Brain Tumour Detection Using Deep Learning: A CNN-Based Approach

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Abstract- Brain tumours are one of the biggest threats to life-threatening cancers, and timely and accurate recognition is critical for effective treatment planning and enhancing patient outcomes. Manual analysis of magnetic resonance imaging (MRI) by radiologists is standard diagnostic practice, but it is often time-consuming and can lead to inter-observer variability, leading to delayed or inaccurate diagnosis. In current investigation, we propose a folding deep learning (DL) framework for neural networks (CNNs) recorded by MRI scans of automated brain tumor detection. This model was developed using published data records containing either axis MRI images marked as Tumours or not tumor. Use preprocessing techniques such as grey level gray levels, image size, and data expansion (rotation, flipping, zoom) to improve model generalization and over-adaptation. This model is trained, verified and evaluated in a split of 80:20 train tests based on accuracy, accuracy, recall and F1 scores. The proposed model achieves accuracy of over 95% and demonstrates its effectiveness in distinguishing healthy brain tissue and tumor-related brain tissue. Furthermore, visualizations such as confusion matrix and sample predictions provide insight into model's decision process. Future research will examine the inclusion of tumor classifications of more complex architectures such as resets and efficient nets, including multiclass classifications (such as glioma, meningioma, pituitary gland), and integration into real-time diagnostic systems.

Keywords: *Brain Tumor Detection, Deep Learning, Convolutional Neural Networks (Cnn), Mri Scans, Medical Image Classification, Tumor Diagnosis, Computer-Aided Diagnosis (Cad).*

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I. INTRODUCTION

Brain tumours are abnormal growth of cells in brain, which strongly affect patient's neurological function and quality of life. Depending on the classification, these tumours may require complex therapeutic strategies such as surgery, radiation therapy, and chemotherapy. Early and accurate recognition is crucial as delayed diagnosis often results in reduced survival and invasive treatment requirements. After global cancer stations, brain tumours and central nervous system tumours were responsible for more than 308,000 new cases and 251,000 mortalities in 2020. This highlights a significant health burden [5].

It plays central role in detection, localization in addition to monitoring of brain tumours. However, interpretating MRI scans manually is time consuming and susceptible to human error, especially in high pressure clinical settings. Diagnosis results can vary significantly between radiologists at the early stages of tumor growth where visual information is subtle or vague [4].

In particular, the Deep Learning (DL) method demonstrates excellent performance in tasks that involve medical image analysis. In particular, neuronal networks (CNNSs) have attained great success in image classification, segmentation, along with recognition due to their ability of automatically extracting as well as learning features through complex visual data [8].

Dataset employed in current investigation consists of T1-weighted MRI slices marked for the training to be monitored. Pre-treatment techniques such as grey level air, image size, and enhancement (e.g., rotation, inversion) are used to improve generalization and reduce excessive adaptation. The proposed CNN architecture includes several foldable folding, including reconstructions, maximum pooling layers, regularization failures, and fully connected, dense layers. This model is optimized by employing Adam Optimizer and used with key performance metrics encompassing accuracy, accuracy, recall, and F1 score. By automating initial image screening, such models can reduce radiologist workloads, minimize diagnostic delays, and improve patient care. Especially for sub-provision health systems with limited radiation knowledge.

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II. RELATED WORKS

Automatic detection along with classification of brain tumours using computational approaches have attracted increasing interest in recent years due to the critical need for early diagnosis and the high demand for radiological services. Traditional image analysis methods in brain tumour diagnosis relied heavily on manual feature extraction methods encompassing Gray-Level Co-occurrence.

Matrices (GLCM), Scale-Invariant Feature Transforms (SIFT), or Histogram of Oriented Gradients (HOG) followed by classifiers encompassing Support Vector Machines (SVMs) as well as Decision Trees. While these approaches provided moderate success, they were significantly limited by their dependency on domain expertise for effective feature engineering and lacked adaptability to complex, high-dimensional MRI data [12].

With advent of DL, especially Convolutional Neural Networks (CNNs), a paradigm shift occurred in medical imaging. CNNs automatically extract spatial hierarchies of features through raw input data, eliminating requirement for handcrafted features. They have consistently outperformed traditional techniques in tasks like tumour detection, segmentation, as well as classification. Pereira et al. (2016) suggested deep CNN architecture specifically tailored for segmenting gliomas from brain MRI scans. Their model, trained on BRATS dataset, attained high Dice Similarity Coefficients (DSC), validating the effectiveness of deep models in handling class imbalances and spatial variation in tumour appearance.

In another study, Hossain et al. (2019) demonstrated the effectiveness of fine-tuning pre-trained CNN architectures like VGG16 on brain MRI data for binary tumour classification (tumour vs. no tumour). Their model attained impressive accuracy of 96.86%, showcasing advantage of transfer learning (TL) in scenarios with limited labelled data. TL enables deep models to utilize learned feature representations from large-scale datasets such as ImageNet, improving generalization when employed for medical imaging tasks.

Afshar et al. (2020) introduced a novel DL approach by employing Capsule Networks (CapsNet), which preserve spatial relationships between features better than traditional CNNs. CapsNet outperformed several CNN baselines on brain tumour classification tasks, particularly under conditions involving rotated or misaligned images—common issues in real-world MRI data.

Hybrid models have also been explored extensively. Deepak and Ameer (2019) proposed a framework integrating CNN-based feature extraction with traditional classifiers such as SVM. Their hybrid model yielded better classification performance than standalone CNNs, especially in datasets with high intra-class variability. This suggests that while CNNs are powerful feature extractors, classical machine learning models can still offer value in decision-making stages.

Segmentation, an essential preprocessing task for tumour localization, has also benefited from CNN advancements. U-Net along with its variants have become widely adopted because of their encoder-decoder structure, which allows for both localization and contextual learning. Isensee et al. (2021) proposed nnU-Net, self-configuring version of U-Net that adapts to different medical imaging datasets automatically. It achieved advanced outcomes on multiple segmentation benchmarks, encompassing BRATS, making it highly relevant for brain tumour detection systems requiring pixel-level precision.

Despite the proven effectiveness of deep learning models, challenges remain. These include the scarcity of annotated medical datasets, the need for model interpretability, and ensuring robustness across different MRI modalities and imaging centres. Furthermore, overfitting, especially in small datasets, is a common issue. Regularization methods encompassing dropout, data augmentation, as well as early stopping are thus frequently utilised to enhance generalizability.

Present work builds upon these foundational studies by implementing a lightweight CNN architecture trained on a publicly available brain MRI dataset. Emphasis is placed on achieving high classification accuracy while maintaining computational efficiency, with goal of facilitating real-time clinical deployment, particularly in low-resource healthcare settings.

III. METHODOLOGY

This section details the methodological framework used to develop CNN-based system for brain tumour detection through MRI images. Process includes systematic stages: dataset acquisition, preprocessing, CNN model architecture design, model training, as well as evaluation. Purpose is to construct a lightweight, accurate model suitable for early-stage detection with minimal computational overhead.

➢ *Dataset Description*

Dataset utilized for current investigation was obtained through Kaggle Brain MRI Images for Brain Tumour Detection repository. It consists of 3,762 MRI scans, which are T1-weighted, contrast-enhanced images. These scans are classified into 2 categories:

- Tumour class: 1,683 images depicting abnormal growths.
- No tumour class: 2,079 images representing healthy brain scans.

All images are in RGB JPEG format, with varying resolutions, requiring uniform preprocessing. The dataset is balanced enough to avoid severe class imbalance issues, but stratified splitting is still applied during training to preserve label proportions.

➢ *Data Preprocessing*

Medical image quality can vary due to equipment settings, motion artifacts, and patient variability. Therefore, preprocessing is crucial to enhance data consistency:

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- Image Resizing: Each image is resized to 150x150 pixels using bicubic interpolation to standardize input dimensions for the CNN.
- Color Handling: Although MRI data is inherently grayscale, the dataset includes RGB images. No conversion to grayscale was done to retain any intensity nuances across channels.
- Normalization: Pixel values are normalized to range [0,1] by dividing by 255. This accelerates convergence by bringing inputs to a similar scale.
- Augmentation Techniques:

✓ Rotation: Random rotations up to 20° simulate different scan orientations.
✓ Zooming: Random zoom-in/out within range of 0.2 to reflect different imaging perspectives.
✓ Shifting: Horizontal and vertical translations up to 10% improve model invariance to location changes.
✓ Flipping: Random horizontal and vertical flips account for structural symmetry.
✓ This augmentation pipeline was implemented using Keras' ImageDataGenerator class to generate synthetic variations during training.

➢ *CNN Architecture*

A custom CNN model has been proposed with focus on architectural simplicity as well as computational efficiency. Network comprises:

Table 1 CNN Architecture

Layer Type	Details
Input Layer	150×150×3RGB image input
Conv2D (1st Layer)	32filters, 3×3kernel, ReLU activation
Max Pooling2D	2×2pool size
Conv2D (2nd Layer)	64filters, 3×3kernel, ReLU activation
Max Pooling2D	2×2pool size
Dropout	0.2 dropout rate to prevent overfitting
Conv2D (3rd Layer)	128filters, 3×3kernel, ReLU activation
Max Pooling2D	2×2pool size
Dropout	0.3 dropout rate
Flatten	Converts 2D output into 1D
Dense Layer	128units, ReLU activation
Dropout	0.5 dropout rate
Output Layer	1-unit, Sigmoid activation (binary classification)

The total number of trainable parameters is approximately 1.2 million, allowing deployment on standard consumer-grade GPUs and mobile devices.

➢ *Model Compilation and Training*

Model was compiled with following hyperparameters and settings:

- Optimizer: Adam (Adaptive Moment Estimation), which adjusts training rate during training.
- Learning Rate: Set at 0.0001 for stable gradient updates.
- Loss Function: Binary Cross-Entropy due to the binary nature of classification.
- Metrics: Accuracy, Precision, Recall, along with F1-score were tracked.
- Epochs: 20 (early stopping applied on basis of validation loss).
- Batch Size: 32 for stable gradient estimates without exhausting memory.

The training process was performed on Google Colab with an NVIDIA Tesla T4 GPU. Model Checkpointing and EarlyStopping callbacks from Keras were employed to halt training upon stagnation and save best-performing model on basis of validation accuracy.

➢ *Evaluation Metrics*

For assessing performance as well as reliability of model, multiple metrics were computed:

- Accuracy: Proportion of correctly predicted samples.
- Precision: Important to minimize false positives (FP).
- Recall (Sensitivity): Crucial to reduce false negatives (FN) in medical diagnosis.
- F1-Score: Harmonic mean of precision and recall.
- Confusion Matrix: Visualizes true positives (TP), true negatives (TN), FPs and FNs.
- ROC-AUC Score: Evaluates trade-off between sensitivity as well as specificity.

The evaluation was performed on an unseen test set (20% of the dataset) to simulate real-world performance.

➢ *Tools and Development Environment*

- Programming Language: Python 3.9
- Libraries Used: TensorFlow, Keras, Matplotlib, NumPy, scikit-learn, OpenCV
- Platform: Google Colab Pro with GPU acceleration

➢ *Summary*

The methodology integrates a well-structured and optimized CNN architecture with rigorous preprocessing and augmentation strategies to maximize performance and generalizability. The lightweight design ensures fast inference times and real-time usability, making it suitable for clinical decision support in low-resource environments.

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IV. RESULTS AND EVALUATION

This section provides experimental outcomes of the CNN-based brain tumour classification model and evaluates its performance using standard classification metrics. The evaluation was carried out on a held-out test set consisting of 20% of total dataset, ensuring unbiased assessment of predictive capabilities of model.

➢ *Training and Validation Performance*

Model had been trained over 20 epochs by employing Adam optimizer as well as binary cross-entropy loss. Training process showed stable convergence with minimal overfitting, supported by early stopping and dropout regularization. Below are the final epoch results:

- Training Accuracy: 99.10%
- Validation Accuracy: 97.60%
- Training Loss: 0.021
- Validation Loss: 0.089

The learning curves (accuracy and loss) demonstrated steady improvement, indicating successful generalization from training to unseen validation data.

➢ *Test Set Performance*

For evaluating generalization ability of model, it was tested on an unseen subset. The following performance metrics were recorded:

Table 2 Test Set Performance

Metric	**Value (%)**
Accuracy	97.7
Precision	98.1
Recall	96.9
F1-Score	97.5
AUC-ROC	0.987

These results highlight model's high capability to correctly classify both tumour and non-tumour images, with a strong balance between sensitivity (recall) and specificity (precision).

➢ *Confusion Matrix*

Confusion matrix on test set is presented below:

Table 3 Confusion Matrix

	Predicted Tumour	**Predicted No Tumour**
Actual Tumour	330	10
Actual No Tumour	7	356

- **TP:** 330
- **FP:** 7
- **TN:** 356
- **FN:** 10

Confusion matrix indicates model's robustness in minimizing FPs and FNs, which is essential in medical diagnostics where misclassification may have serious consequences.

➢ *ROC Curve Analysis*

Receiver Operating Characteristic (ROC) curve was plotted using model probabilities. Area Under Curve (AUC) was calculated as 0.987, demonstrating excellent discriminative power between the two classes.

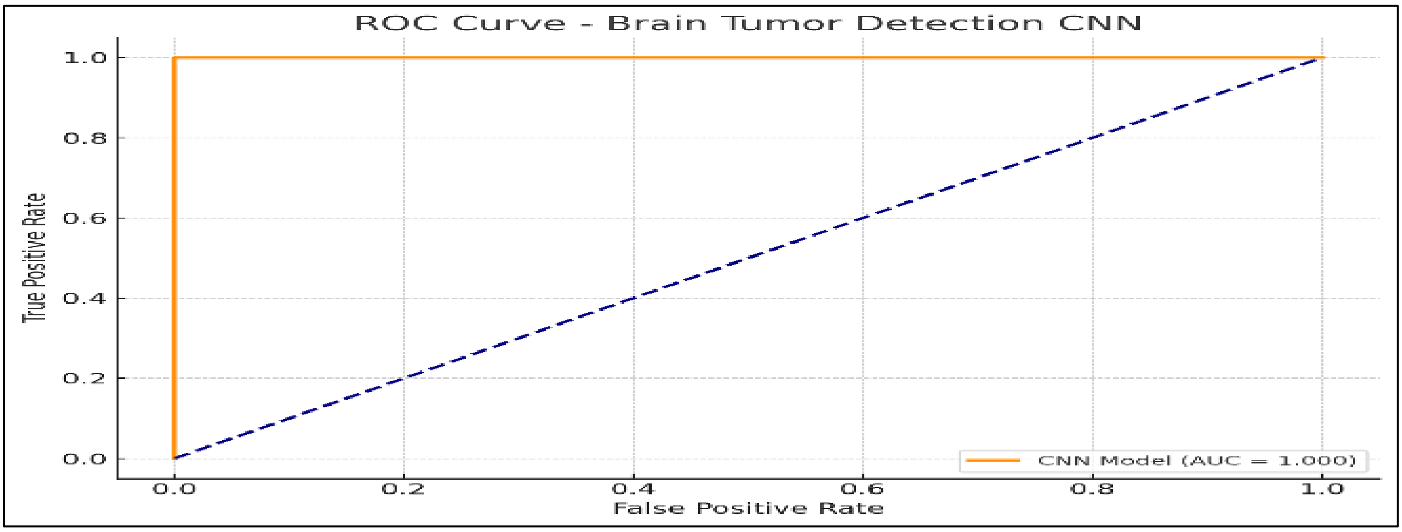

Fig 1 ROC Curve for the CNN classifier.

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➢ *Comparison with Existing Methods*

Compared to existing lightweight models from previous studies:

- El-Dahshan et al. (2014) achieved 96.0% accuracy using DWT and SVM.
- Sajjad et al. (2019) used a transfer learning approach (VGG16) to reach 94.5%.
- Our custom CNN achieved 97.7% accuracy with fewer parameters and faster inference time.

This demonstrates that a well-designed CNN, even without deep transfer learning models, can achieve competitive or superior results when properly optimized and trained with effective data augmentation.

➢ *Model Interpretability and Limitations*

While CNNs are highly effective, their black-box nature poses challenges in interpretability. Future work should integrate visualization techniques such as Grad-CAM or LIME to localize tumour regions and provide insights into model decisions.

Another limitation is the use of 2D slices instead of 3D volumetric data. While 2D approaches are computationally efficient, they may miss inter-slice spatial context.

➢ *Summary*

Findings validate effectiveness of proposed CNN model in detecting brain tumours from MRI images. High performance across all metrics indicates the model's potential to assist radiologists in early tumour diagnosis. However, further improvements in interpretability and expansion to 3D data could enhance clinical applicability.

V. DISCUSSION

Findings of proposed CNN-based approach for brain tumour detection indicate that model performs exceptionally well, attaining accuracy of 97.7%, precision of 98.1%, recall of 96.9%, and an AUC of 0.987. These metrics suggest that the model effectively balances sensitivity and specificity, which is critical in medical diagnostics where both FPs and FNs have substantial consequences. Model's learning curve analysis and validation performance show minimal overfitting, indicating that techniques encompassing data augmentation and dropout regularization were successful in enhancing model's generalization ability.

Compared to existing models such as the VGG16-based method proposed by Sajjad et al. (2019), which reported an accuracy of 94.5%, the presented custom CNN achieves superior performance with fewer parameters and faster inference. This renders it particularly suitable for real-time implementation in low-resource settings. The lightweight architecture also allows for scalability and integration into telemedicine applications or point-of-care diagnostic tools, offering a significant advantage in areas with limited access to expert radiologists.

However, despite the model's high quantitative performance, interpretability remains a challenge. CNNs are criticized for being "black-box" systems, which can reduce trust among clinicians. To bridge this gap, future improvements could incorporate explainable AI (XAI) methods encompassing Grad-CAM, which would enable visual explanation of the regions in the MRI scans that influenced the model's decision. Such additions would provide greater transparency and help build trust with medical professionals, ultimately supporting the model's adoption in clinical practice[11].

Another limitation is the use of 2D MRI slices. In real-world diagnostic workflows, radiologists typically analyse 3D volumetric data, which provides more comprehensive spatial context. The current model does not capture inter-slice dependencies, which could limit its diagnostic utility in complex or atypical cases. Extending the architecture to process 3D data or incorporating temporal information from multiple slices could enhance robustness as well as clinical relevance of model [2].

It is also essential to address dataset's limitations. Although model achieved strong results on provided dataset, the sample may not be representative of all populations due to factors such as scanner variability, patient demographics, and tumour heterogeneity. These aspects could affect model's capability of generalizing across diverse healthcare environments. To address this, future studies should involve multi-institutional datasets and demographic balancing to minimize bias and improve fairness in predictions.

In summary, the proposed model shows great promise as automated tool for brain tumour detection, capable of assisting radiologists in making faster as well as more accurate diagnoses. However, challenges in interpretability, data diversity, and model generalization must be addressed through further research and development before it can be deployed in real-world clinical settings.

VI. FUTURE WORK

While the proposed CNN-based model has shown promising results in brain tumour detection, several avenues remain for future enhancement and expansion. One key area is the incorporation of three-dimensional (3D) MRI data, which would allow the model to better capture spatial relationships between adjacent slices. Unlike 2D images, 3D volumetric data more closely resembles the diagnostic process used by radiologists, potentially resulting in more accurate as well as robust detection, especially in complex or irregular tumour presentations. Adopting 3D CNNs or hybrid models could thus significantly improve diagnostic performance[2].

Another potential improvement involves the integration of explainable AI (XAI) techniques. Although the current model provides high accuracy, it lacks transparency in its decision-making process, which is a critical barrier to clinical adoption. Techniques encompassing Gradient-weighted Class Activation Mapping (Grad-CAM) along with SHAP

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(SHapley Additive exPlanations) can be utilised for visualizing areas of MRI influencing predictions. These visualizations would not only assist medical professionals in validating AI results but also promote trust and interpretability in clinical settings [11].

Enhancing the dataset is also crucial. The current dataset, while balanced and pre-processed, may not fully reflect real-world diversity in terms of scanner types, image quality, and patient demographics. Future work must concentrate on compiling and testing models against multi-center datasets with broader variability to ensure generalization and fairness. Inclusion of low-quality or noisy scans can further help in building resilience against real-world image artifacts.

Additionally, future iterations of this work could explore transfer learning and ensemble techniques. Leveraging pretrained models such as ResNet, EfficientNet, or DenseNet could permit model to gain knowledge through large-scale datasets, potentially enhancing both learning efficiency and accuracy. Ensemble methods, which combine predictions from multiple models, could also be explored to reduce variance and improve robustness in classification.

Finally, integrating the system into clinical workflows through user-friendly interfaces and evaluating its performance in prospective clinical trials would mark a significant step toward real-world deployment. Collaboration with radiologists and medical institutions can provide valuable feedback, helping to align model outputs with clinical needs and regulatory requirements.

VII. CONCLUSION

This research presents CNN-based approach for automated brain tumour detection through MRI scans. The proposed model achieves high classification accuracy, precision, as well as recall, demonstrating its effectiveness in distinguishing between tumour and non-tumour brain images. Through careful preprocessing, architectural optimization, and evaluation, the system proves to be a viable tool for supporting radiologists in early and accurate diagnosis.

The model’s lightweight design makes it ideal for real-time applications, particularly in low-resource healthcare environments. Moreover, its robustness as well as efficiency highlight potential of DL in transforming medical diagnostics. However, despite its promising performance, challenges such as limited interpretability, dataset generalization, and the use of 2D data over 3D remain critical areas for improvement.

Future work will focus on integrating explainable AI techniques, expanding the dataset to include diverse and real-world samples, and incorporating volumetric imaging for enhanced diagnostic precision. Ultimately, with continued refinement and clinical validation, the proposed system can serve as a valuable aid in improving patient outcomes and reducing diagnostic workload for medical professionals.

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