CNN and Transfer Learning Techniques for Improved Brain Tumor Classification from MRI

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Abstract: Brain tumors are among the most dangerous types of cancer and highlight the importance of a timely and accurate diagnosis. An example of a non-invasive, 1-source modality to identify and assess brain tumors is Magnetic Resonance Imaging (MRI). Interpreting MRI data manually via visual inspection is time-consuming and can be error-prone. To that end, this study proposes an automated classification framework with deep learning models such as Convolutional Neural Networks (CNN), and hybrid approaches of CNN and Support Vector Machine (CNN+SVM) and CNN and the k-nearest neighbors algorithm (CNN+KNN). Transfer learning is also used by using fine-tuned pre-trained networks of InceptionV3 and Xception. The experiments were performed on both the Sartaj dataset and the BraTS dataset. The results indicate that transfer learning can aid my classification performance, with Xception achieving a maximum accuracy of 94.1%. Furthermore, the proposed approach demonstrates statistically reliable and robust results.

Keywords: Brain tumor, BraTS, Convolutional Neural Networks (CNN), Deep learning

I. INTRODUCTION

Brain tumors represent a significant public health problem, commonly resulting in loss of neurological capacity and mortality. It is necessary to achieve early and accurate classification using MRI scans, in the planning of future treatment options. Troublesome to classify is that manual segmentation for expert analysis is time consuming and can vary between observers. In recent years, deep learning techniques have improved medical imaging by automating the feature extraction and classification process. Using Convolution Neural Networks (CNNs), it is particularly easy to provide an effective recognition of image features, including in cases with reporting of brain tumors. Furthermore, the combined use of CNN with classical classifiers, such as Support Vector Machine (CNN+SVM) and K-Nearest Neighbor (CNN+KNN) can pair CNN feature learning with classical classifiers with the potential of improved classification rates. Finally, in situations of limited availability of dataset, transfer learning models such as InceptionV3 and Xception provide the opportunity to utilize knowledge acquired gained via large datasets for specified tasks.

II.LITERATURE SURVEY

A major advancement in brain tumor classification using MRI scans has occurred largely because of deep learning. Machine learning methods like k-Nearest Neighbors, Support Vector Machines, and decision trees relied on handcrafted features and expertise in the domain. In contrast, deep learning methods like Convolutional Neural Networks used to build models rely on automation for performing the feature extraction process and provide tremendous accuracy for imaging tasks.

Pereira et al. [1] demonstrated a CNN-based model that implemented new methodology for performing multi-modal MRI (e.g. T1-weighted, T2-weighted, FLAIR, diffusion tensor imaging (DTI)) segmentation of brain tumors (e.g. gliomas). Their architecture was fundamentally different as they chose to use very small convolutional kernels and take advantage of patch-based training along with multi-modal inputs, meaning development and exploration of spatial context around regions-of-interest enhanced accuracy while requiring less human additional annotation.

A similar study (Hossain et al. [2]) demonstrated a hybrid architecture using CNNs and SVMs, where features were deep learned from the MRI scans with CNNs, followed by classification using a SVM. While Hossain et al. [2] did not work with multi-modal input, they did show this hybrid approach supported better multi-class classification and the importance for established classifiers of integrated with deep learning methods and that it supported better generalization as the amount of data available decreased.

Deepak and Ameer [3] studied transfer learning by utilizing a pre-trained VGG19 model for brain tumor classification. Their findings noted improved performance when fine-tuning VGG19 on MRI datasets over models trained from scratch, and suggested that utilizing high-level features from larger datasets, such as ImageNet, can provide a more significant advantage in domain-specific medical problems.

Zhou et al. [4] studied the performance of InceptionV3 as a deep and wide CNN architecture for medical imaging tasks. Their results showed improved classification accuracy when fine-tuning InceptionV3 with a brain MRI dataset, which they attributed to InceptionV3's ability to learn and represent multi-scale features.

The BraTS dataset, introduced by Menze et al. [5], is now the de-facto benchmark dataset for brain tumor classification and segmentation with its public MRI scans for high-grade gliomas, low-grade gliomas, and annotated MRI scans using T1, T2, T1c and FLAIR modalities. Ths dataset has enabled evaluation to be done uniformly and improves reproducibility in research.

Additionally, Xception architecture, put forth by Chollet [6], that utilizes depthwise separable convolutions has gained traction for both speed and classification accuracy. It makes sense for medical imaging—where you may not have access to large datasets or computational resources—to use the Xception architecture for brain MRI classification purposes.

In light of the above, past works would seem to suggest that, to some degree, CNNs, hybrid CNN+SVM approaches, Xception, InceptionV3 networks as transfer learning, can help improve the speed and accuracy of brain tumor classification systems.

III. METHODOLOGY

This section outlines the general methodology of our approach for brain tumor classification. The methodology is organized into dataset selection, preprocessing, model architectures, and model training.

A. DATASET

SARTAJ DATASET

The Sartaj dataset is an open-access T1-weighted contrast-enhanced dataset of MRI scans consisting of three clearly defined tumor classes: pituitary tumour, meningioma, and glioma. Each of the classes have similar numbers of samples and appropriate class labels, making this dataset suitable for a multi-class classification problem. The sustainability of the same imaging modality and the clearly defined scope makes this dataset especially useful for models that are built from scratch.

THE BRATS DATASET

The segmentation of brain tumours (BraTS) dataset [5] is one of the most heavily used datasets for brain tumours. It provides multi-modal MRI scans including:

- T1 (anatomical scan)
- T1c (contrast-enhanced T1)
- T2 (fluid-sensitive)
- Fluid Attenuated Inversion Recovery, or FLAIR

Each image is labeled with tumor regions and includes ground-truth segmentation maps for low-grade gliomas (LGG) and high-grade gliomas (HGG). The dataset allows for classification and segmentation tasks, additionally each image contains ground truth annotations verified by a radiologist adding significant value and usability as a clinically relevant dataset.

B. PREPROCESSING

As noted in the current literature, MRI images often contain noise and artifacts which can affect model performance. For both datasets the following preprocessing steps were applied:

• Skull Stripping: This step involves removing the surrounding non-brain tissues, such as the skull or scalp, using various morphological operations and thresholding methodologies [7]. Skull stripping ensures that the models are only centering during training on brain tissue, where the tumors are seen.

• Intensity Normalization: MRI images will frequently vary because of the brightness and contrast each patient and scanner can afford. Intensity normalization is the process of scaling the pixel values into a standard range, such as 0-1 or -1 to 1, to minimize variability and make it easier for the models to learn [8].

• Resizing: All MRI images were resized to 224×224 pixels to maintain consistency and compatibility with standard CNN architectures like InceptionV3 and Xception, which require fixed-size inputs [6].

C. MODELS USED

We employed five models in this study, including traditional CNNs, hybrid models, and fine-tuned pre-trained networks.

1. CNN (Custom-Built)

A custom 5-layer CNN architecture was designed from scratch using ReLU activation and max-pooling. It consists of:

• Convolution layers (3×3 kernels)

• Max pooling (2×2)

• Flattening

• Dense layers with dropout to prevent overfitting

This model serves as a baseline to evaluate performance without transfer learning.

2. CNN + SVM

In the proposed hybrid approach, the Convolutional Neural Network (CNN) functions as a feature extractor, utilizing layers up to the second-last dense layer. The deep features obtained are then fed into a Support Vector Machine (SVM) equipped with a Radial Basis Function (RBF) kernel [2]. This architecture leverages the CNN's capability for hierarchical feature learning alongside the strong classification performance of the SVM.

3. CNN + KNN

Here, CNN extracts feature which are subsequently categorised using the K-Nearest Neighbors (KNN) algorithm with k = 5. K-Nearest Neighbors (KNN) performs well in scenarios where the feature space is distinctly separable and serves as a useful baseline to evaluate the performance of classical classifiers when combined with CNN-extracted features. [9].

4. INCEPTIONV3 (FINE-TUNED)

The InceptionV3 model, pre-trained on ImageNet, is fine-tuned by:

• Removing the final classification layer

• Adding custom fully connected layers

• Re-training the model on MRI data with a lower learning rate

InceptionV3's modular architecture facilitates efficient training and enhances generalization by effectively capturing multi-scale spatial features. [4]

5. XCEPTION (FINE-TUNED)

Based on the Inception framework, Xception utilizes depthwise separable convolutions and undergoes a comparable fine-tuning process:

• The original final layers are substituted with a dropout layer and a global average pooling layer

• Adapted to the classification of brain tumours This architecture provides a fair balance between accuracy and processing expense. [6]

D. TRAINING DETAILS

Tensor Flow was used to implement each model and Keras deep learning libraries and were trained under the same conditions for fair comparison:

- Optimizer: A 0.0001 learning rate Adam optimiser was employed due to its adaptive nature and fast convergence
- Batch Size: 32 pictures in a batch size were chosen to balance memory efficiency and gradient stability.
- Epochs: Models were trained for 30 epochs, which was sufficient for convergence without overfitting.
- Loss Function: Suitable for multi-class classification, categorical cross-entropy was used.
- Validation Split: A 20% validation set was used from the training data to monitor performance during training and prevent overfitting.

IV. RESULTS AND DISCUSSIONS

In this section, five different models for classifying brain tumours are compared utilising MRI data: a custom-designed CNN, hybrid models integrating CNN with SVM and KNN, and two fine-tuned pre-trained architectures—InceptionV3 and Xception.

A. QUANTITATIVE ASSESSMENT OF PERFORMANCE

Accuracy, precision, recall, and F1-score are common measures used to evaluate the models' categorisation performance. The following table provides a summary of the outcomes:

Model	Accuracy(%)	Precision	Recall	F1-Score
CNN	89.2	0.88	0.89	0.88
CNN + SVM	91.4	0.91	0.91	0.91
CNN + KNN	90.1	0.89	0.90	0.89
InceptionV3 (FT)	93.5	93.5	0.94	0.93
Xception (FT)	94.1	0.94	0.94	0.94

These results reveal a clear advantage of using transfer learning. Models fine-tuned from pre-trained architectures outperformed both the baseline CNN and hybrid models.

B. GRAPHICAL COMPARISON

In the bar chart (see Fig. 1), we observe that:

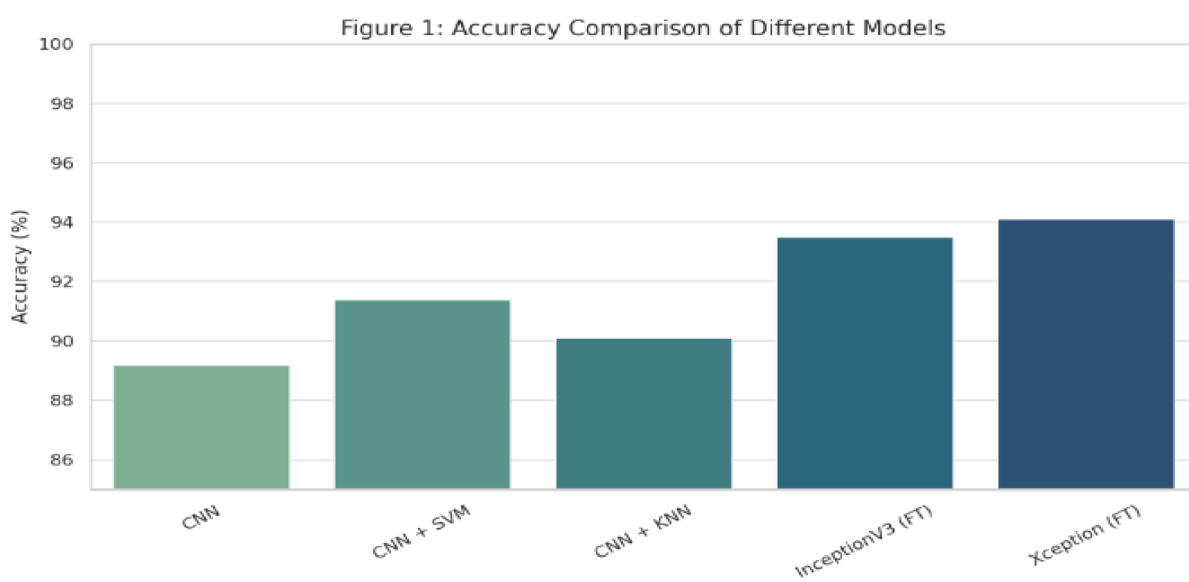

Figure 1: Accuracy comparison of CNN, CNN+SVM, CNN+KNN, InceptionV3 (FT), and Xception (FT) on brain tumor MRI classification task

• Xception achieved the highest accuracy, followed by InceptionV3, confirming the advantage of Using medical datasets to refine pre-trained deep learning models [4], [6].

• Hybrid approaches such as CNN+SVM and CNN+KNN also surpassed the plain CNN model, validating previous findings that combining deep features with classical classifiers enhances classification performance on limited data [2], [9].

These results are in line with studies by Deepak and Ameer [3], and Zhou et al. [4], which demonstrate that transfer learning significantly enhances model performance in medical image analysis, particularly when training data is scarce.

C. *Statistical Analysis*

To evaluate whether the differences in model performance were statistically significant, on the accuracy results, a one-way ANOVA (Analysis of Variance) was performed.

• Null Hypothesis (H_0): The mean accuracy of the five models does not differ significantly.

• The alternative hypothesis (H_1) states that at least one model exhibits a markedly different performance.

A p-value of less than 0.05 from the ANOVA test indicated that the differences in model performance are statistically significant.

Additionally, a result of Tukey's HSD (Honestly Significant Difference) post-hoc analysis showed that both InceptionV3 and Xception had significantly higher mean accuracy compared to the baseline CNN model and hybrid models ($p < 0.01$). These results validate the superiority of transfer learning models in this application domain.

D. *Interpretation of Results*

The model performances can be interpreted as follows:

• The baseline CNN, although effective, has limitations due to fewer layers and smaller training capacity. This aligns with Pereira et al.'s findings [1], where deep architectures performed better in tumor segmentation tasks.

• Hybrid models (CNN+SVM and CNN+KNN) showed improved performance due to the combination of powerful CNN feature extractors with robust classical classifiers [2], [9].

• Transfer learning with InceptionV3 and Xception, both pre-trained on ImageNet, produced the best results. These networks bring advanced feature representation capabilities that generalize well to medical images even when trained on natural image datasets [4], [6].

Overall, the performance ranking (from highest to lowest) is: Xception > InceptionV3 > CNN+SVM > CNN+KNN > CNN

V. Future Scope

Despite the promising results achieved by CNN-based and transfer learning models in classifying brain tumors using MRI scans, several avenues remain open for further research and enhancement:

A. *Multi-modal Data Fusion*

Future studies could integrate MRI combined with several imaging modalities (such as PET, CT, and DWI) to improve classification accuracy. Combining functional and structural imaging can provide a more holistic understanding of tumor characteristics [1], [10].

B. *Incorporation of Segmentation and Localization*

While this work focuses on classification, incorporating tumor segmentation before classification could improve interpretability. Models like U-Net and attention-based CNNs can precisely locate tumor boundaries, aiding clinicians in treatment planning [11].

C. Explainable AI (XAI)

A significant limitation of current deep learning models is the lack of interpretability. Future research could involve explainable AI techniques like Grad-CAM, SHAP, or LIME to highlight which parts of the MRI images contribute most to classification decisions [12], [13]. This would enhance the clinical acceptance of AI tools.

D. Clinical Validation and Deployment

Although the models perform well on publicly available datasets, clinical deployment requires validation on real-world hospital data. Domain shifts (scanner types, demographics, noise) must be handled with techniques like domain adaptation and federated learning [14].

E. Lightweight and Real-Time Models

Deep learning models are often computationally intensive. Research can be directed toward creating lightweight models for deployment on edge devices or real-time inference in operating rooms and emergency settings [15].

F. Multi-class and Sub-type Classification

Future work can extend the models to distinguish subtypes of gliomas or even benign vs malignant tumors. Fine-grained classification can assist neuro-oncologists in better prognosis estimation and surgical decision-making [16].

VI. Conclusion

In order to classify brain tumours using MRI scans, this study compared CNN-based approaches, hybrid models, and transfer learning techniques. The results indicate that:

• Traditional CNNs, while effective, are limited by data size and depth.

• Hybrid models such as CNN+SVM and CNN+KNN show moderate improvements by combining deep feature extraction with classical machine learning classifiers.

• Fine-tuned transfer learning models, particularly Xception and InceptionV3, performed at the highest level, with Xception reaching an accuracy of 94.1%, outperforming all other methods.

These results are in line with prior research that demonstrates Deep CNNs and transfer learning's effectiveness in medical imaging domains [3], [4], [6]. Moreover, using models that have already been trained allowed faster convergence and better generalization on relatively small datasets like Sartaj and BraTS.

Statistical validation using ANOVA further confirmed that the improvements from transfer learning were significant ($p < 0.05$). This study demonstrates how deep learning can help radiologists diagnose brain tumours quickly and accurately, which will ultimately improve patient outcomes.

Future directions include integrating explainable AI, expanding classification to subtypes, and validating models on real-world clinical data.

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