The Classification of Brain Tumours by Means of Feature-based Transfer Learning

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Abstract. Brain tumours are abnormal growths of cells in the brain and can be life-threatening if not detected early. Traditionally, radiologists manually assess magnetic resonance imaging (MRI) scans of the brain to identify and evaluate brain tumours; however, this process is prone to misinterpretation. This study investigates the application of a deep learning technique known as feature-based transfer learning to automate brain tumour detection from MRI images. A dataset of MRI scans labelled with different types of brain tumours was utilised in the study, in which a MobileNet pre-trained convolutional neural network was used to extract discriminative features from the images. The different classes of the tumors were then classified by three vanilla machine learning models, i.e., *k*-Nearest Neighbors (*k*NN), Support Vector Machine (SVM) and Logistic Regression (LR). The study showed that the MobileNet+LR pipeline could distinguish the classes well. The proposed method demonstrates its potential for augmenting and enhancing radiologist assessment of medical imaging.

Keywords: Brain Tumor, Computer Aided Diagnosis, Feature-based Transfer Learning, Machine Learning, Deep Learning.

1 Introduction

Brain tumors are a common form of human cancer caused by the uncontrolled growth of cells in the brain, and are among the top 10 cancer diseases in terms of mortality [1]. Timely, accurate diagnosis of brain tumors is therefore critical for patients. Magnetic resonance imaging (MRI) is an advanced medical imaging technique that has proven to be an effective tool for studying brain tumors [2]. However, due to the fact that the brain itself has a very complex organ structure, different brain tumors exhibit a wide variety of sizes, locations, and shapes, which makes the clinical diagnosis a very time-consuming and challenging task [3]. Owing to the advancement of computational technology, data-driven machine vision appears to be a viable approach to assist in brain tumor diagnosis. Specifically, deep convolutional neural networks (CNNs) represent a promising strategy for classifying and identifying brain tumors from MRI scans.

Mohsen et al. [4] employed the use of deep neural networks in the classification of four classes of brain tumours, i.e., normal, glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumor. The Fuzzy C-means was utilised to segment the tumours from the MRI images. Consequently, discrete wavelet transform (DWT) was used to extract the features from the segmented images. It was reported that the principal components analysis was used to reduce the dimensionality of the feature vectors prior to feeding it to a seven hidden layer NN structure. A classification accuracy of 96.97 % was reported from the study that performed better than other pipelines evaluated.

Saeedi et al. [5] investigated the efficacy of two deep learning architectures, viz 2D CNN and a convolutional auto-encoder network in classifying three types of tumours, i.e., glioma, meningioma, and pituitary gland tumours and normal. Data augmentation was performed on the MRI images by rotating the images by 90° and flipper the images vertically to increase the dataset to 9792 images. A hold-out strategy of 80:10 ratio was used for training and testing, respectively. It was demonstrated from the study that the test accuracy achieved by the 2D CNN and Convolutional auto-encoder network is 93.44 and 90.92%, respectively.

However, it is worth noting that training CNNs requires large labeled datasets, which is extremely difficult and expensive to obtain in the medical domain. Therefore, whilst intelligent recognition via deep CNNs holds promise for augmenting brain tumor screening, lack of sufficient training data remains a critical obstacle to feasibly implementing this computer-aided diagnostic (CAD) approach. Transfer learning is a machine learning approach that exploits similarities from one domain to another [6]. The approach has been reported to be positive in various different fields [7–12].

In the present study, a feature-based transfer learning approach is employed in classifying brain tumours. A pre-trained CNN model, i.e., MobileNet, is utilised to extract features from MRI images whilst the efficacy of different 'vanilla' machine learning models is evaluated towards its efficacy in discriminating the classes.

2 Methods

In this study, the dataset of the brain tumour MRI images was retrieved from an online repository (https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri). The dataset is divided into four different brain tumour classes, namely glioma, meningioma, no tumour and pituitary taken from the axial plane. The dataset was undersampled to 500 images per category. Figure 1 shows sample images from the four different classifications investigated. The 70:15:15 hold-out cross-validation technique was employed for training, testing, and validation, respectively.

The features from the MRI images were extracted the pre-trained MobileNet CNN architecture. MobileNet is a pioneering deep neural network architecture that enables efficient deployment of CNNs on mobile and embedded systems with limited computational resources [13] . A key innovation of MobileNet is its lightweight, streamlined design that drastically reduces model complexity and with its novel convolution approach, it decreases the number of parameters and required calculations, allowing MobileNet models to achieve competitive accuracy with far fewer resources than larger CNNs.

It is worth noting at this juncture that the fully connected layers of the pre-trained CNN were removed, and the efficacy of three distinct classifiers, i.e., *k*-Nearest Neighbour (*k*NN), Support Vector Machine (SVM) and Logistic Regression (LR) are investigated on its ability to distinguish the tumours. The performance of the pipelines was evaluated by means of the classification accuracy (CA) as well as the confusion matrix. The analysis was performed using the VSCode IDE that is running on Python 3.9.13. The pre-trained model was imported from Keras and TensorFlow libraries, whilst the 'vanilla' versions of the classifiers were imported from sklearn library.

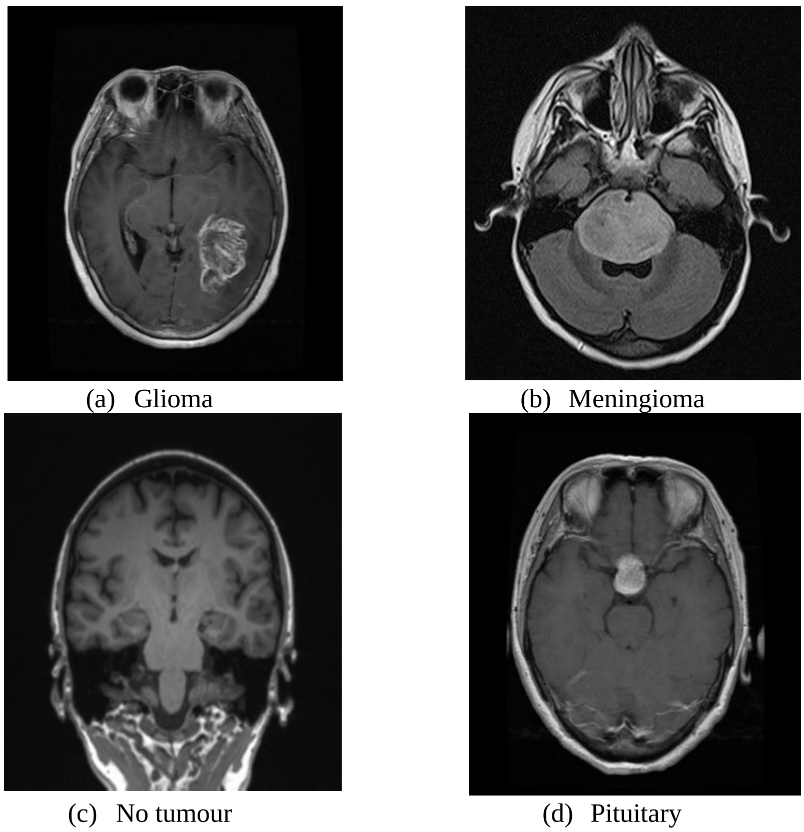

Fig. 1. Sample of the brain tumour MRI images.

3 Results and discussion

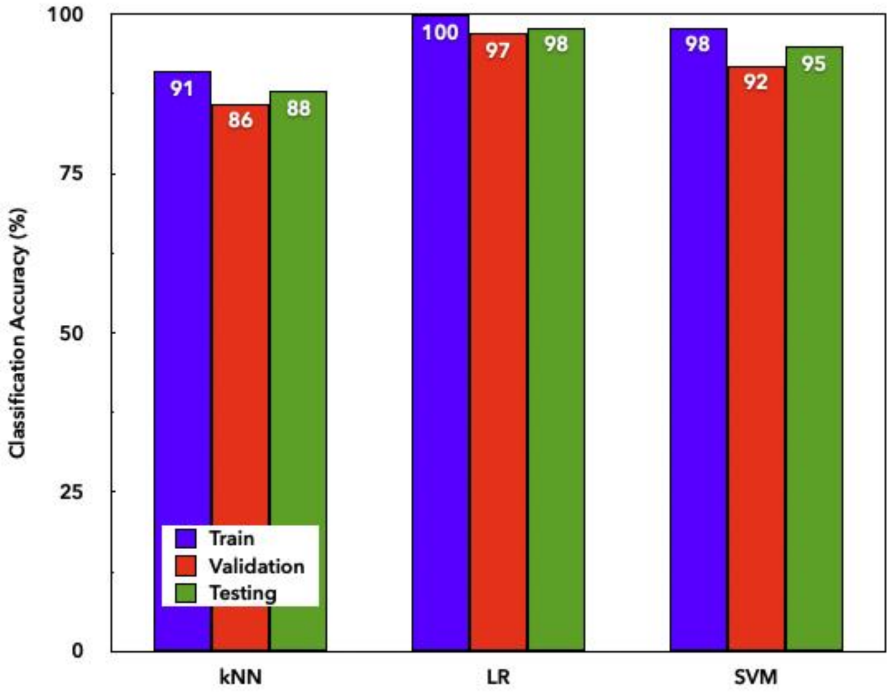

Fig. 2. MobileNet pipeline performance.

Figure 2 depicts the performance of the evaluated pipelined in classifying the brain tumours. It is evident that the MobileNet+LR pipeline appears to be the best pipeline in discriminating the classes based on the curated dataset. The high training CA indicates the model is effectively learning discriminative features from the MobileNet feature extractor. Critically, the minimal gap between training and validation performance suggests little overfitting. This is further validated by the strong 98% CA on the test set, demonstrating the pipeline's excellent generalisation.

In contrast, the MobileNet+*k*NN achieves a training, validation, and testing CA of 91%, 86%, and 88%, respectively. The significant gap between training and validation performance indicates higher variance and overfitting compared to the LR classifier. This is probably due to the *k*NN's sensitivity to the training set memorization. Convesely, the MobileNet+SVM pipeline attains a training, validation, and testing CA of 98%, 92%, and 95%, respectively. It appears that the SVM classifier exhibits less overfitting than *k*NN, likely owing to its maximal margin property that enhances generalisation.

Nonetheless, it is evident that the *k*NN and SVM classifiers are unable to fully capitalise on the representational features extracted the MobileNet architecture. Fig. 3 depicts the confusion matrix of the MobileNet+LR pipeline on the test dataset. The categories of the tumours are denoted as 0, 1, 2 and 3 for glioma, meningioma, no tumor and pituitary, respectively. The minimal misclassification transpired on the unseen testing data further demonstrate robust generalisation ability of the pipeline.

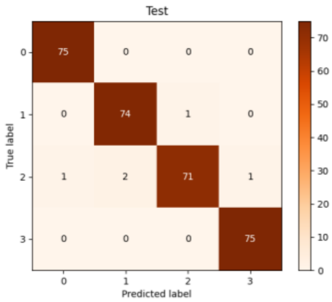

Fig. 3. Confusion Matrix of the MobileNet+LR pipeline on the test dataset.

4 Conclusion

The results of the present study suggest the MobileNet-based pipelines demonstrates promising performance for brain tumor classification, with the MobileNet+LR combination achieving the highest accuracy of 98% on unseen testing data. This suggests that MobileNet CNN architecture provides an efficient yet accurate feature extractor. Further research could explore the effectiveness of other lightweight pre-trained CNN models on their ability in extracting meaningful features as well as the use of different classifiers. Conclusively, the study highlights the viability of proposed artchitecture for computer-aided diagnosis of brain cancer on MRI scans.

5 Acknowledgement

The authors would like to thank XJTLU for funding this study via RDF-22-02- 063.

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