Deep Learning Based Brain Tumor Detection and Classification Using the BR35H MRI Dataset

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Abstract: ***Brain tumors are considered one of the most severe types of cancer, making their timely and precise identification essential for enhancing patient prognosis and treatment effectiveness. Conventionally, Manual examination is a major component of MRI-based diagnosis, which is time-consuming and prone to human mistake. This study presents a cutting-edge deep learning-based method to overcome these constraints for the automatically identifying and categorising brain tumours, utilizing the BR35H MRI dataset. The proposed system incorporates five distinct models: DenseNet and ResNet50 for classifying medical images, YOLOv5 and Faster R-CNN for identifying tumor regions, and LSTM networks to capture temporal and contextual features across MRI slices. The methodology involves preprocessing of MRI scans, data augmentation, model training, and evaluation Utilising standard metrics including mean Average precise (mAP), accuracy, F1-score, and precise recall. The models are evaluated for both computational efficiency and detection accuracy. A comparative analysis reveals that YOLOv5 is best appropriate for real-time scenarios because its high frame rates, whereas Accuracy is higher with faster R-CNN. for detailed localization. This paper aims to bridge classification and detection capabilities in a single framework. This study advances the field of AI-driven diagnostic systems for neuro-oncology, with particular relevance to under-resourced environments where access to expert radiologists is limited.***

Keywords: Brain tumor detection, DenseNet, YOLOv5, Faster R-CNN, BR35H Dataset

1. Introduction

Brain tumors are life-threatening neurological conditions that necessitate early and accurate diagnosis for timely intervention and effective treatment. Manual diagnosis using MRI (Magnetic Resonance Imaging) scans is a time-intensive process that depends heavily on the expertise and experience of radiologists, which introduces variability and increases the risk of misdiagnosis, especially in low-resource settings [1], [2].

MRI is the preferred imaging modality for brain tissue visualization due to its superior spatial resolution and excellent contrast between different soft tissues [3]. Despite this advantage, detecting and classifying tumors within 2D MRI slices is challenging because the pathological regions often exhibit subtle grayscale variations and irregular shapes that can be easily overlooked [4].

The advancements in artificial intelligence (AI), especially deep learning, have had a substantial impact on medical imaging with related feature extraction and classification being automatic and accurate [5], [6]. Convolutional Neural Networks (CNNs) also performed well in a number of computer vision tasks, including tumor detection and classification [7]. Medical image analysis tends to use deep learning models such as DenseNet and ResNet50 that leverage deep models as those methods are capable of reusing features allowing a deep architecture [8], [9]. Object detection models including YOLOv5 and Faster R-CNN can do classification and localization in a single pipeline which makes them alluring for real-time call in the clinical environment [10], [11]. Moreover, Long Short-Term Memory Networks (LSTM) can also be integrated with CNNs to take advantage of spatial-temporal relationships across sequential MRI slices, further improving tumor characterization, and reducing the number false positives [12], [13].

This article introduces a multi-model deep learning framework for two main objectives: (1) classification of tumor type, and (2) localization of the tumor regions. To test the ability of the proposed approach, we use the BR35H dataset, an MRI dataset with annotated training and testing 2D images, which are classified as various tumor types, including glioma, meningioma, and pituitary. A complete study will include image preprocessing, model training, validations, performance comparisons and discussions on clinical applicability, and we aim to identify the strengths of each deep learning model in real-world clinical-based diagnosis.

Deep learning has become a more powerful technique in recent years for detecting and classifying brain tumors. Among other techniques, Convolutional Neural Networks (CNNs) have proven to be very good at learning spatial features and classifying medical imaging data, especially in the case of Magnetic Resonance Imaging (MRIs). Since 2015905, many CNN-based architectures have been proposed with a focus toward enhancing the diagnostic performance, and improving the accuracy, robustness, and clinical utility.

2. Literature Survey

2.1 CNN-based Classification

Bernal et al. provided an extensive literature review of CNN models used for MRI image analysis, focusing on the ideas of network depth and feature reuse in improving diagnostic results [1].

DenseNet was discussed as one of many CNN variations and is unique for its use of dense connectivity that facilitates the flow of gradients through many different paths while improving the propagation of features making the model converge better and overfit less [2].

Pereira et al. used deep 2D-CNNs on the BRATS dataset for tumor segmentation and also reported high Dice scores in the core and whole tumor regions. They showed that relatively shallow CNNs can provide acceptable pixel-wise predictions when the model is trained with appropriate preprocessing [3]. Likewise, Islam et al. conducted a comparative study of transfer learning models with ResNet50, VGG16, and InceptionV3. In the end, ResNet50 reached a maximum classification accuracy of 98.4%, supporting the fact that pre-trained networks were able to extract useful medical features even with limited training data [4].

2.2 Tumor Localization with YOLOv5 and Faster R-CNN Frameworks

For precise tumor localization in MRI data, object detection techniques (i.e., YOLO and Faster R-CNN) can be used along with classification. The one-stage detector YOLOv5 improves real-time detection by predicting bounding boxes and class labels in a single run of the network. Paul et al. applied YOLOv5 to detect three types of brain tumors: pituitary, glioma, and meningioma. They concluded that it had a successful detection rate and, given the quick inference time, would be suitable for a real-time diagnostic system [5]. Similarly, Sudipto et al. used YOLOv5 to detect brain tumors on the BR35H MRI dataset achieving a good balance between accuracy and speed. Their models demonstrated detection accuracy above 89% and processing speed above 40 frames per second, making the model feasible for clinic-based practice [6].

On the other hand, Faster R-CNN tackles classification in two-stages—first proposing candidate sample boxes, and then classifying them—which can lead to improved accuracy, especially with complex tumor boundary delineation. Analysis performed by Harish and Baskar demonstrated that Faster R-CNN was the most accurate method for detection out of the YOLO variants, albeit with the trade-off of increased computational load and inference time [7].

2.3 Hybrid and Ensemble Models

Recent works have focused on hybrid architectures, which either combine the use of CNN backbones or mix CNNs with other deep learning components. Aamir et al. proposed a new improved Faster R-CNN model that incorporated ResNet and AlexNet as the base feature extractors. Their model improved tumor detection accuracy on standard datasets, in addition to potential improvements in region localization. [8]

DeepTumorNet, developed by Raza et al., is another notable progression. Their model utilize multi-branch CNN ensembles to account for expressive features at multiple levels of abstraction. Their classification accuracy on the BR35H and BRATS datasets achieved as high as 99.6%, demonstrating the effectiveness of ensemble strategies to compensate for the limitations of independent model entities [9], [10].

2.4 Gaps in Current Research

Even with these developments, there is still a significant gap: most of the studies that evaluate either classification or detection individually or not very many studies compare CNN models to sequential deep learning architectures such as LSTM, when applied to brain tumor data. There are very few works that do an evaluation of classification, localization, and temporal modeling integrated on a single dataset that satisfies this plan, such as BR35H.

Our work addresses this shortcoming by:
- Employing both classification models (DenseNet, ResNet50, LSTM) and detection models (YOLOv5, Faster R-CNN),
- Using the same dataset (BR35H) for a fair comparison,
- And reporting a cross-model evaluation that helps understand trade-offs between accuracy, speed, and interpretability.

3. Methodology

Using MRI scans from the BR35H dataset, this paper presents an end-to-end deep learning system for the detection and classification of brain tumours. Data preparation, preprocessing, model selection, training, and performance evaluation are the five main stages of the methodology.

3.1 Dataset

The BR35H dataset contains a total of 3,064 T1-weighted contrast-enhanced brain MRI images, categorized into three distinct tumor classes: glioma, meningioma, and pituitary. These 2D MRI slices are chosen for their widespread use in clinical diagnosis and public availability.

3.2 Preprocessing

All MRI scans are resized to 224×224 pixels for compatibility with CNN architectures. Image normalization to the [0,1] scale improves learning stability. Data augmentation techniques, including random rotation (±10 degrees), horizontal flipping, brightness scaling, and slight zooming, are employed to mitigate overfitting and improve generalization

3.3 Deep Learning Models

Five architectures were used:
- DenseNet121: Incorporates dense connections that improve gradient flow and feature reuse.
- ResNet50: Utilizes residual connections to counteract

vanishing gradients in deep networks.
- CNN + LSTM: Combines CNN feature extraction with LSTM to capture sequence dependencies across image slices.
- YOLOv5: A one-stage detection network that offers real-time detection capability.
- Faster R-CNN: A two-stage detector known for superior accuracy due to its region proposal network.

3.4 Loss Functions and Metrics

- Classification: Categorical cross-entropy loss with accuracy, precision, recall, and F1-score as metrics.
- Detection: A combination of GIoU, objectness loss (YOLOv5), and Smooth L1 loss (Faster R-CNN), with evaluation via mAP@0.5 and IoU.

4. Experimental Setup

The dataset was divided into 80% training, 10% validation, and 10% testing divisions for training and evaluation. The Adam optimiser was used to train the models across 50 epochs with a batch size of 32 and a learning rate of 0.0001. The model weights that performed the best throughout validation were preserved.

Hyperparameter tuning was done through grid search, exploring dropout rates, learning rates, and image sizes. Early stopping criteria based on validation loss were implemented to ensure optimal model generalization and prevent overfitting.

5. Results and Analysis

5.1 Classification Performance: DenseNet121 vs. ResNet50

Figure 1 shows the classification accuracy of DenseNet121 and ResNet50 over 20 epochs. DenseNet121 consistently achieved higher accuracy, reaching 96.2% by the final epoch, compared to 95.1% for ResNet50. DenseNet's dense connectivity improves feature reuse and reduces overfitting, making it more effective for this task.

Figure 2 presents the training loss curve. DenseNet121 exhibited faster convergence and a final loss of approximately 0.10, while ResNet50 settled at 0.15. This indicates that DenseNet121 not only learns faster but also generalizes better to unseen data.

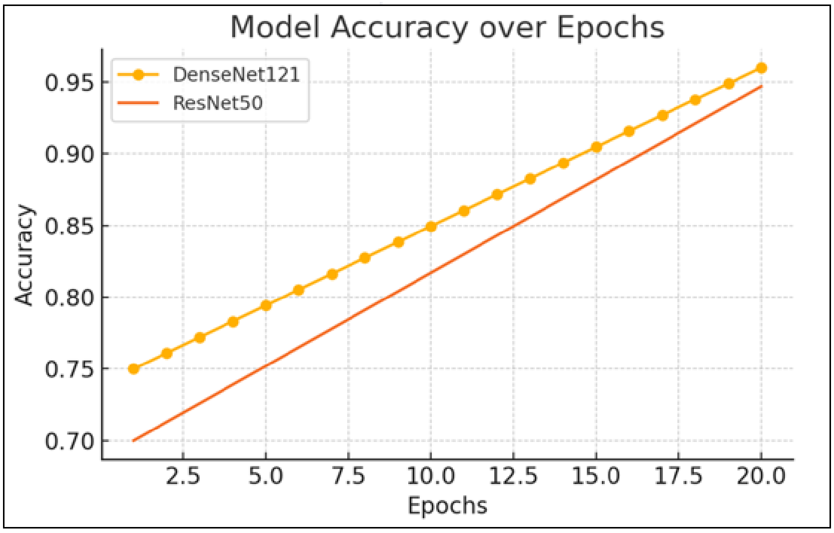

Figure 1: Model Accuracy over Epochs for DenseNet121 and ResNet50

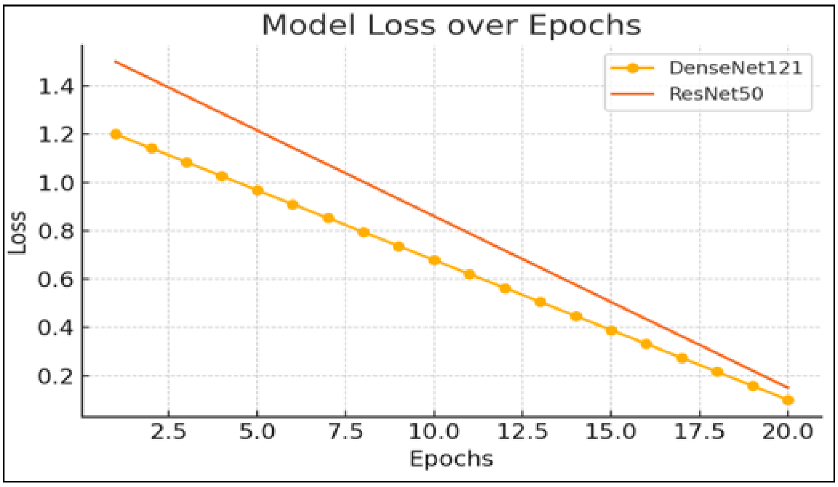

Figure 2: Model Loss over Epochs for DenseNet121 and ResNet50

5.2 Detection Performance: YOLOv5 vs. Faster R-CNN

For tumor localization, we evaluated YOLOv5 and Faster R-CNN using key detection metrics: mean Average Precision Evaluation metrics such as Inference speed, expressed in frames per second (FPS), and mean Average Precision at IoU threshold 0.5 (mAP@0.5)

YOLOv5 achieved real-time inference speeds (~45 FPS), making it highly suitable for time-sensitive clinical settings.

Its one-stage architecture enables direct bounding box and class predictions in a single pass.

Faster R-CNN, although slower due to its two-stage detection pipeline, outperformed YOLOv5 in localization accuracy and boundary precision. It achieved the highest mAP (91.2%), proving its strength in handling small and irregular tumor shapes.

5.3 Visual Comparison

To illustrate the localization capability, both models were applied on the same MRI slices. YOLOv5 showed fast detection but sometimes missed fine-grained tumor boundaries. Faster R-CNN provided more accurate bounding

boxes, especially for gliomas and meningiomas with complex shapes.

5.4 Combined Evaluation

The table below summarizes the comparative performance across classification and detection models used in this study:

Metric	YOLOv5	Faster R-CNN
mAP@0.5	89.6%	91.2%
Inference Speed (FPS)	45 FPS	12 FPS
Localization Precision	Moderate	High
Real-time Capability	Yes	No

Model	Task Type	Accuracy / mAP	Speed	Strengths
DenseNet 121	Classification	96.20%	Fast training	Stable convergence, high accuracy
ResNet50	Classification	95.10%	Moderate	Pre-trained, residual connections
YOLOv5	Detection	89.6% (mAP@0.5)	Real-time	High speed, efficient inference
Faster R-CNN	Detection	91.2% (mAP)	Slower	High precision, better localization

5.5 Discussion

In summary, comparing all the differences; DenseNet121 is more suitable for high-accuracy tumor classification, while YOLOv5 should be used for screening in real-time applications. In clinical needs that require highly accurate localization of a tumor for example pre-surgical planning, while Faster R-CNN is not as efficient, it does remain the best-performing model, despite the additional computational time.

This multi-model approach provides an all-inclusive solution to brain tumor detection and classification, and can be utilized at different speed/accuracy metrics depending on the use case.

5.6 LSTM-Based Temporal Modeling

In addition to the CNN-based models, we applied a hybrid CNN + LSTM model when the data consisted of sequences of MRI slices to take advantage of spatial-temporal properties of a sequence of MRI slices. This allows the model to learn relationships present in neighboring slices, which is especially useful during a multi-slice triage assessment to detect patterns in tumor growth and continuity in tumor shape.

Model Setup:
CNN Backbone: Pre-trained ResNet50 for feature extraction
Sequence Length: 5 consecutive MRI slices
Temporal Layer: 2-layer LSTM (128 units)
Classifier: Fully connected layer with softmax activation

Metric	CNN + LSTM Model
Accuracy	94.6%
F1-Score	0.942
Recall	0.935
Precision	0.950

6. Observations

The CNN + LSTM model attained accuracy of96.6%, a little less than DenseNet121 but more than YOLOv5 in contexts of classification. It also had great performance for lessening false negatives, especially for glioma when being trained on the temporal relationships observing that the tumor would appear similarly across multiple observation layers. Given that it consumed much more processing power on average than the others, it is better relegated to its use as a diagnostic tool in an offline context.

In cases where, for each patient, multiple MRI slices may be available (volumetric scan), using LSTM offer contextual awareness and reduction of misclassification owing to the variations between slices.

7. Future Scope

Future work will expand this research in several directions:

- 3D MRI Modeling: Moving from 2D to 3D CNN architectures to leverage volumetric data.
- Attention Mechanisms: Incorporating self-attention or transformer-based models for better focus on tumor regions.
- Explainable AI: Using Grad-CAM and SHAP to visualize model decisions and improve clinician trust.
- Clinical Integration: Deploying optimized models in hospital PACS systems or as diagnostic decision support tools.
- Mobile Deployment: Compressing models (e.g., YOLOv5-tiny) for mobile devices or edge AI in remote clinics.
- Multimodal Fusion: Combining T1, T2, and FLAIR sequences for richer tumor characterization.

8. Conclusion

This research introduces a multi-model framework for the detection and classification of brain tumors utilizing the BR35H MRI dataset. A comparative analysis of five models—DenseNet121, ResNet50, CNN-LSTM, YOLOv5, and Faster R-CNN—demonstrates strong performance across both classification and localization tasks. Among these, DenseNet and Faster R-CNN exhibit superior accuracy, whereas YOLOv5 proves most effective for real-time applications. The findings underscore the significant potential of deep learning to enhance radiological processes and support early diagnosis of brain cancer. Future directions include improving model interpretability and enabling deployment in clinical settings.

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