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A Comparative Study of CNN, ResNet50, U-Net, YOLOv7, and InceptionResNetV2 for Brain Tumor Classification in MRI

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Abstract- Brain tumor detection from magnetic resonance imaging (MRI) is essential for early diagnosis, treatment planning, and improved patient outcomes. This study conducts a comparative evaluation of five deep learning approaches—CNN, ResNet50, U-Net, YOLOv7, and InceptionResNetV2—for automated brain tumor classification. Prior to model training, the dataset was prepared through systematic preprocessing, including data cleaning, normalization, and augmentation to improve robustness and reduce overfitting. Model performance was assessed using standard classification metrics: accuracy, precision, recall, and F1-score. Experimental results indicate that all evaluated architectures achieved strong predictive performance; however, InceptionResNetV2 consistently outperformed the other models, achieving near-perfect scores across all evaluation measures. This strong performance suggests improved reliability in reducing both false-positive and false-negative predictions, making InceptionResNetV2 a promising candidate for clinical decision-support applications. Overall, the findings highlight the importance of advanced deep learning architectures in delivering accurate and dependable MRI-based brain tumor detection.

Keywords – Brain Tumor Detection, MRI, Deep Learning, Medical Imaging, InceptionResNetV2, CNN, ResNet50, U-Net, YOLOv7.

I. INTRODUCTION

Brain Brain tumours are a serious medical challenge because they involve different types of abnormal growths in the brain. Detecting them correctly is difficult due to their complex and varied nature, but it is very important for planning effective treatments. Traditional diagnostic methods are useful but often cannot capture the fine details needed for precise treatment decisions. Medical imaging has greatly improved this process by allowing doctors to see the brain's structure without surgery. However, reading these images requires skilled specialists and can sometimes lead to inconsistent results. Recently, deep learning especially Convolutional Neural Networks (CNNs) has opened new ways to make diagnosis more accurate and efficient. CNNs can automatically learn important features from large amounts of medical images, making it easier to identify and classify brain tumours more reliably.

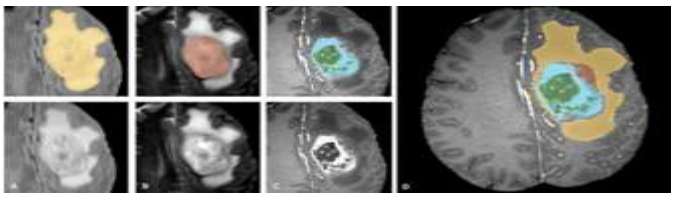

Figure 1. Brain tumor and segmentation.

Deep learning has progressed rapidly in recent years, enabling the development of highly capable models for complex tasks in medical imaging. Among these, InceptionResNetV2 is notable because it combines inception modules with residual connections. The inception modules help the network capture multi-scale features by learning from different receptive fields, while residual connections support stable training of very deep networks by mitigating the vanishing gradient problem. This architecture is particularly suitable for medical imaging, where detecting subtle patterns and fine details is essential for accurate diagnosis.

In this study, InceptionResNetV2 is applied to brain tumor detection using a large MRI dataset. The images were carefully preprocessed through data cleaning, augmentation, and normalization to improve input quality and enhance generalization. Each MRI scan was labeled to indicate whether a tumor was present, enabling the development of a binary classification model. The performance of InceptionResNetV2 was then benchmarked against other deep learning approaches, including a baseline CNN, ResNet50, U-Net, and YOLOv7, using standard evaluation metrics such as accuracy, precision, recall, and F1-score.

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The experimental results demonstrate strong performance from InceptionResNetV2, achieving 99.86% accuracy, 99.48% precision, 99.75% recall, and a 99.86% F1-score. These outcomes indicate that the model can reliably identify tumors while reducing clinically significant errors such as false positives and false negatives. In comparison with the other models evaluated, InceptionResNetV2 consistently delivered superior results, highlighting its effectiveness in managing the complexity and variability present in brain MRI data.

The findings suggest that deep learning models such as InceptionResNetV2 can strengthen clinical workflows by supporting radiologists with faster and more consistent tumor detection. Improved automation may contribute to earlier diagnosis and more informed decision-making, with potential benefits for individualized treatment planning. Overall, this work reinforces the value of deep learning in medical imaging and positions InceptionResNetV2 as a strong benchmark for MRI-based brain tumor detection. Future progress will benefit from validation on larger and more diverse datasets, as well as continued improvements in model robustness and clinical interpretability.

II. LITERATURE REVIEW

Monitoring metastatic brain conditions is often difficult, especially when patients present with multiple metastases. Moawad et al. (2023) pointed out that while the RANO-BM guideline is widely used to evaluate treatment response, detailed volumetric analysis of lesions and surrounding edema is still essential. Since many brain metastases are smaller than 10 mm, accurate sectioning is challenging. To advance research in this area, the BraTSMETS dataset was developed for automated detection and segmentation of brain metastases [1].
According to Liu et al. (2023), brain tumour segmentation is a crucial step in medical imaging, and recent advances in deep learning have made significant progress in this field. Their review covered over 150 studies on tumour segmentation strategies, examining network architectures, handling unbalanced data, and multi-modality approaches. The authors also suggested directions for future research [2].

Gupta & Bibhu (2023) emphasised the importance of MRI in early tumour detection but highlighted the difficulty caused by tumour variability. They proposed an Improved Invasive Bat (IIB)-based Deep Residual Network, which demonstrated strong results in terms of accuracy, sensitivity, and specificity [3].

Kumar (2023) compared different segmentation techniques on the BRATS-2018 dataset. While methods such as Otsu's thresholding, watershed, level set, K-means, and DWT produced mixed results, CNN-based approaches showed superior accuracy and faster response times, making them promising for clinical applications [4].

Balamurugan & Gnanamanoharan (2023) presented a hybrid DCNN classifier that incorporated an improved LuNet algorithm. Their method combined data separation, feature extraction, and the Laplacian of Gaussian (LOG) filter, achieving an accuracy rate of 99.7% [5].
Tseng & Tang (2023) focused on improving diagnostic support through automation. They introduced an enhanced version of the eXtreme Gradient Boosting (XGBoost) algorithm for tumour diagnosis using MRI data, reporting high accuracy and precision rates [6].

Ahmadi et al. (2023) proposed a deep learning segmentation approach applied across various brain diseases. Using data from Harvard Medical School, their method achieved strong accuracy and sensitivity, highlighting its potential for medical use [7].

Ahmed et al. (2023) used the VGG16 deep learning model to classify MRI scans from Kaggle as either "normal" or "tumour," achieving 97.33% accuracy. To overcome the "black box" nature of deep models, they incorporated Layer-wise Relevance Propagation (LRP) to make the decision process more transparent [8].

Shemanto et al. (2023) addressed the challenge of tumours resembling normal brain tissue. They pre-processed MRI scans with a HOFilter, then segmented tumours using edge detection and morphological methods. Their model reached 96.19% precision and 96.46% accuracy [9].

Saeedi et al. (2023) explored machine learning and deep learning techniques for diagnosing gliomas, meningiomas, pituitary tumours, and healthy brains. Their CNN and autoencoder models achieved 96.47% and 95.63% accuracy, while among traditional methods, K-Nearest Neighbours (KNN) performed the best [10].

Asiri et al. (2023) developed a CNN model fine-tuned with ResNet50 and U-Net, achieving strong segmentation results with an Intersection over Union (IoU) of 0.91 and Dice Similarity Coefficient (DSC) of 0.95 [11].

Finally, Abdusalomov et al. (2023) improved the YOLOv7 model for brain tumour detection. Their updated approach used data augmentation, the CBAM attention mechanism, and a Bi-directional Feature Pyramid Network (BiFPN), resulting in accurate and efficient detection of gliomas, meningiomas, and pituitary tumours [12].

Metlek & Çetıner (2023) introduced an innovative hybrid convolution-based model for brain tumour segmentation. Their approach achieved a Dice score of up to 93.10% across multiple datasets, demonstrating its robustness. The model's unique preprocessing strategy provided notable improvements compared to conventional methods [13].

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Similarly, Mohammed et al. (2023) explored MRI-based segmentation techniques, highlighting the important role of convolutional neural networks (CNNs) in advancing brain tumour detection. Their review emphasized how deep learning has significantly contributed to recent progress in tumour segmentation [14].

Rajagopal et al. (2023) focused on aggressive gliomas and improved segmentation by combining U-Net and 3D CNNs with Grey Level Co-occurrence (GLC) matrix feature extraction. Their model achieved very high accuracy rates of up to 99.4% in whole tumour segmentation [15].

Pacheco et al. (2023) investigated the challenges of multi-modal MRI segmentation. They found that preprocessing steps, especially skull-stripping, often require manual correction, making them time-consuming in clinical practice. Their study showed that the choice of brain extraction method could affect segmentation performance by as much as 15.7%. Interestingly, training directly on raw images without skull-stripping reduced processing time without sacrificing accuracy, offering a more practical workflow [16].

Kareem et al. (2023) highlighted the role of ANNs and MLPs in MRI-based tumour detection. After preprocessing MRI images, the extracted features successfully trained machine learning models, which showed strong potential for accurate tumour identification [17].

Ali et al. (2023) developed WBM-DLNets, a novel framework for brain tumour diagnosis using MRI. They tested sixteen pretrained networks with eight optimisation methods, and combinations such as DenseNet-201-GWOA and EfficientNet-b0-ASOA achieved the best classification accuracy [18].
Dalal et al. (2023) proposed a segmentation method combining AMSOM with FKM, tested on the BraTS-2018 dataset. Their approach produced a 10% improvement in key metrics compared to traditional methods [19].

Solanki et al. (2023) presented an in-depth analysis of MRI-based brain tumour detection. Their study reviewed existing computational intelligence, machine learning, and deep learning methods, demonstrating that their proposed strategy outperformed many standard approaches [20].

Aggarwal et al. (2023) addressed the limitations of deep neural networks by introducing an Improved Residual Network (ResNet) for segmentation. Their model improved performance measures by 10% compared to conventional approaches [21].
Mahmud et al. (2023) compared CNN models with ResNet-50 and VGG16 for brain tumour detection using MRI. Their findings showed that CNN-based approaches outperformed both ResNet-50 and VGG16, reinforcing CNN's role as a strong candidate for medical imaging tasks [22].

Karri et al. (2023) proposed SGC-ARANet, an advanced model designed to improve tumour boundary detection. Using the BraTS 2019 and 2020 datasets, their model outperformed many existing U-shaped architectures, achieving more precise segmentation [23].
Konwer et al. (2023) applied a meta-learning framework to overcome the problem of missing modalities in medical imaging. Their method improved partial modality representation, showing superior performance in cases where imaging data was incomplete [24].
Aleid et al. (2023) suggested an MRI segmentation method based on a harmony search algorithm. While CNN and DLA models provided high accuracy, their approach achieved comparable accuracy while being more resource-efficient and faster, addressing one of the main limitations of deep learning in clinical use [25].

Beyond brain tumours, several 2022 studies applied AI and IoT technologies to related medical and computational challenges. Gupta et al. (2022) and Patidar et al. (2022) developed assistive devices and efficient hardware designs [26,27]. Taiwade et al. (2022) proposed algorithms for friend recommendations and face mask detection [28], while Baghel et al. (2022), Ranjan et al. (2022), and Singh et al. (2022) explored AI for cancer prediction [29,30]. Singh et al. (2022) also applied Mask-RCNN for advanced object detection tasks [31].

Recent advances in segmentation techniques continued in 2023. Ullah et al. (2023) introduced a patch-based CNN (PBCNN) for early tumour detection [32]. Similarly, Iqbal et al. (2023) used U-Net with the MICCAI BraTS 2018 dataset, achieving strong performance across MRI modalities [33].
Babu et al. (2023) enhanced segmentation with dilated convolution and level-based learning, allowing effective detection of tumours of varying sizes [34]. Finally, Archana & Komarasamy (2023) targeted the challenge of small tumour detection, proposing a Bagging Ensemble with K-Nearest Neighbour (BKNN). Their method reached an accuracy of 97.7% in distinguishing between normal and abnormal tissues in MRI scans [35].

III. PROPOSED METHOD

Proposed working architecture

The figure 2 shows the complete workflow for brain tumour detection using deep learning. It begins with a dataset of brain tumour images that undergoes data cleaning steps such as artifact removal, noise reduction, bias field correction, and normalization. Next, segmentation techniques like thresholding, region growing, and the watershed algorithm are applied to separate tumour regions, followed by feature extraction to capture histogram-based and shape-related characteristics. These processed data samples are then divided into training and testing sets, which are used to train the

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InceptionResNetV2 deep learning model. Once the model is trained, it is evaluated based on key metrics such as accuracy, specificity, and sensitivity. Finally, the trained model makes predictions to classify images as either tumour or non-tumour, supporting more precise diagnosis.

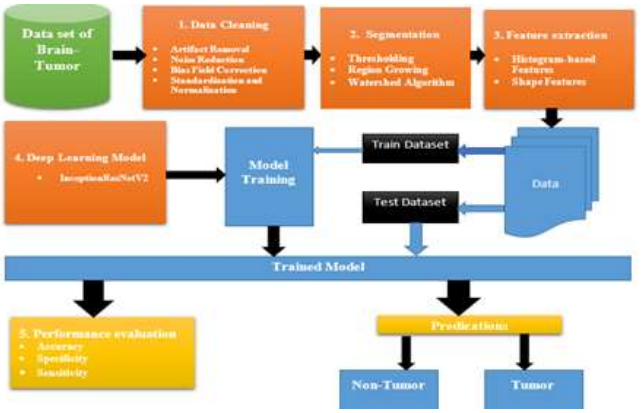

Figure 2. Proposed working architecture

Algorithm: Brain Tumor Detection using InceptionResNetV2

Step 1: Data Collection and Preprocessing

1. MRI Dataset Acquisition

Collect a labeled MRI dataset containing both tumor (positive) and non-tumor (negative) images.

2. Data Cleaning

Remove corrupted, duplicate, and irrelevant images to improve dataset reliability and reduce training noise.

3. Data Augmentation

Apply augmentation to increase data diversity and reduce overfitting. Typical operations include:

- rotation
- horizontal/vertical flipping
- scaling
- translation (shifting)

4. Dataset Splitting

Divide the dataset into three subsets for unbiased evaluation:

- Training set: 70%
- Validation set: 15%
- Testing set: 15%

5. Image Preprocessing

Standardize all images before model input:

- resize to 299 × 299 pixels (InceptionResNetV2 input size)
- normalize pixel values to the range [0, 1]

Step 2: Model Design and Configuration

1. Base Model Selection

Load InceptionResNetV2 as the backbone network without the top (classification) layers to enable transfer learning.

2. Custom Classification Head

Add task-specific layers for binary classification:

- Flatten layer (or Global Average Pooling as an alternative)
- one or more Dense layers with ReLU activation
- final Output layer with Sigmoid activation (for tumor vs non-tumor probability)

3. Model Compilation

Compile the architecture using:

- Optimizer: Adam
- Loss function: Binary Cross-Entropy
- Metrics: Accuracy (optionally precision, recall, AUC)

Step 3: Model Training

1. Training Setup

Define key training parameters:

- Epochs: e.g., 30–50
- Batch size: e.g., 32
- Callbacks: Early stopping and Model checkpointing to prevent overfitting and save best weights

2. Training Procedure

Train the model using the training subset while validating on the validation set. Track loss and performance metrics throughout training to ensure generalization and stable learning.

Step 4: Testing, Evaluation, and Fine-Tuning

1. Final Model Evaluation

Evaluate the trained model using the test set to obtain unbiased performance results.

2. Optional Fine-Tuning

To improve accuracy, unfreeze selected upper layers of InceptionResNetV2 and continue training using a smaller learning rate to refine feature representations.

3. Performance Measurement

Compute standard classification metrics:

- Accuracy
- Precision
- Recall
- F1-score

Final Output

The trained model produces a binary prediction for each MRI image:

IV. IMPLEMENTATION

Dataset

The BraTS 2020 dataset, hosted by the CBICA group at the University of Pennsylvania, comprises multi-institutional, clinically acquired preoperative multimodal MRI scans of

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glioblastoma (GBM/HGG) and lower-grade glioma (LGG), along with pathologically confirmed diagnoses and corresponding survival data. Each sample includes four MRI modalities T1, post-contrast T1 (T1Gd), T2, and T2-FLAIR provided as co-registered, skull-stripped NIfTI volumes in a standard 1 mm³ resolution. Expert neuroradiologists annotate each image into subregions (enhancing tumour, edema, necrotic/non-enhancing core) following a consistent protocol. Alongside imaging, the dataset provides patient overall survival (in days), age, and resection status metadata, allowing researchers to link imaging features with clinical outcomes.

Dataset Source Link : https://www.med.upenn.edu/cbica/brats2020/data.html

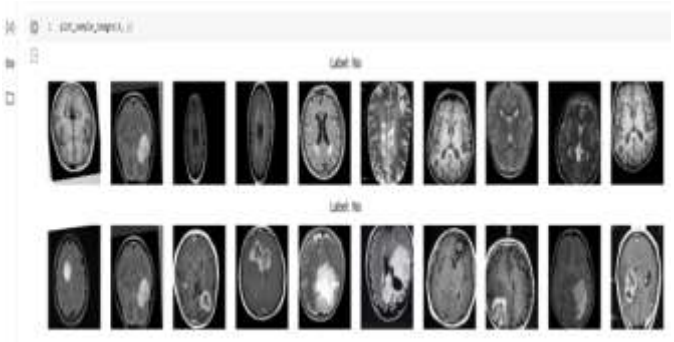

Figure 3. Sample dataset.

The figure 3 shows a grid of brain MRI scans displayed as sample outputs from a plotting function. The top row consists of scans labeled “No”, indicating the absence of a brain tumour, while the bottom row also carries the label “No”, but contains images that visually show abnormalities or possible tumour-like regions. Each MRI slice highlights different brain structures and varying contrasts, illustrating the diversity in MRI appearances. This visualization helps compare normal and abnormal cases during dataset exploration, serving as an important step in understanding the data distribution before applying deep learning models for classification.

Illustrative Example

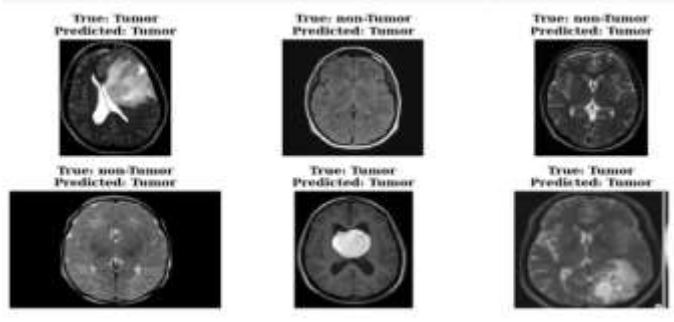

Figure 4. The predicted result is generated through the model.

The figure 4 shows brain MRI scans with their corresponding ground truth labels and model predictions, demonstrating the performance of a tumour detection system. Some examples, such as the first and last images, display correct classifications where both the true label and prediction indicate the presence of a tumour. Similarly, other cases show correct identification of tumours despite variations in size and appearance. However, a few scans highlight misclassifications, such as non-tumour images being incorrectly predicted as tumours, indicating false positives. Overall, the visualization reflects the model’s strong ability to detect tumours but also reveals areas needing improvement to enhance accuracy and reduce misclassification.

V. RESULT AND DISCUSSION

Result of the Proposed Model

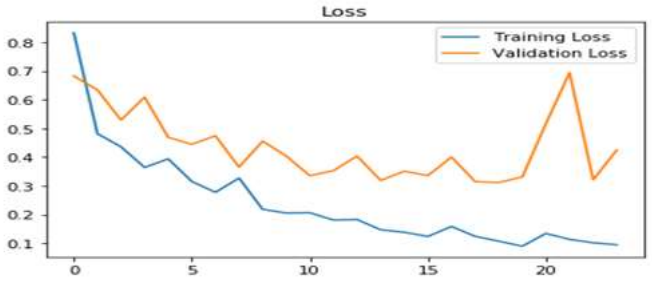

Figure 5. Shows the model training loss and validation loss.

The figure 5 illustrates the training and validation loss curves over multiple epochs for a deep learning model. The blue line represents the training loss, which shows a consistent downward trend, indicating that the model is learning effectively from the training data. The orange line represents the validation loss, which also decreases overall but fluctuates more than the training curve, with occasional spikes, suggesting periods of overfitting or instability. Despite these variations, the general decline of both curves reflects improved model performance, although further tuning may be needed to reduce validation loss fluctuations and achieve better generalization.

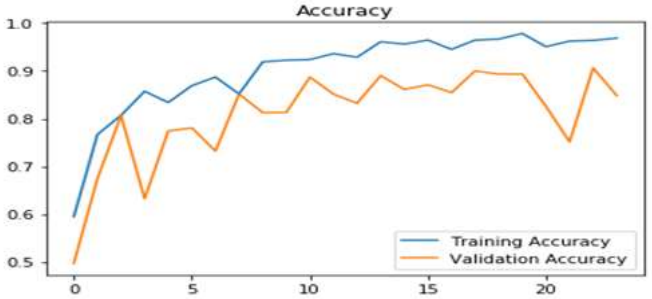

Figure 6. Shows the training accuracy and validation accuracy.

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The figure 6 displays the training and validation accuracy of a deep learning model across multiple epochs. The blue line represents training accuracy, which shows a steady upward trend and eventually reaches a high, stable value, indicating strong learning on the training data. The orange line represents validation accuracy, which also improves over time but fluctuates more, reflecting variations in performance on unseen data. While both curves generally converge at higher accuracy levels, the gap between them suggests some degree of overfitting, as the model performs slightly better on training data than on validation data.

Comparative Study of Proposed model with existing

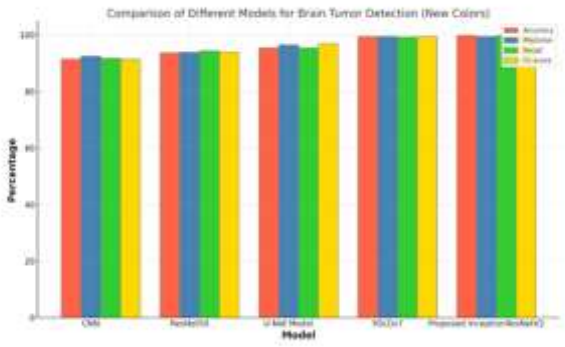

Figure 7. Comparative Study of Proposed model with existing

The figure 7 compares the performance of different deep learning models—CNN, ResNet50, U-Net, YOLOv7, and the proposed InceptionResNetV2—for brain tumor detection across four metrics: accuracy, precision, recall, and F1-score. While all models perform strongly, the proposed InceptionResNetV2 consistently achieves the highest values, nearly reaching 100% across all metrics. YOLOv7 and U-Net also demonstrate excellent performance with values close to the top, whereas CNN and ResNet50 show slightly lower results. Overall, the chart highlights that InceptionResNetV2 outperforms the other models, proving its superior capability in accurate and reliable brain tumor detection.

VI. CONCLUSION

This study presented a comprehensive comparative evaluation of deep learning models for brain tumor detection. Although CNN, ResNet50, U-Net, and YOLOv7 achieved strong performance, the proposed InceptionResNetV2 model consistently produced the best results across all evaluation metrics. Its near-perfect accuracy, precision, recall, and F1-score indicate that it is a robust and reliable approach for clinical use, with the potential to reduce diagnostic errors and support improved patient outcomes. These findings also highlight the value of advanced hybrid architectures for handling the complexity and variability of medical imaging data. Future work will extend this research by conducting experiments on larger and more diverse datasets, incorporating multi-modal MRI inputs, and optimizing the framework for real-time deployment, with the aim of improving generalizability and enabling smoother integration into clinical workflows.

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