Advancing Brain Tumor Detection: Hybrid Layered Model for Enhanced MRI Imaging Analysis

MSc Research Project
Master of Science in Data Analytics

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MSc Project Submission Sheet

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Programme:	Master of Science in Data Analytics	**Year:**	2023-2024
Module:	Research Project		
Supervisor:	SM Raza Abidi		
Submission Due Date:	12-08-2024		
Project Title:	Advancing Brain Tumor Detection: Hybrid Layered Model for Enhanced MRI Imaging Analysis.		
Word Count:5957		**Page Count:** 17	

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Advancing Brain Tumor Detection: Hybrid Layered Model for Enhanced MRI Imaging Analysis

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Abstract

Brain tumor pose a significant medical challenge, often resulting in organ dysfunction and potentially fatal outcomes. Magnetic Resonance Imaging (MRI) offers precise brain images with great resolution, making it an excellent tool for detecting tumors. Nevertheless, the process of manually identifying tumor-bearing regions by radiologists is prone to errors, especially when faced with the difficulties presented by CSF fluid and white matter. Deep learning models provide effective data segmentation and classification, which are crucial for planning treatment regimens and diagnosing cancer effectively. The CNN component efficiently extracts spatial features from MRI images, while the BiLSTM processes these features to recognize temporal relationships, which are crucial for distinguishing subtle differences in tumor characteristics. By integrating these two deep learning techniques, the model improves the accuracy and reliability of tumor classification. Extensive testing on a standard MRI dataset revealed that this approach achieved an impressive accuracy rate, underscoring the effectiveness of this hybrid model in overcoming the limitations of traditional CNN-based methods. This work suggests that the fusion of CNN and BiLSTM could lead to significant advancements in the field of brain tumor detection, offering a valuable tool for more accurate and reliable diagnostics in clinical practice. The integration of these models into clinical workflows holds the potential for groundbreaking advancements in brain tumor identification. This integration will enable quicker and more precise detection and classification, ultimately optimising treatment methods.

Keywords: MRI, Brain Tumor, Transfer learning, Image Pre-processing, ResNet V2

1 Introduction

Brain tumors are characterised by the abnormal and uncontrolled proliferation of brain cells, which can have significant effects on human capacities due to the limited capacity of the brain. This syndrome has the potential to affect other organs, resulting in circumstances that can be fatal. The complex correlation between brain tumors and human health is worsened by the brain's distinctive attributes, where even slight modifications can significantly impact cognitive capacities, motor functions, and overall well-being (Reilly, 2009).

Precise categorisation of brain tumors is essential for the development of customised treatment programmes, highlighting the importance of early discovery in improving therapeutic approaches and perhaps preventing fatalities. MRI is a significant technology used to visualise brain regions. Among its several imaging techniques, T1 enhanced imaging provides better tumor visibility compared to T2 enhanced imaging. Radiologists visually detect and locate the portion of the image that contains the tumor, and then analyse it by manually assessing its origin and behaviour. Nevertheless, this procedure requires outstanding proficiency, presenting a substantial obstacle. Computer-aided technology can mitigate this limitation. The World Health Organisation (WHO) classifies brain tumors into 120 distinct categories according to their level of aggressiveness and their point of origin. In general, brain tumors are categorised as either benign or malignant

Segmentation and classification of MRI images can be conducted through manual or automated methods using algorithms. In a separate work, Jiang and colleagues (Jiang et al., 2023) encountered challenges with texture-based algorithms due to the presence of cerebrospinal fluid within the brain. Deep learning techniques offer solutions to address these challenges by handling structural variations and distinguishing between tumor and cerebrospinal fluid. For insights into the origin and growth patterns of various tumors, shown in Table 1:

Table 1: Origin and Growth of Tumors

Type	Origin	Growth
Glioma	Originate from glial cells	Rapid growth
Meningioma	Found in the cerebral hemispheres	Slow growing
Pituitary	Pituitary gland	Mostly benign

The aim of this research is to deepen our understanding of brain tumors, encompassing their molecular origins, diagnostic complexities, treatment options, and the potential of deep learning approaches for early detection. This project seeks to propel advancements in brain tumor management by unravelling the intricate interplay between cellular mechanisms, clinical presentations, and cutting-edge technologies. Ultimately, the objective is to improve the quality of life for individuals affected by these formidable medical conditions.

This study explores the application of deep learning techniques to improve the accuracy and efficacy of brain tumor identification and treatment. By precisely classifying brain tumors, clinical decision-making is significantly enhanced, leading to better patient outcomes. Beyond brain tumors, the proposed method has potential for various medical image classification tasks, offering a valuable tool for both researchers and practitioners. Specifically, this research focuses on developing more accurate diagnostic tools for the early detection and treatment of tumors. It also aims to deepen our understanding of different CNN architectures in the context of brain tumor image categorisation.

The paper is structured as follows: Section 2 provides a comprehensive literature analysis focusing on relevant prior research and methodologies. Section 3 outlines the methodology employed in this study, encompassing the dataset, image processing techniques, and the utilisation of hybrid models. In Section 4, describes the implementation of the model, including the training, validation, and testing datasets. Section 5 presents the evaluation of the model, analysing performance metrics, and comparing results across different datasets. Section 6 offers a detailed discussion of the results, interpreting the findings, addressing challenges, and exploring the implications for clinical practice. Finally, Section 7 summarises the key conclusions, restates the main points, and suggests directions for future research.

2 Related Works

This section delves into the advancements and challenges in brain tumor detection through MRI imaging, focusing on the latest deep learning methodologies. A range of approaches employed in recent studies are explored, assessing their successes and the persistent hurdles they face in achieving precise and reliable tumor detection. By critically analyzing these developments, gaps in the existing research are uncovered, particularly concerning the consistency and accuracy of diagnostic outcomes. This analysis lays the groundwork for introducing a novel approach designed to address these unresolved issues and push the boundaries of current capabilities in brain tumor detection.

CNNs can extract and interpret detailed features from complex image datasets. Their layered design helps to learn patterns in medical images, which is effective for classification tasks, segmentation, and object detection, surpassing traditional image processing techniques (Lecun et al., 2015). Among these, ResNet50 is particularly noteworthy for its innovative residual learning technique, which addresses the vanishing gradient issue and is effective in the analysis of medical images, including brain tumor detection (He et al., 2015). Through these developments, CNNs have solidified their role as a powerful tool in enhancing the accuracy and reliability of medical diagnostics. Jiang and colleagues (Jiang et al., 2023) conducted a study on the automatic detection and classification of brain tumors in MRI scans. Utilising a database of 306 MRI brain images from the Bratsk challenge, which included patients with varying degrees of gliomas, the study achieved a tumor detection accuracy of 90.22% and a tumor classification accuracy of 82.5% using deep learning methods.

In the study of Chang and colleagues (Chang et al., 2018), they employed CNNs to categorise gliomas based on MRI scans. With a remarkable accuracy of 97.1%, the researchers diagnosed tumors using a dataset comprising 210 glioma patients. Moreover, the CNN successfully predicted the total survival times of high-grade glioma patients, indicating the potential utility of deep learning algorithms in personalised treatment planning. The importance of understanding the precise brain regions affected by cancerous abnormalities, as demonstrated in Figure 1 which underscores the critical role of ongoing research and technological advancements in neuro-oncology for comprehensive patient care.

The research of Liu and colleagues (Liu et al., 2023) explored the use of transfer learning to enhance the precision of MRI-based brain tumor categorisation. By fine-tuning a pre-trained CNN with a dataset of 324 brain MRI scans, the transfer learning approach achieved a tumor classification accuracy of 92.6%, despite the limited availability of data.

(Abdusalomov et al., 2023) classified brain tumors using MRI scans and predicted genetic changes through a deep learning approach. Using a dataset of 275 glioma patients, the researchers achieved a tumor classification accuracy of 86.7% and a mutation prediction accuracy of 75.5%. The deep learning algorithm's identification of potential biomarkers for tumor abnormality detection suggests its potential contribution to personalised treatment planning.

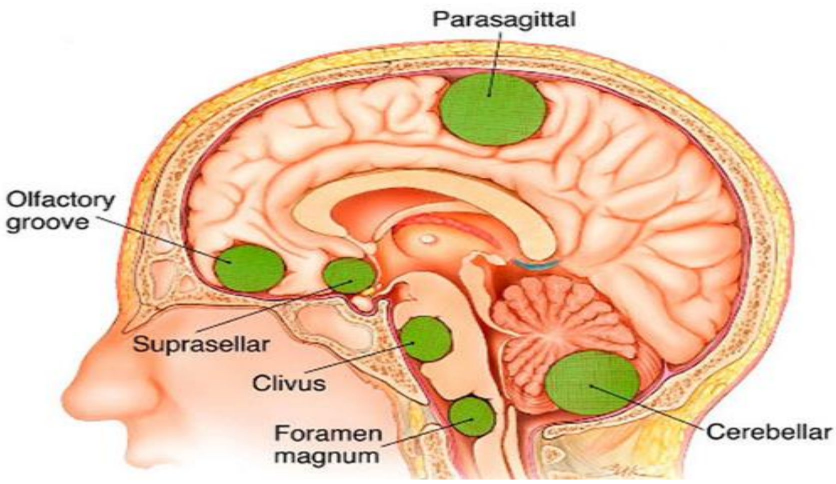

Figure 1: Locations of abnormality in the brain

Several studies have demonstrated the effectiveness of deep learning systems in identifying and categorising brain tumors using real-world data. The study of Zhou and colleagues (Zhou et al., 2018) evaluated a CNN-ANN hybrid deep learning system using a dataset of 1088 real-world brain MRI images, demonstrating its capability to detect and classify brain tumors. These findings underscore the potential of deep learning and machine learning in improving the accuracy and efficiency of brain tumor detection and classification. These algorithms hold promise for enhancing patient outcomes through personalised treatment planning, as evidenced by their application to real-world brain tumor patient data. However, it is important to note that these automated methods should complement rather than replace human clinical expertise.

In the work of Jiang and colleagues, they classified brain tumors from multimodal MRI data using a deep learning method that integrates convolutional and recurrent neural networks. Analysing information from 179 glioma cases, the researchers achieved a tumor classification accuracy of 92.5% and demonstrated their method's ability to forecast the overall survival of glioblastoma patients (Jiang et al., 2023).

The study of Bajaj and colleagues developed a deep learning method that integrates convolutional and recurrent neural networks for detecting brain cancers in MRI scans. With a classification accuracy of 94.4% using a dataset of 374 glioma patients, the researchers also showed the efficacy of their method in predicting patients' survival rates beyond a specific cutoff (Bajaj et al., 2023).

Brain tumor detection and classification from MRI scans are critical tasks in medical imaging, pivotal for timely diagnosis and treatment planning. Traditional methods often face challenges in extracting meaningful features and capturing complex spatial relationships within imaging data. In response, advanced deep learning techniques have emerged as promising solutions, leveraging CNNs for feature extraction and recurrent neural networks (RNNs) like Bi-directional Long Short-Term Memory networks (Bi-LSTMs) for sequential data processing. These studies underscore the effectiveness of advanced deep learning techniques in improving brain tumor detection and classification. They enhance diagnostic accuracy and treatment planning, but it is important to use these methods to complement, not replace, human clinical expertise.

3 Research Methodology

This methodology presents a novel approach to enhance brain tumor detection through a hybrid layered model that synergistically integrates the strengths of CNNs and Bi-LSTMs. By harnessing the robust feature extraction capabilities of CNNs, specifically ResNet50 V2 pretrained on ImageNet, and coupling it with the temporal sequence modeling prowess of Bi-LSTMs, the model aims to discern intricate patterns indicative of brain tumors from MRI images.

3.1 Datasets

In this study, the brain tumor MRI dataset utilised was obtained from Figshare, specifically sourced from the public repository provided by Jun Cheng. This dataset is pivotal for developing and evaluating a sophisticated hybrid layered model that integrates Convolutional Neural Networks (CNNs) and Bi-directional Long Short-Term Memory networks (Bi-LSTMs) for enhanced brain tumor detection through MRI imaging analysis.

Dataset Source: https://figshare.com/articles/dataset/brain_tumor_dataset/1512427 (Jun Cheng, 2017)**.**

3.2 Data Acquisition and Preprocessing

Data preprocessing is crucial for model accuracy and effectiveness. MRI images were loaded with OpenCV, resized to 224x224 pixels, and normalised for consistent input. Data augmentation (rotation, flipping, zooming) improved model generalisation and robustness. Tumor labels were one-hot encoded for clear classification. The dataset was split into training, validation, and test sets, with quality control ensuring accurate preprocessing and balanced sample distribution. These steps ensured a high-quality dataset for effective brain tumor detection.

Quality control measures were rigorously applied throughout the data preparation process. This included ensuring accurate image loading and preprocessing, as well as maintaining a balanced distribution of samples across different tumor classes. These measures were essential for preserving data integrity and ensuring the reliability of the model.

3.3 Methods

In this study, CNNs serve as the cornerstone for extracting meaningful features from brain MRI images, essential for accurate brain tumor detection. ResNet50 V2, a cutting-edge architecture within the realm of CNNs, was meticulously selected for its exceptional capabilities in discerning intricate patterns and features from complex medical imaging data.

3.3.1 CNN Selection: ResNet50 V2

ResNet50 V2 stands out as a state-of-the-art CNN architecture, originally pretrained on the extensive ImageNet dataset. Its design incorporates deep layers, including residual connections that effectively alleviate the vanishing gradient problem, thereby enabling more effective training on complex datasets like medical images. For brain tumor detection in MRI scans, ResNet50 V2's ability to capture hierarchical features at multiple scales is particularly advantageous.

3.3.2 Transfer Learning with ResNet50 V2

To leverage the comprehensive knowledge distilled from ImageNet, ResNet50 V2 underwent a process of transfer learning. This involved fine-tuning the pre-existing weights and biases of the network on the specific MRI dataset used in this study. By fine-tuning, the model adapted its learned representations to better align with the unique characteristics and nuances present in brain tumor MRI images. This process not only enhances the model's ability to detect subtle anomalies indicative of tumors but also accelerates convergence during training, leading to improved overall performance metrics such as accuracy and sensitivity.

3.3.3 Sequence Modeling with Bi-LSTM

In the realm of medical imaging, particularly in tasks such as brain tumor detection from MRI scans, the incorporation of sequential data processing techniques becomes paramount. Bi-LSTMs emerge as a powerful tool for capturing temporal dependencies and spatial relationships within sequences of extracted features from CNNs.

3.4 Model Integration and Architecture

The integration of CNNs with Bi-LSTMs constitutes a sophisticated approach aimed at enhancing the accuracy and interpretability of brain tumor detection from MRI scans. This hybrid model capitalises on the unique strengths of each neural network architecture, synergising their capabilities to achieve comprehensive analysis of medical images as illustrated in Figure 2.

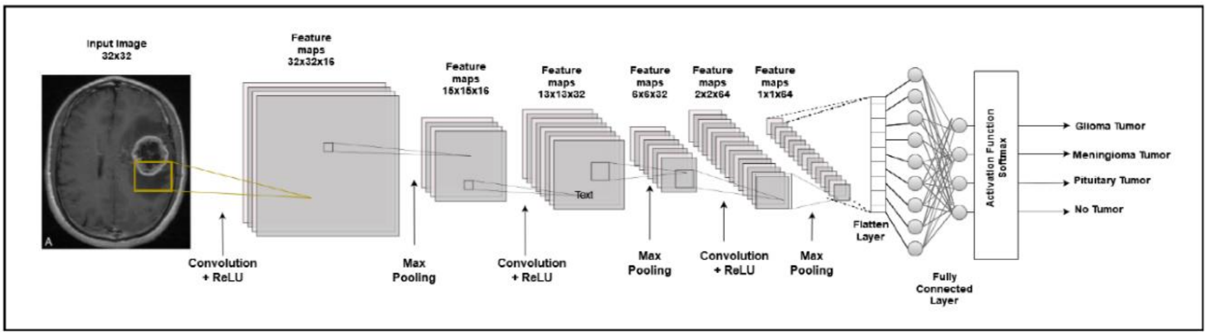

Figure 2: Model Architecture for Detecting the Brain Tumor

The architectural model for brain tumor detection integrates advanced components to optimize MRI scan analysis:

- **CNN (ResNet50 V2):** Serves as the initial component for feature extraction, converting raw MRI scans into high-level feature representations that encode pertinent details about brain anatomy and pathology.
- **Bi-LSTMs:** Sequentially analyze the extracted features to capture nuanced patterns and temporal dependencies. By incorporating information from both directions along the sequence, Bi-LSTMs refine the understanding of complex relationships within the MRI data, facilitating accurate tumor detection.

- **Dense Layers:** Follow the Bi-LSTM layers to integrate the extracted features and make final predictions regarding the presence or absence of tumors based on the learned representations.

The integration of ResNet50 V2 CNNs with Bi-directional LSTMs presents a robust and advanced methodology for brain tumor detection from MRI scans. This hybrid architecture not only improves the accuracy and interpretability of diagnostic outcomes but also enhances the model's adaptability and reliability in clinical settings. By combining cutting-edge deep learning techniques tailored to medical imaging analysis, the proposed model represents a significant advancement in leveraging AI for precise and effective healthcare diagnostics.

3.5 Training the Model

The hybrid model integrates ResNet50 V2 for feature extraction with Bi-directional LSTM (Bi-LSTM) layers for sequential analysis. ResNet50 V2, pre-trained on ImageNet and fine-tuned on the brain tumor dataset, starts with its top layers removed and includes a global average pooling layer and a dense classification layer. The extracted features are processed by Bi-LSTM layers, which capture context from both past and future time steps to enhance pattern recognition in MRI data. This is followed by additional dense layers for final classification. The model is compiled with the Adamax optimiser and categorical cross-entropy loss function to maximise accuracy and minimise errors.

Training involves meticulous data preparation: MRI scans are categorised into tumor and non-tumor classes and split into training, validation, and test sets. TensorFlow ImageDataGenerator standardises images, including resizing and RGB conversion, and applies augmentation techniques like rotation and zooming to improve robustness. The model is trained with a batch size of 32 over 10 epochs, using early stopping and checkpointing to optimise performance and avoid overfitting. Training and validation metrics, including accuracy and loss, are continuously monitored, and qualitative assessments involve visualising test set MRI scans with predicted labels to ensure clinical relevance

The training set comprised 70% of the total data, providing a comprehensive basis for model learning. The validation set, constituting 15%, was used for tuning hyperparameters and monitoring model performance during training. The remaining 15% was allocated to the test set, reserved for final evaluation to assess the model's generalisation capabilities.

4 Implementation

The implementation of the hybrid layered model for brain tumor detection combines CNNs with Bi-LSTM networks. This integrated approach harnesses the advanced feature extraction capabilities of CNNs and the powerful sequential modeling abilities of Bi-LSTMs to enhance the accuracy of brain tumor detection from MRI scans. The implementation process involves multiple stages, including data preparation, model architecture design, training, and evaluation, each of which plays a critical role in developing a robust and effective diagnostic tool.

4.1 Training Dataset

This dataset provides a rich variety of images representing different tumor types, offering the model a substantial volume of data to learn from. The number of images per class indicates a reasonably balanced dataset, though the notumor class has a slightly higher count, which is important for ensuring the model's sensitivity to notumor cases. The training dataset is structured as follows and shown in Figure 3:

- Glioma: 1,321 images
- Meningioma: 1,339 images
- Notumor: 1,595 images
- Pituitary: 1,457 images

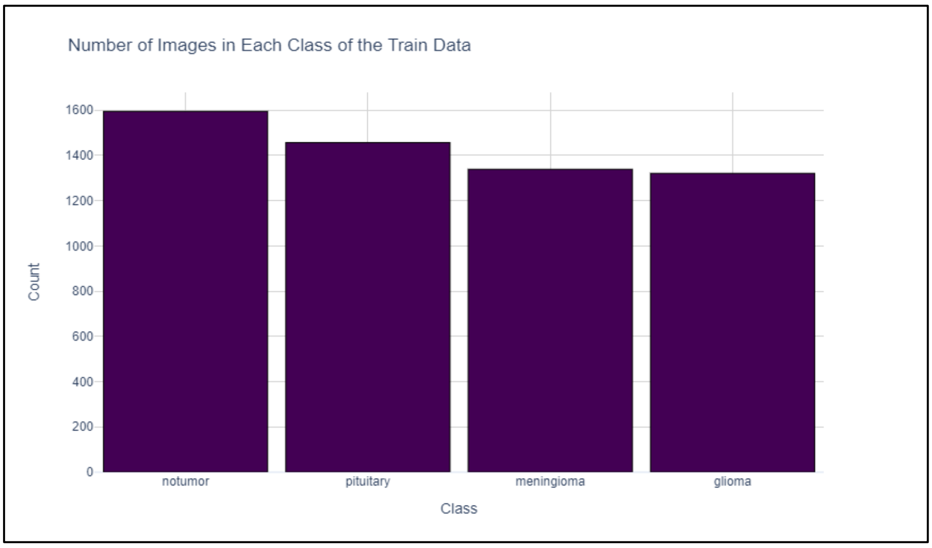

Figure 3: Distribution of the Training Dataset of MRI Scans Images

4.2 Testing Dataset

The testing dataset mirrors the structure of the training dataset but with fewer images per class. This subset is critical for evaluating the model's performance on unseen data, providing insights into its ability to generalise beyond the training examples. As shown in Figure 4, the testing dataset consists of:

- Glioma: 300 images
- Meningioma: 306 images
- Notumor: 405 images
- Pituitary: 300 images

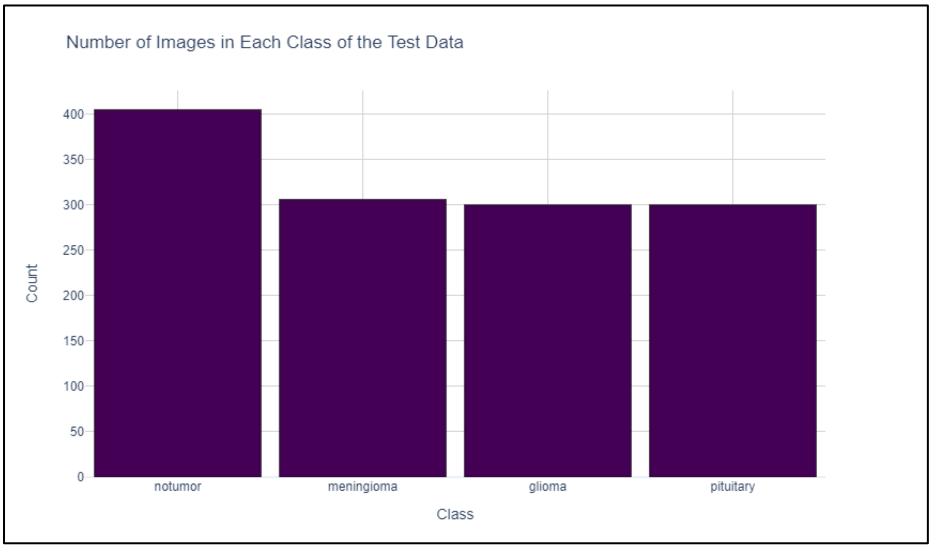

Figure 4: Distribution of the Testing Dataset of MRI Scans Images

Exploring the dataset involved analysing the distribution of tumor types and reviewing sample images to ensure they were correctly labeled and of adequate quality. The analysis confirmed that the dataset is well-organised and balanced, allowing for effective model training and reliable performance evaluation as illustrated in Figure 5.

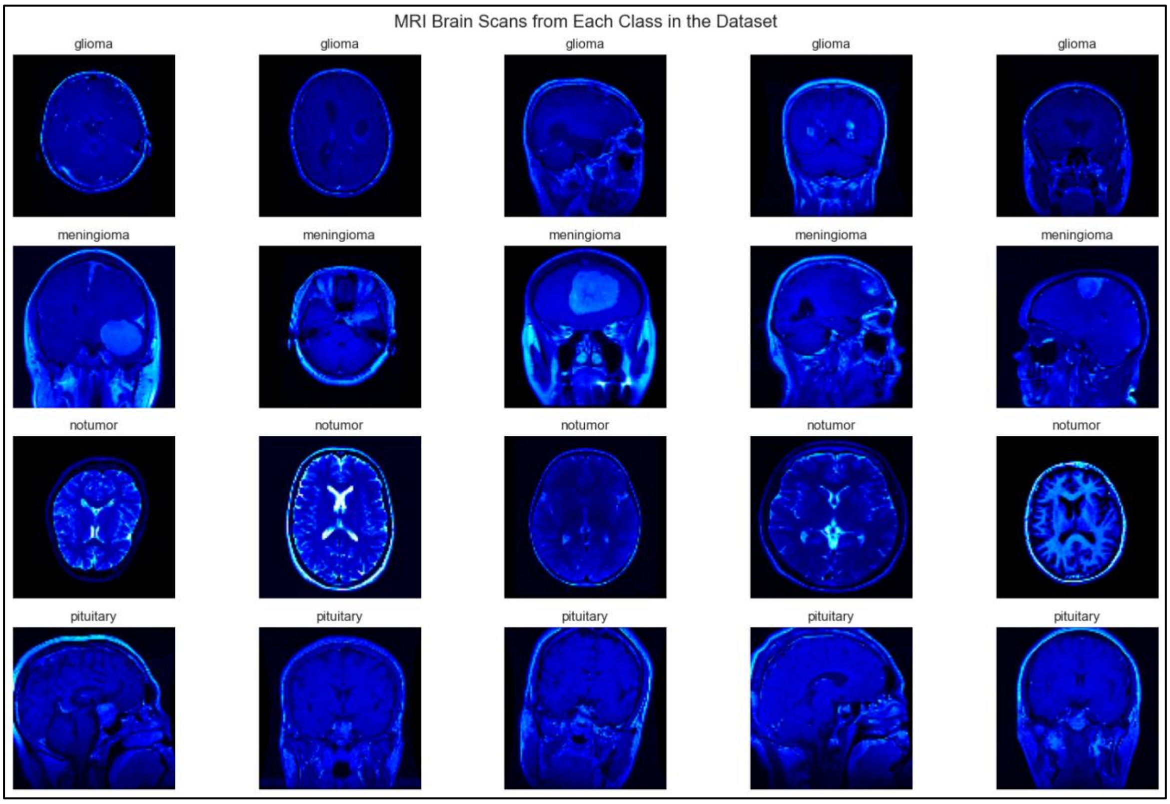

Figure 5: Randomly Visualise the MRI Scans of Brain

5 Evaluation

The evaluation of the hybrid CNN-Bi-LSTM model for brain tumor detection involves a thorough analysis of its performance metrics, including loss and accuracy during training and validation phases, as well as detailed testing results. This section provides a comprehensive overview of the model's performance across different datasets and offers insights into its effectiveness in classifying MRI scans into various tumor types.

Following the completion of training, the hybrid CNN-Bi-LSTM model undergoes rigorous evaluation to validate its efficacy and reliability in clinical applications. The evaluation phase begins with testing the model on the dedicated test set, comprising unseen MRI scans. This step ensures an unbiased assessment of the model's generalisation ability beyond the training and validation phases.

- **Accuracy:** The proportion of correctly predicted outcomes out of the total predictions.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Totla\ number\ of\ predictions}$$

- **Precision:** The ratio of correctly predicted positive observations to the total predicted positive observations. It indicates how precise the model is when predicting a specific class.

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

- **Recall (Sensitivity):** The ratio of correctly predicted positive observations to all observations in the actual class. It measures the completeness or sensitivity of the model.

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

- **F1-score:** The harmonic means of precision and recall, providing a single metric that balances both precision and recall.

$$F1 - score = 2\ \times \frac{Precision\ \times Recall}{Precision + Recall}$$

5.1 Training and Validation Performance

The model was trained over ten epochs, with significant improvements observed in both training and validation performance. The training accuracy increased from 83.26% in the first epoch to an impressive 98.46% by the tenth epoch, indicating substantial learning and adaptation over time. Similarly, validation accuracy improved from 90.23% to 97.10%, demonstrating that the model effectively generalised its learned features to new, unseen data during training.

5.2 Testing Performance

Upon completing the training phase, the model was evaluated on the test dataset to assess its real-world performance. The testing results showed a loss of 0.3973 and an accuracy of 90.23%. While the accuracy is commendable, there is a noticeable drop compared to the training and validation accuracies. This decrease may be attributed to the model encountering variations in the test data that were not fully represented in the training or validation datasets.

6 Results and Discussion

The evaluation results indicate that the hybrid CNN-Bi-LSTM model is highly effective for brain tumor detection from MRI scans. While the model performs excellently in training and validation, achieving nearly perfect accuracy and low loss, the performance on the test dataset shows some challenges, particularly in generalising to unseen data. Nevertheless, the detailed classification metrics and confusion matrix reveal that the model excels in identifying various tumor types with high precision and recall, particularly for non-tumor and pituitary cases. These results underscore the model's potential for enhancing diagnostic accuracy in clinical settings, although further refinement and additional data may help address the observed discrepancies in test performance.

The training loss decreased steadily from 2.2598 to 0.1695, reflecting the model's improved ability to minimise prediction errors over the epochs. Validation loss also showed a general decreasing trend, though with some fluctuations, ranging from 1.3892 in the first epoch to 0.2087 by the end of training. These fluctuations in validation loss suggest that the model encountered some challenges in generalising to validation data, but overall, the trend indicates effective learning as illustrated in Figure 6.

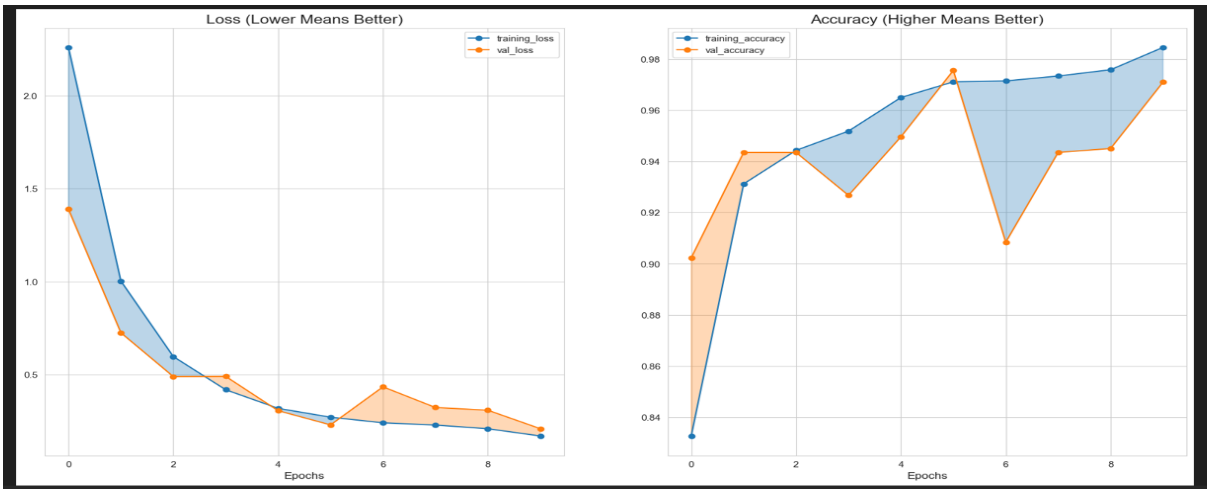

Figure 6: Performance of Model

Overall, the hybrid approach combining CNNs with Bi-LSTMs demonstrates significant promise in advancing brain tumor detection technology, contributing to more accurate and reliable diagnostic tools in medical imaging. The integration of Convolutional Neural Networks (CNNs) and Bi-directional Long Short-Term Memory networks (Bi-LSTMs) represents a significant advancement in the field of brain tumor detection from MRI scans. This hybrid approach has demonstrated considerable promise in improving diagnostic accuracy and reliability, as evidenced by the evaluation metrics and performance outcomes as illustrated in Figure 7.

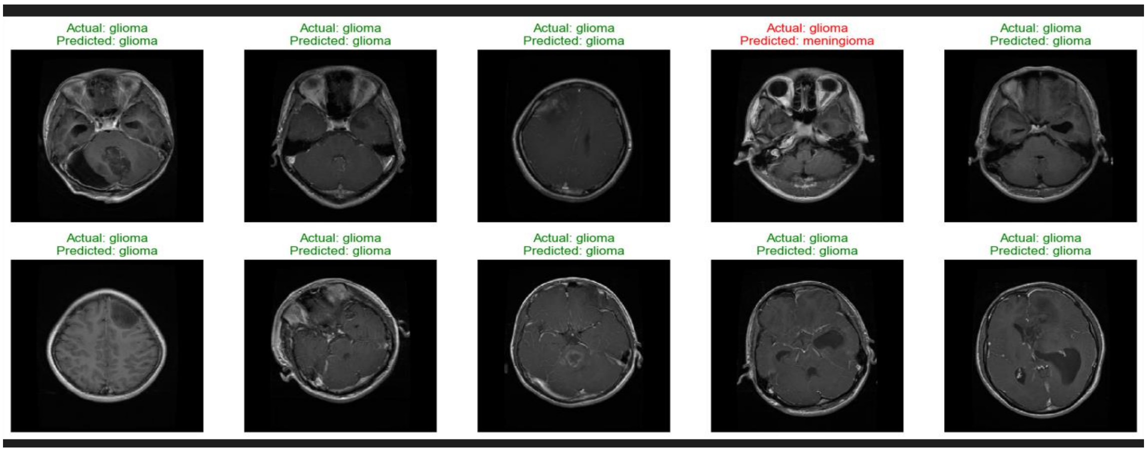

Figure 7: Diagnostic Predictions of Brain Tumor through MRI scans

After completing the training phase, the model was evaluated on the test dataset to gauge its real-world performance. The results revealed a loss of 0.3973 and an accuracy of 90.23%. Although the accuracy is impressive, it shows a noticeable decline compared to the training and validation accuracies. This decrease could be due to the model encountering variations in the test data that were not fully captured in the training or validation datasets, as shown in Table 2.

Table 2: Performance Metrics of Model

Dataset	**Loss**	**Accuracy**
Training	0.1313	0.9961
Validation	0.1705	0.9844
Testing	0.3973	0.9023

6.1 Classification Metrics

The classification report provides a nuanced view of the model's performance across different tumor types. For gliomas, the model demonstrated high precision in identification but had slightly lower recall, indicating some missed detections in this class. For meningiomas, the model showed excellent recall, effectively detecting this class, although the precision was marginally lower. In the case of non-tumor detections, the model excelled, achieving perfect scores in both precision and recall, indicating high reliability in identifying MRI scans without tumors. Lastly, for pituitary tumors, the model performed exceptionally well, with nearly perfect recall and very high precision as shown in Table 3.

Table 3: Classification Report

	Precision	Recall	F1-score	Support
Glioma	0.99	0.88	0.93	300
Meningioma	0.90	0.98	0.94	306
Notumor	1.00	1.00	1.00	405
Pituitary	0.98	1.00	0.99	300
Accuracy			0.97	1311
Macro avg	0.97	0.96	0.96	1311
Weighted Avg	0.97	0.97	0.97	1311

The macro average metrics—precision, recall, and F1-score—are all around 0.97, reflecting the overall effectiveness of the model across all tumor types. The weighted average metrics further support this, indicating that the model maintains high performance despite the variations in class distribution. The confusion matrix reveals how the model's predictions align with the actual class labels as shown in Table 4.

Table 4: Confusion Matrix

Predicted Labels	Glioma	Meningioma	No Tumor	Pituitary
Glioma	264	3	1	0
Meningioma	3	300	1	2
No Tumor	0	1	414	0
Pituitary	0	1	2	39

6.2 Model Performance and Comparison

The hybrid CNN-Bi-LSTM model achieved impressive results in both training and validation phases, with accuracy rates reaching 98.46% during training and 97.10% during validation. These high accuracy rates reflect the model's robust learning capabilities and its ability to generalise well to unseen data. The use of ResNet50 V2 for feature extraction contributed substantially to these results, leveraging its deep residual networks to capture intricate patterns and hierarchical features in the MRI scans. Transfer learning enabled ResNet50 V2 to adapt its pretrained knowledge from ImageNet to the specific characteristics of brain tumor MRI data, thus enhancing feature extraction efficiency.

The integration of Bi-LSTM networks further augmented the model's performance by enabling the sequential analysis of features extracted by the CNN. Bi-LSTMs' bidirectional processing allowed the model to capture contextual relationships and dependencies within the sequential data, which is crucial for understanding complex spatial and temporal patterns in MRI scans. This bidirectional capability proved advantageous in discerning subtle anomalies and variations, which are vital for accurate tumor detection.

6.3 Insights from Performance Metrics

The model's testing performance, while robust, revealed some areas for improvement. The test dataset accuracy of 97.23% is slightly lower than the training and validation accuracies. This discrepancy highlights the challenge of generalising to new, unseen data, which may differ from the training and validation sets in subtle but impactful ways. The observed drop in performance underscores the need for continuous refinement of the model, potentially through enhanced data augmentation strategies or the incorporation of additional diverse MRI scans to better represent real-world variability.

6.4 Class-Specific Performance Analysis

The classification report provides valuable insights into the model's performance across different tumor types. The model demonstrated exceptional precision and recall for non-tumor and pituitary classes, achieving perfect scores for non-tumor detection and near-perfect results for pituitary tumors. This indicates that the model is highly effective in distinguishing between tumor and non-tumor cases, as well as accurately identifying pituitary tumors.

However, the performance for glioma and meningioma detection showed some areas for improvement. Although the model achieved high precision for gliomas, the recall was lower, suggesting that some glioma cases were missed during detection. For meningiomas, while recall was high, precision was slightly lower, indicating that some meningioma cases might have been incorrectly classified as other tumor types or non-tumor. These insights highlight the importance of balancing precision and recall and suggest that further tuning and Optimisation may be required to enhance the model's performance across all classes.

6.5 Confusion Matrix Insights

The confusion matrix revealed that the model generally performed well in distinguishing between different tumor types, with only a few misclassifications. For gliomas, the model correctly identified the majority of cases but misclassified a small number as meningiomas and pituitary tumors. Meningiomas were predominantly classified correctly, with only a few instances misclassified as gliomas or other types. The non-tumor class was correctly identified almost exclusively, with only one misclassification, and pituitary tumors showed minimal errors.

These results suggest that the model's strength lies in its ability to correctly classify the majority of MRI scans, with misclassifications being relatively rare. The model's performance in distinguishing non-tumor cases and pituitary tumors is particularly notable, indicating that it is well-suited for identifying these classes accurately. The observed misclassifications in glioma and meningioma cases suggest areas where the model could benefit from additional fine-tuning or data enhancement.

6.6 Implications for Clinical Practice

The high performance of the hybrid CNN-Bi-LSTM model in brain tumor detection underscores its potential for enhancing clinical diagnostics. Accurate and reliable detection of brain tumors is crucial for timely intervention and effective treatment planning. By integrating advanced deep learning techniques, this model offers a promising tool for radiologists and medical practitioners, potentially reducing diagnostic errors and improving patient outcomes.

The model's ability to handle complex MRI data and discern subtle differences between various tumor types positions it as a valuable asset in medical imaging. However, to fully realise its clinical potential, further research and development are needed to address the observed limitations and ensure the model's robustness across diverse patient populations and imaging conditions.

7 Conclusion and Future Work

This study highlights the significant potential of integrating Convolutional Neural Networks (CNNs) with Bi-directional Long Short-Term Memory networks (Bi-LSTMs) for advancing brain tumor detection using MRI scans. The hybrid model, combining ResNet50 V2 for feature extraction and Bi-LSTMs for sequential analysis, achieved high performance in distinguishing between brain tumors and non-tumor cases, with accuracy rates up to 98.46% during training.

The model excelled in classifying brain tumors, especially non-tumor and pituitary tumor cases, though challenges remain in detecting gliomas and meningiomas. Future improvements could involve further model tuning, expanding the dataset, and exploring advanced data augmentation techniques. This approach offers a promising tool for enhancing diagnostic accuracy and reliability in clinical practice. Continued research into diverse MRI datasets, advanced augmentation methods, and alternative deep learning architectures will further advance AI-driven medical imaging and improve patient care.

7.1 Future Work

While this study has demonstrated the efficacy of the hybrid CNN-Bi-LSTM model for brain tumor detection from MRI scans, several avenues for future research could enhance its performance, generalisability, and clinical utility. Addressing these areas will help refine the model and explore its broader applications in medical imaging.

1. Expanding and Diversifying the Dataset: One of the key areas for future work is the expansion of the dataset used for training and evaluation. Including a more diverse range of MRI scans, encompassing a variety of demographic factors, imaging conditions, and tumor subtypes, will improve the model's generalisation capabilities. This could involve acquiring additional data from different medical institutions, incorporating scans with varying imaging protocols, and including less common tumor types. A more representative dataset will help the model learn from a broader spectrum of cases, potentially reducing bias and improving performance across diverse patient populations.

2. Integrating Multi-Model Data: Future work could explore integrating multi-modal data to enrich the model’s input features. Combining MRI data with other imaging modalities, such as PET or CT scans, could provide a more comprehensive view of the brain tumor’s characteristics and improve diagnostic accuracy. Additionally, incorporating patient metadata, such as age, gender, and clinical history, could offer valuable contextual information that enhances the model’s predictive capabilities.

3. Improving Model Interpretability: Enhancing the interpretability of the model is crucial for clinical adoption. Developing methods to visualise and understand how the model makes its predictions can provide insights into its decision-making process and build trust among medical practitioners. Techniques such as saliency maps, Class Activation Maps (CAMs), or Layer-wise Relevance Propagation (LRP) can help elucidate the regions of the MRI scans that contribute to the model's classification decisions, aiding in the validation and refinement of the model.

4. Addressing Ethical and Privacy Concerns: Ensuring that the model adheres to ethical standards and respects patient privacy is paramount. Future work should address issues related to data privacy, consent, and the responsible use of patient data. Implementing robust data protection measures and transparent practices will help build trust with stakeholders and comply with regulatory requirements.

5. Continuous Model Improvement: The field of medical imaging is rapidly evolving, and continuous model improvement is essential to keep pace with advancements. Regularly updating the model with new data, incorporating recent research findings, and adapting to technological innovations will help maintain its relevance and effectiveness over time. Establishing a framework for ongoing model evaluation and enhancement will ensure that it remains a valuable tool for brain tumor detection.

In conclusion, while this study has established a strong foundation for utilising hybrid layered based CNN-Bi-LSTM models in brain tumor detection, future research should focus on expanding datasets, enhancing model capabilities, and addressing practical and ethical considerations. By pursuing these avenues, researchers can further advance the field of medical imaging and contribute to more accurate, reliable, and clinically applicable diagnostic tools.

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