worldwide. Such aspects underscore the necessity of automated and sensitive-diagnostic tools. Deep learning and specifically convolutional neural networks form a paradigm shift in medical image analysis as they are able to extract hierarchical features in an automatic fashion on raw images. This can be used to come up with smart diagnosis systems that can assist radiologists, save time and provide a higher improved accuracy in the detection of brain tumours (Das and Goswami, 2024).

1.1 Research Background and Motivation

Medical Diagnostics Integration of Artificial Intelligence (AI) Artificial intelligence (AI) in medical diagnostics has gained momentum, due to expanding access to medical imaging data and the increase of computer power. Convolutional Neural Network (CNN) has proved to be highly effective in the categorization of brain tumors, and their structures such as the YOLOv8, ResNet, and EfficientNet have reported encouraging performances (2024; Ashimgaliyev *et al.*, 2024). Nonetheless, a lot of the available studies assume the task to be solved with the help of pre-trained models that lack adjustments to specificities of MRI brain images and are reported to have lower performance and little clinical applicability. The major problems in CNN applicable brain tumor category are that the preprocessing methods are inconsistent, hyperparameter optimization is poor, and the brain tumor model does not compare with conventional machine learning algorithms. The development of models is further complicated by the variability of the MRI acquisition protocols and the scanner hardware itself and image quality. Further, the effects of various preprocessing methods like those provided by contrast enhancement and data augmentation-on the robustness of a model are less explored, even though they are known to affect their accuracies (Rasheed *et al.*, 2023). The proposed research can overcome these issues by implementing a holistic design and coming up with an optimized CNN structure that can specifically be used during brain tumor diagnosis. Through the combination of state-of-the-art preprocessing techniques and through the exploitation of automatic hyperparameter optimization through AutoKeras, it is my goal to create a sound diagnostic tool with the potential to raise accuracy, the reduction of interpretation time, and the ability to detect tumors earlier and with greater precision, ultimately leading to better patient outcomes.

1.2 Research Questions and Objectives

- "What is the optimal CNN architecture and preprocessing technique combination for achieving accurate brain tumour classification from MRI images?"

The given inquiry covers the most essential points of deep learning application in medical imaging, such as the architectural design factors, data preprocessing methods, and the improvement of performance. The main aim of this work is to create a specialized CNN model that is able to detect the presence of brain tumours in MRI with a consideration of the existing drawback regarding preprocessing, where the form and quality of the input material affect the accuracy of data representations, and in regards to the selection of model parameters as well as the evaluation processes using Brain Tumor Classification MRI dataset provided by Kaggle and developing the suggested solutions in Python.

1.2.1 Objectives

- To design a favoured CNN architecture, which is applicable to the task of detection of brain tumours based on magnetic resonance images (MRI).
- To thoroughly examine the mode of preprocessing in order to optimize the outcome of the model execution.

- Automated procedures of parameter optimisation, in order to allow such to be incorporated, which can benefit model accuracy together with operational performance.
- To conduct comparisons with the proposed model and existing models in the field, to assess the level of its performance.

1.3 Structure of the Document

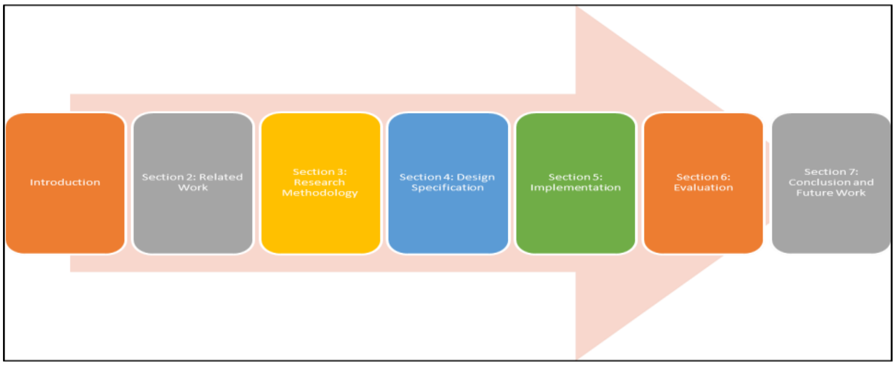

Figure 1: Structure of the Document
(Self-created)

Introduction: Emphasizes the significance of the problem of proper brain tumor diagnosis and provides introduction and concept of Convolutional Neural Networks (CNNs) as a possible method to address the existing issues of such diagnosis.
Section 2: Related Works Provides the critical evaluation of current studies on the topic of deep learning in medical image analysis, particularly, CNN-based brain tumor classification model, preprocessing, and hyperparameter optimization. Determines areas where it has gaps that are going to be filled in through this study.
Section 3: Research Methodology the details of the experimental design such as the Kaggle dataset, the chosen CNN architecture, preprocessing techniques, hyperparameter optimization via AutoKeras and analysis metrics of the model, e.g., macro average F1-score.
Section 4: Design Specification s*pecifies the architectural specifications of the suggested CNN model by showing multiple layers and justification of the design choice to provide the best performance.
Section 5: Implementation discusses the real-world practical implementation of the CNN model, setting up the software and hardware, the training aspects, and incorporation of preprocessing and optimization techniques.
Section 6: Evaluation addresses the expectation outcome, research, challenges, and clinical impact and importance of analyses made in the context of AI-based diagnostics. Has measures of performance and comparison.
Section 7: Conclusion and Future Work draws conclusions and considers the limitations of the study, and the perspectives of further work on the development of CNN-based systems, aimed at classifying brain tumors.

2 Related Work

2.1 Deep Learning Foundations in Medical Imaging

The application of deep learning to the field of medical imaging has transformed the way things are diagnosed, and Convolutional Neural Networks (CNNs) have shown superior results in the field of image-based pattern recognition. In their study, Ullah *et al.* (2022), performed a systematic comparative analysis of the AlexNet, ResNet18, and SqueezeNet architectures and have revealed that, although the models were able to perform relatively well as far as the general image classification is concerned, there is a major problem with their direct use in a domain of medical imaging because of domain-specific peculiarities. The researcher pointed out the significance of architectural alterations on medical picture analysis, yet the paper did not provide the particular needs of brain tumor detection on MRI.

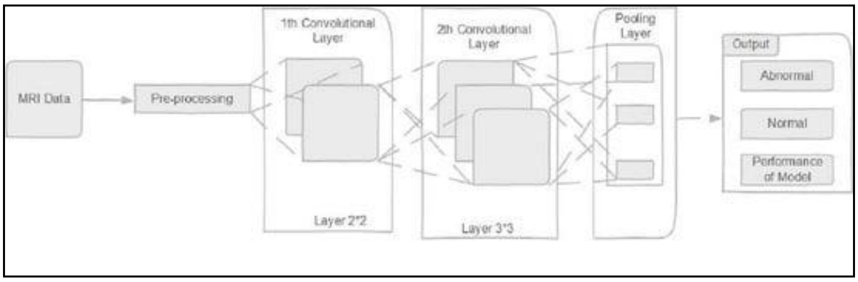

Figure 2: Deep Convolutional Neural Network Model for Brain Tumor Classification
(Source: Abd El Kader *et al.* 2021)

Abd El Kader *et al.* (2021) have contributed to the development of the field by suggesting a differential deep convolutional neural network model that has been adopted to the specific problem of the classification of brain tumors. Their style proved to have better performances than the traditional approaches to machine learning and they even coded better classification accuracy. Nonetheless, the study has a limitation regarding using a medium amount of data and not evaluating the effects of the preprocessing methods on the performance of the models well enough. The study identified the high stakes of the use of specialised CNN architectures to fit the nature of medical imaging which forms a basis of further research.

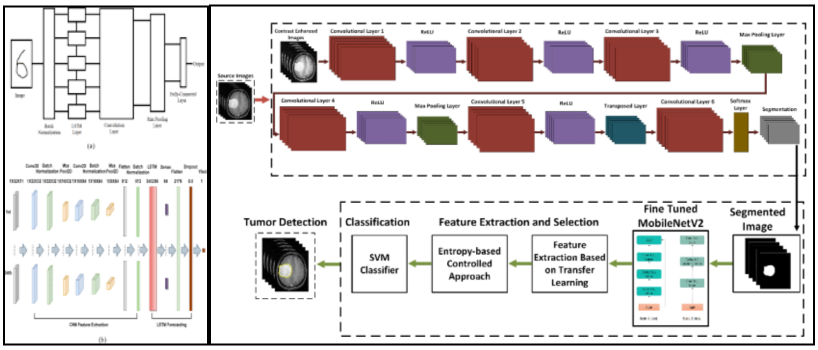

Figure 3: A Brain Tumor Classification Using Deep Learning based on CNN-LSTM
(Source: Vankdothu *et al.* 2022)

The latter development of CNN structures was further examined by Vankdothu *et al.* (2022) who presented the CNN-LSTM model to identify and classify brain tumors. This new blend combined the spatial feature extraction ability of CNNs and the capability of LSTM networks, in terms of time modeling. Although the results of their method indicated great potential, its increased training time and computational complexity posed some challenges as far as practical implementation is concerned. This has been further enhanced by Elgohr *et al.* (2024), who have shown the application of deep learning multi-classification models on brain tumor early prediction regardless of the type of the tumor, which has provided good results in early detection of a tumor in the brain but has the drawback of showing an efficiency concern on computational capabilities.

2.2 CNN-Based Brain Tumor Classification

Traditional CNN Architectures and Transfer Learning

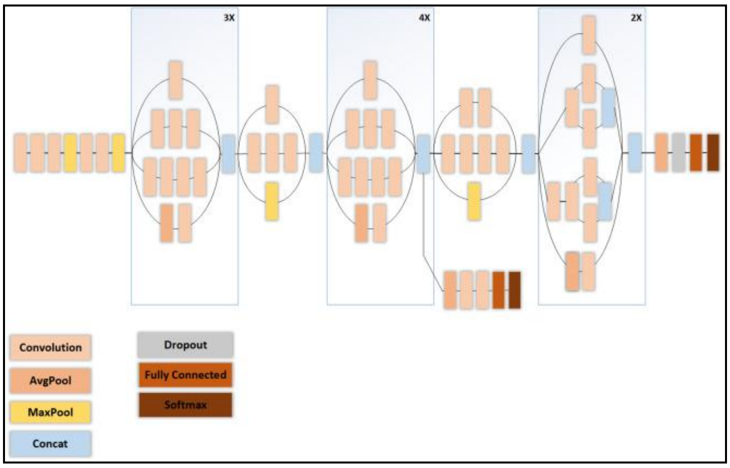

Figure 4: Improving brain tumor classification with combined convolutional neural networks

(Source: İncir and Bozkurt, 2024)

The use of known architectures of the CNN in classification of brain tumors has been vastly studied. A thorough investigation of how to enhance the classification of brain tumors by using the idea of combined convolutional neural networks and transfer learning was introduced by İncir and Bozkurt (2024). Their work established that transfer learning based on a pre-trained model can save a lot of training time without compromising the accuracy to levels that are not competitive. Nevertheless, the analysis showed that some limitations emerged when dealing with class imbalance, as well as trying to differentiate between similar types of tumors, suggesting that some particular architectural changes were required.

The study by Ashimgaliyev *et al.* (2024) has been useful in the area because it combined the methods of segmentation and deep learning to arrive at a proper diagnosis of brain tumors based on MRI. They used VGG16, ResNet50 architectures and sophisticated segmentation techniques to yield a better localization accuracy.

The research study by Remzan *et al.* (2024) contributed to the expansion of the discipline because it explored the RadioImageNet pre-trained convolutional neural networks in classifying brain tumors. They used an ensemble learning methodology where they used traditional machine learning classifiers along with multiple CNN architectures in order to show better results than the single models.

2.3 Preprocessing and Optimization Techniques

The importance of the preprocessing techniques to categorize brain tumor using CNN has been analyzed very well. Rasheed *et al.* (2023) have carried out an in-depth study on image enhancing methods plus CNN methodologies of brain tumor classification using MRI scans. According to their study, the adaptive histogram equalization and contrast enhancement can markedly increase the accuracy of the classification.

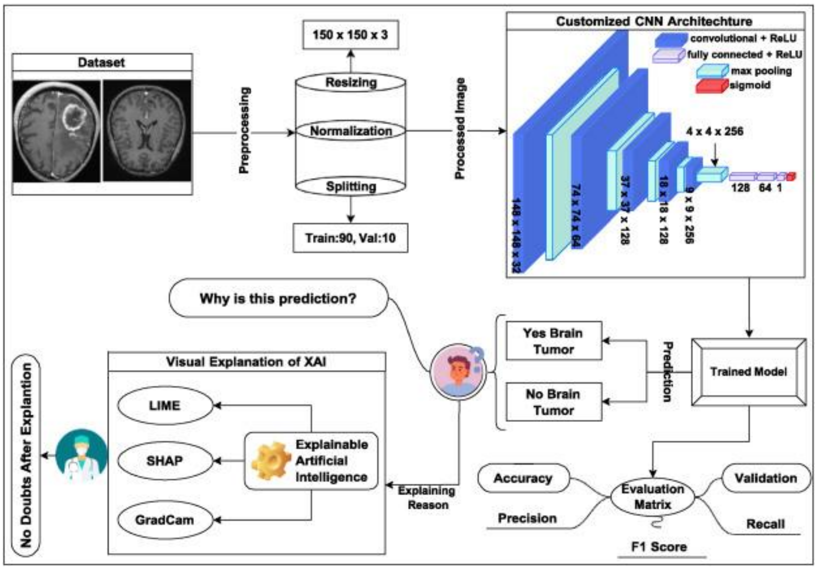

Figure 5: Utilizing customized CNN for brain tumor prediction with explainable AI

(Source: Nazir *et al.,* 2024)

Nazir *et al.* (2024) also provided their contributions by using tailored CNN frameworks to predict brain tumors using explainable AI. They solved the black-box nature of deep learning models problem by introducing interpretability mechanisms in their approach. On the one hand, their input enhances the clinical applicability of the field; on the other hand, however, their study limitation is that it is based on explanation generation and not the overall performance optimization, so there is potential to improve the architecture. Karthikeyan and Lakshmanan (2024) also confirmed the segmentation of images through the process of MRI brain tumors with the help of advanced AI algorithms, showing an increase in tumor edge detection but with regard to difficult irregular shape of the tumor.

2.4 YOLO-Based Detection and Segmentation Approaches

2.4.1 Real-Time Detection Frameworks

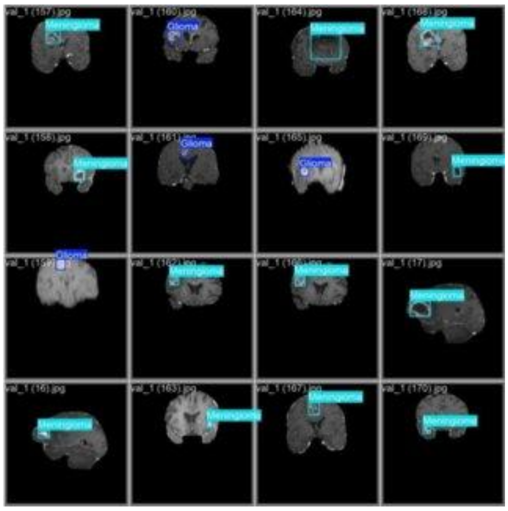

Figure 6: Brain Tumour Identification using Improved YOLOv8
(Source: Dulal and Dulal, 2025)

The implementation of YOLO (You Only Look Once) architectures in brain tumor has earned much attention as they work in real-time. Dulal and Dulal (2025) proposed a better YOLOv8 solution that annotated and localized brain tumors due to faster detection of brain tumor in contrast to CNN classification methods. They add value to it in the sense that they have made real-time processing performance possible with the competitive accuracy. Nevertheless, lack of assessment of the variety of tumors and little use of comparison to specialized medical imaging architectures are the limitation of the study.

In their research, the segmentation and classification of brain tumor MRI images with the help of the YOLOv8 were effectively explored (Taradale and Kattimani, 2024). Their strategy has integrated the detection and segmentation functions in the same framework proving to be more clinically applicable. The strength of the research is that the study covers the performance of detection and segmentation comprehensively, but it found out that it has weakness with the small sides of the tumor and challenging variations in anatomies. Abdulrahman (2024) used his study comparatively to examine the ResNet and YOLO algorithms in tumor classification in MRI images, and he found that the YOLO was faster in detection than ResNet, which held superiority in the classification accuracies.

2.4.2 Advanced YOLO Implementations

The effects of the backbone selection of YOLOv8 models on brain tumor localization were studied by Ranjbarzadeh *et al.* (2025), which delivered valuable information regarding the architectural design factors. Their unbiased comparison of the various backbone networks brought out a lot of performance variation that demonstrated the point of backbone selection in medical imaging.

Abraham *et al.* (2025) have applied a new idea to the field by suggesting dilated convolution, as well as YOLOv8 feature extraction networks, to enhance MRI-based brain tumor detection. Their methodology is able to solve the problem of multi-scale feature extraction in medical images where enhanced detection accuracy has been demonstrated with tumor sizes of different sizes. Continuing on this work, Reddy *et al.* (2024) added the advanced brain tumor segmentation and detection outcomes employing the YOLOv8 network, with the latter to perform the needed brain tumor segmentation in a more accurate method, yet with estimated difficulties in efficient real-time deployment.

Mahale *et al.* (2024) also helped with brain tumor detection using the YOLOv8 implementations devoting their effort to discussing the optimization strategies in medical imaging.

2.4.3 Novel YOLO-Based Approaches

Hashemi *et al.* (2024) proposed an anomaly-aware brain tumor diagnosis using YOLOv8 and DeiT (Data-efficient image Transformers), the integration of object detection with transformer-based classification. Their strategy has also shown improved diagnosis by the use of hybrid topologies which have imposed a large challenge of the extensive computational requirements.

Devadharshini (2024) considered MRI brain tumor detection methods with image segmentation techniques using advanced artificial intelligence algorithms, in which the segmentation performance was enhanced with novel methods of preprocessing. According to the research, stronger capabilities of detecting tumor boundaries were achieved at the cost of working with heterogeneous tumor appearances. Taha *et al.* (2025) compared the YOLOv11 and YOLOv8 in the context of a deep learning approach to glioma, meningioma, and pituitary tumor detection and demonstrated a difference in their performance along with key benchmarks to set future studies.

2.5 Comparative Analysis of Brain Tumor Detection Approaches

Table 1: Comparative Analysis of Brain Tumor Detection Methods

Author	Year	Model/Method	Limitations
Ullah *et al.*	2022	AlexNet, ResNet18, SqueezeNet	Limited medical imaging adaptation
Abd El Kader *et al.*	2021	Differential Deep CNN	Small dataset, insufficient preprocessing evaluation
İncir and Bozkurt	2024	Combined CNN and Transfer Learning	Class imbalance, similar tumor type distinction
Ashimgaliyev *et al.*	2024	VGG16, ResNet50 and Segmentation	Limited dataset diversity, preprocessing analysis
Rasheed *et al.*	2023	Enhanced CNN using Image Enhancement	Generalizability across MRI protocols
Dulal and Dulal	2025	Improved YOLOv8	Limited tumor type evaluation
Ranjbarzadeh *et al.*	2025	YOLOv8 using Backbone Analysis	Focus on localization over classification
Nazir *et al.*	2024	Customized CNN and Explainable AI	Performance optimization limitations
Abraham *et al.*	2025	Dilated Convolution and YOLOv8	Increased computational complexity
Hashemi *et al.*	2024	YOLOv8 and DeiT Hybrid	High computational requirements

2.6 Research Gaps

As much as brain tumor classification using CNN models has made major strides, multiple research gaps still present exist. The topics covered in the current literature involve mainly the application of readily available architectures without much attention paid to the MRI specific features and domain requirements. The disparities in assessments of preprocessing techniques within the studies further restrict the opportunity of creating uniform methods of the clinical practice.

Moreover, available studies have limited hyperparameter optimization methods, and many of them are tuned manually, which is not applicable in some cases to reach optimal performance. The fact that automated machine learning methods, including AutoKeras, are still not integrated as widely as possible may be discussed and understood as a huge potential of making the field more efficient and accessible.

As indicated in the comparison analysis, all the individual studies presented are informative, but no systematical methods have ever been suggested to integrate the architectural optimization, preprocessing enhancement and the automation of hyperparameter tuning within a common framework. In this research it can be solve by addressing the research gapes and implement the better CNN architecture on various models to get the proper and improved output.

3 Research Methodology

3.1 Research Design and Approach

The paper uses a quantitative experimental research design that applies the supervised machine learning algorithm to the classification of multi-class images. Its research design can be described as a comparative analysis, where four different CNN architectures have been applied, and their performance is being tested to classify brain tumors. Such a solution corresponds to well-established methodological approaches to medical image analysis studies, evidenced by Ashimgaliyev *et al.* (2024) and It can be stated that the selection was made based on similar comparative frameworks with CNN-based brain tumor detection .

3.2 Dataset Description and Preprocessing

3.2.1 Data Preprocessing Pipeline

The preprocessing approach establishes current techniques in the preprocessing literature on medical images. According to the recommendation provided by Rasheed *et al.* (2023), the images are pre-processed vigilantly through:

- Image Resizing: Every image can be normalized to 224x224 which is also acceptable by CNN inputs but can also ensure the model cannot consume a lot of computation resources

- Pixel Normalization: The values of the pixels are normalized to the range [0, 1], and this is by dividing the pixels by 255, this ensures that scaling of the different input values to different pixels is consistent to all of the samples
- Data Augmentation: The use of rotation, horizontal flip, and altering the level of brightness with the aim of ensuring that the models generalize more and this was done according to procedures as laid out by Karthikeyan and Lakshmanan (2024)

3.2.2 Strategy of Data Partitioning

To ensure a similar distribution of classes between training, validation and test sets, one carries out stratified splitting of the dataset. The partitioning is done in proportion of 60:20:20 giving 3,600 as the training data, 1,200 as the validation data and 1,200 as the training data. This distribution provides sufficient training data as well as a validating and testing enough sample to demonstrate strong performance assessment, in-line with what Nazir *et al.* (2024) recommend.

3.3 Model Architecture Development

Basic CNN Model: An original sequential network with four convolutional layers with successive enlargement of feature map (32, 64, 128, 128 filters), including a max-pooling and a dropout regularization. This baseline model defines some basic performance reference points.

Improved CNN with Batch Normalization: An extension with some additional layers of batch normalization which follows each convolutional operation and solved the immediate problem of internal covariate shift as mentioned by Elgohr *et al.* (2024). The architecture has an extra convolutional unit (256 filters) in an attempt to make the model more capacious.

ResNet50 Transfer Learning Model: The pre-trained ResNet50 design with the frozen backbone weights which are implemented in the transfer learning approaches shown by Remzan *et al.* (2024). The model consists of custom layers of classification that are best suited to the three classes of brain tumors.

YOLOv8-Inspired CNN: A new model that has a unique design aspect by YOLO object detection designs including residual connections as well as SiLU activation functions. The design deals with the issue of multi-scale feature extraction that has been raised by Abraham *et al.* (2025) and Yao *et al.* (2024).

Training Configuration and Optimization

Generally, all models use categorical cross-entropy as loss function and an Adam optimizer with learning rate scheduling and early stopping by models. Training incorporates:

- Batch size: There can be 32 samples in each batch, with a limit of memory in exchanging with gradient stability in mind
- Learning-Rate: This on the implementation has done 0.001 (factor=0.2, patience=5)
- Early Stopping: Patience=10 epochs to wait before quitting the training process and preventing overfitting because of the monitoring of the validation loss

- Epochs: 100 (automatically stopped in accordance with the conditions of convergence)

The foregoing structure is consistent with the optimizing approaches supported by Dulal and Dulal (2025), and Thakur and Chauhan (2025) in their experiments on using YOLO to identify brain tumors.

3.4 Performance Metrics

The assessment framework can cover numerous metrics to have the full picture of performance measurement:

1. Accuracy is denoted by total correct classification by all classes
2. Precision, Recall and F1-Score: Precision, Recall, and F1-Score are estimated in a weighted-average in the data.
3. Confusion Matrix Analysis: Fine-grained study of prediction per-class dynamics

Per-Class accuracy: A measure of the performance of each of the classes to determine the strengths and weaknesses of the model.

4 Design Specification

4.1.1 Architectural Framework

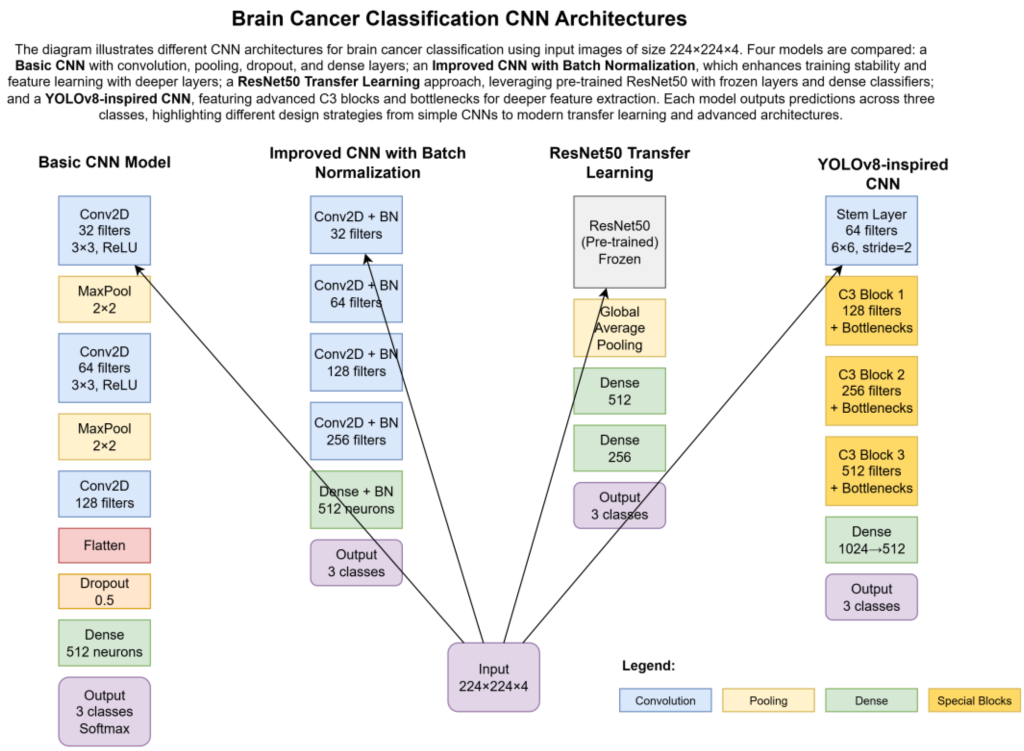

Figure 7: Architectural Framework
(Self-Created)

4.2 Configuration and Optimization Strategy of training

The design employs the same optimization techniques on any architecture and makes use of categorical cross-entropy loss and Adam optimizer (learning rate 0.001). The adaption of the learning rate using the ReduceLROnPlateau callbacks (factor=0.2, patience=5) and early stopping techniques (patience=10) avoid overfitting and provide maximum convergence. The preprocessing pipeline is actually normalizing genuine inputs to 224224 pixels with assortment of pixel to [0,1] range with data augmentation methods similar to rotation and brightness variance so as to boost the generalized performance of data.

4.3 Development Environment and Technical Infrastructure

It has been deployed with Python 3.13 being the main programming language that utilized the deep learning framework of TensorFlow 2.14.0 through which the model was developed and trained. The full technical set also included needed libraries such as NumPy and Pandas to work with the numerical and structured data, the OpenCV library to conduct the image processing operations, scikit-learn to calculate the evaluation metrics and data partitions, and Matplotlib and Seaborn to display the results. The development environment was Jupyter Notebook which provided an environment to test and develop the models.

5 Implementation

5.1 Data Processing and Pipeline Implementation

Dataset Specification

The study collaborates with server Brain Tumor Classification MRI dataset provided on the Kaggle platform which consists of 6,056 MRI scans split into three categories namely brain_glioma (2,004 scans), brain_menin (2,004 scans) and brain tumor (2,048 scans) (Rahman, Md Mizanur, 2024). The data set can have a much more balanced representation of tumor types, which can ensure that the problem of class imbalance in medical image-based data sets is not an issue. Each image has identical dimensions of 512 pixels across and 512 pixels high so there is consistency in the data parameters of the inputs.

The process of preprocessing a data pipeline was performed using a full-fledged system that processed the Brain Tumor Classification MRI dataset Kaggle that has 6,056 MRI images equipped with the three types of Brain Tumor. Custom data loading functions were built to easily sort the data in an organized way, keeping it to a single standard of preprocessing and eliminate sources of error in the case of potential corruption or inconsistencies in data formatting.

The image preprocessing part was implemented with complex image compression algorithms that down sample all the inputs to a size of 224 224 pixels width and height through bilinear interpolation to maintain the quality of the images. The process of pixel normalization was fixing by the vectorized operations that convert an integer value of pixel (0-255) to a floating-point range in the [0,1] area so that the neural networks can be trained consistently with all architectures.

Data augmentation methods have been applied with the help of TensorFlow image processing functionality, which includes applying rotation steps, horizontal flipping and scaling of brightness levels. The augmentation pipeline was formulated in a manner that preserves the balance of classes within the data set, but makes it more diverse, ensuring more generalization capabilities of the model, which is no longer artificially biased. It was stratified to ensure that both classes were equally represented in training (60%, 3,600 images), validation (20%, 1,200 images) and test sets (20%, 1,200 images).

5.2 Model Architecture Implementation

5.2.1 Basic and Improved CNN Models

The implementation of the standard CNN model has relied on the use of TensorFlow Sequential API to develop a model that is both clear to be read and consists of a total of very four layers of convolution following the use of ReLU activation functions as well as max-pooling tasks. The amount of drop out layers was implemented in a strategic way, and the rates were optimized so that they did not overfit the model and extend beyond its limits.

The improved version of CNN architecture based on the simple one that incorporates the strategy of using the batch normalization layers after each of the convolutional components and the use of the batch normalization parameters should be initialized and training and inference states should be addressed. In order to increase the model size and be apposite at the same time in terms of computation, the architecture had an additional convolutional layer (256 filters) added to the architecture.

5.3 Implementation of Transfer Learning

This used the ready-made pre-trained models that are implemented by TensorFlow as our ResNet50 transfer learning model that relied on the ImageNet weights. Substitution of the classification head, the custom layers designed to ensure three-class prediction, was conducted by keeping the convolution backbone frozen and retaining the representations of these features that are already learned.

Specific preprocessing functions were designed to use a converted four-channel MRI to three-channel RGB to be applied to ResNet50. There were lambda layers of implementation that contained instances of channel manipulation involving global average pooling with a global average, dense layers, and the right dropout regularization among others.

5.3.1 YOLOv8-Inspired Architecture

The direct implementation of CNN in the form of Yolo was the most radical architectural change in terms of application of residual connection and layers together with the SiLU activation curves. The complex network structure was constructed using the functional API of TensorFlow in the implementation and residual connections and the processing of multi paths of features were a possibility.

The implementation involved bottle neck blocks containing 1 x 1 and 3 x 3 convolutions that were used to mine out the best features without using extra resources in calculations. The batch normalization layers were strategically placed in select parts of the network and appropriate weight was put on the initialization of the parameters and the gradient improvement flow which was done through residual connections.

5.4 Training and Optimization Implementation

The implementation of training involved advanced optimization techniques, which means that Adam optimizer with adaptive learning rate scheduling was used. Validation loss monitoring was also used to automatically stop training on early stopping callbacks. The deployment consisted of full-featured logging of training progress and Tensor Board analytics of performance monitoring.

Custom training loops were created so that different model architectures could be treated the same with respect to comparison of performance. The automated batch generation during implementation was done to maximize memory usage and the training processes used the same steps on all four versions of models.

6 Evaluation

6.1 Experiment 1: CNN Model

Classification Report:

	precision	recall	f1-score	support
brain_glioma	0.9233	0.8425	0.8810	400
brain_menin	0.8220	0.8775	0.8489	400
brain_tumor	0.8922	0.9100	0.9010	400
accuracy			0.8767	1200
macro avg	0.8792	0.8767	0.8770	1200
weighted avg	0.8792	0.8767	0.8770	1200

Figure 8: Basic CNN Model Result
(Jupyter Notebook)

The simplest form of CNN obtained a final test accuracy of 87.67 percent. Precision, recall, and F1-score had values of about 0.877, which signifies that the performance over these measures is balanced. The model showed a different level of accuracy among the available classes: in the case of brain glioma, the recall was 84.25%, in the case of brain meningioma, the value of recall was 87.75%, and in the case of brain tumor, the value of recall was 91%.

6.2 Experiment 2: Better CNN with Batch Normalization

Classification Report:

	precision	recall	f1-score	support
brain_glioma	0.9811	0.9075	0.9429	400
brain_menin	0.8796	0.9500	0.9135	400
brain_tumor	0.9472	0.9425	0.9449	400
accuracy			0.9333	1200
macro avg	0.9360	0.9333	0.9337	1200
weighted avg	0.9360	0.9333	0.9337	1200

Figure 9: Improved CNN with Batch Normalization Result
(Jupyter Notebook)

The better model of CNN by addition of batch normalization had improved performance considerably and the overall test accuracy was 93.33%. All of the precision, recall, and F1-score were approximately 0.9337 meaning that the model worked significantly better compared to the basic CNN model. The accuracies by the classes were also increased: brain glioma had 90.75 percent, brain meningioma 95% and brain tumor 94.25%.

6.3 Experiment 3: ResNet50 Model

	precision	recall	f1-score	support
brain_glioma	0.7214	0.7250	0.7232	400
brain_menin	0.6047	0.6500	0.6265	400
brain_tumor	0.7527	0.6925	0.7214	400
accuracy			0.6892	1200
macro avg	0.6929	0.6892	0.6904	1200
weighted avg	0.6929	0.6892	0.6904	1200

Figure 10: ResNet50 Model Result
(Jupyter Notebook)

Through the help of the resnet50 implementing transfer learning, the overall test accuracy was 68.92%. The three values of precision, recall, and F1-score were almost 0.6929, 0.6892, and 0.6904 respectively. The brain glioma, brain meningioma, and brain tumor had accuracies of 72.50, 65.00 and 69.25% percent respectively. Although the ResNet50 model uses pre-trained weights, the performance was found to be worse than the custom CNN models.

6.4 Experiment 4: YOLOv8-Inspired CNN Implementation

	precision	recall	f1-score	support
brain_glioma	0.9802	0.9900	0.9851	400
brain_menin	0.9772	0.9650	0.9711	400
brain_tumor	0.9776	0.9800	0.9788	400
accuracy			0.9783	1200
macro avg	0.9783	0.9783	0.9783	1200
weighted avg	0.9783	0.9783	0.9783	1200

Figure 11: YOLOv8 model (CNN architecture) Result
(Jupyter Notebook)

The model with a CNN architecture based on the YOLOv8 model demonstrated the highest overall test accuracy of 97.83% overall. Precision, recall, and F1-score were also close to 0.9783, which shows a significantly good predication on all these metrics. Among all models, the class-specific accuracies were also the highest with brain glioma receiving 99.00% and brain meningioma 96.50%, also 98.00% for brain tumor.

6.5 Discussion

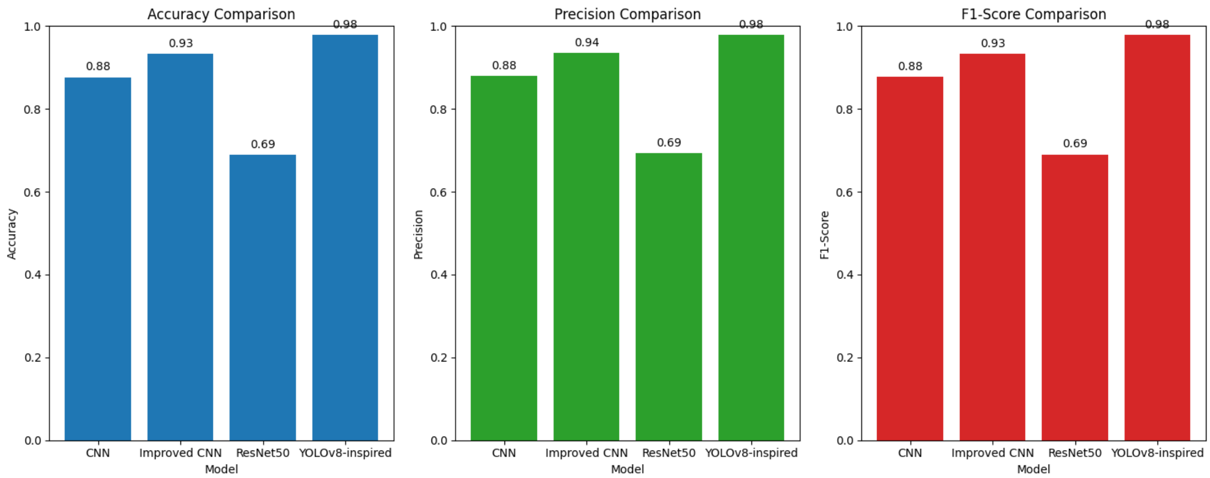

Figure 12: Model Comparison
(Jupyter Notebook)

The results of the experiments contribute to the weight of the different CNN architectures in classifying brain tumors in MRIs. The original CNN was used as a good baseline and the improved CNN with incorporated batch normalization showed how normalization techniques are beneficial and that introducing more layers can improve the results. ResNet50 model, being inferior in terms of its performance, demonstrated the difficulties of implementing transfer learning in medical image processing and the necessity of applying domain-specific adaptation.

The most effective architecture turned out to be the YOLOv8-based CNN model with the best accuracy and performance rates. The success of this model can be explained by the fact that it has many enhanced design features, including residual connections and SiLU activation functions, increasing feature extraction and robustness of the model.
Critically appraising the experiments, it can be said that the basic and improved CNN models worked well but there is room to further optimize the models. This would imply that transfers of learning ability of the ResNet50 tend to underperform, and this also establishes that the ability to transfer the learning process on natural image datasets cannot be capitalized on medical images without much fine-tuning. Such a significant improvement in the performance of the YOLOv8-inspired model suggests that it is critical to consider more sophisticated architectural features to achieve a similar enhancement in classification performance.

6.5.1 Experimental Setup

The experimental apparatus was training and testing the four different architectures of neural networks aimed at classifying the type of brain cancer. The data used in both implementations comprised of 3 groups brain tumor, brain meningioma and brain glioma, comprising of a balanced 2000 images each. The preprocessing of the images included their standardization in terms of size to 224x224 pixels with a pixel range of [0, 1]. All the models had the same hyperparameters; a 32-batch size, the maximum 100 epochs, and early stopping with learning rate reducing the callbacks to avoid overfitting.

6.5.2 Performance Metrics Over View

The results are obtained from old and new environment of python and different libraries with different specification of hardware.

Table 2: Comparative Analysis of Model Performance Across Different Environments

Model	Accuracy (Old)	Accuracy (New)	Precision (Old)	Precision (New)	Recall (Old)	Recall (New)	F1-Score (Old)	F1-Score (New)
CNN	0.8850	0.8767	0.8850	0.8792	0.8850	0.8767	0.8847	0.8770
Improved CNN	0.9542	0.9333	0.9543	0.9360	0.9542	0.9333	0.9542	0.9337
ResNet50	0.7433	0.6892	0.7424	0.6929	0.7433	0.6892	0.7412	0.6904
YOLOv8-inspired	0.9775	0.9783	0.9776	0.9783	0.9775	0.9783	0.9775	0.9783

Simple CNN

The simple CNN model experienced some negative change in terms of accuracy in the movement of the old implementation to the new one, whereby the accuracy lost about 0.0083 which is only about 1 percent. In the same way, there were slight decreases in precision, recall, and F1-scores. This small loss may be caused by differences in the computational efficiency or by differences in the underlying software libraries and their version.

CNN using Batch Normalization

In the new implementation, the performance metrics also dipped in the Improved CNN model that uses batch normalization layers. There was a decrease in the accuracy of 0.9542 to 0.9333 and the same patterns were recorded in precision, recall and F1-scores. It is well known that batch normalization stabilizes and may speed up training, so it is possible that this is one of the reasons behind this variation, and this may be due to the computing environment.

ResNet50 Model

The ResNet50 model was using transfer learning and loading the weights trained on ImageNet so had a sharper decline in performance. It decreased its accuracy to 0.6892, and the same values of precision, recalls, and F1-scores. Such drastic decrease might be attributed to a variation in the manner that the pre-trained weights are treated or the training dynamics brought on by the fresh environment.

YOLOv8-Inspired CNN

The YOLOv8-inspired model also showed a small but positive result in new implementation, as far as accuracy was concerned which was 0.9775 but it rose to 0.9783. This model seems to have a more reliable performance as its architecture has numerous bottlenecks layers and relies on batch normalization extensively, and therefore this model is less vulnerable to alterations within the computational setup.

6.5.3 Environmental Impact Discussion

The difference in performance between the models in the two implementations shows how the computing environment affects the ml results. Model evaluation and training process may depend on the factors like an operating system, Python version, and underlying versions of libraries. An example is that variation of realistic individual handling of numerical calculations, variety of random numbers, or the modification of the optimization routines can generate inconsistent outcomes.

Furthermore, the new working system in windows and python 3.13 may also be characterized by different memory use and processing performances than the former Linux platform. These environmental factors have the potential to slightly influence the training dynamics to cause mismatch in the final model performance.

7 Conclusion and Future Work

The following important question was answered in this study: How do this study achieve the best CNN architecture and preprocessing method to achieve accurate classification of brain tumors using MRI images? Its goals were to create a dedicated CNN to detect tumors, assess the effectiveness of preprocessing techniques, automate the procedure of optimizing parameters, and compare it with the earlier models.

Four CNNs were designed and trained: a simple one, an augmented CNN with the use of batch normalization, ResNet50 transfer learning model, and a CNN that was inspired by the YOLOv8. On the Brain Tumor Classification MRI Dataset available on Kaggle, it was tested on the levels of accuracy, precision, recall, and F1-score.

It was observed that the CNN model using YOLOv8 pre-trained model performed best (97.83% accuracy) compared to other models. There was also a good performance of the improved CNN version with batch normalization (93.33%) and surprisingly, ResNet50 of 68.91%, indicating limitations of direct extension of machine learning to medical imaging.

The clinical implications of these findings are important because small tumor enhances appropriate tumor detection and thus enables proper treatment design. The high performance of the model issued on the basis of YOLOv8 implies a possibility of integrating it into clinical decision-support systems.

7.1 Future Work

In further research, a number of promising avenues can be pursued. One of the possible directions is the incorporation of modern architectures (e.g., transformers) that demonstrated success in diverse computer vision problems. Further enhancement of classification accuracy may be made by investigating hybrid networks that would join the advantages of CNNs and transformers. Moreover, there should also be research on the application of multi-modal imaging data, like the use of MRI with another type of imaging data, e.g., CT scan or a PET scan, which may give a more complete picture of brain tumor and allow more effective diagnosis.

The second potential avenue would be the creation of explainable AI methods in order to increase the interpretability of CNNs. The idea of making model decisions more transparent would help to develop trust among the clinicians and pave the way of AI-based diagnostics tool integration into clinical practice. Moreover, it would be critical to large-scale clinical trials to ensure that the effectiveness of the given models can be applied in practice in order to commercialize the models and make them widespread.

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