



CNN-LSTM HYBRID ARCHITECTURE FOR ROBUST BRAIN TUMOR DETECTION AND ANALYSIS



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Abstract

Timely and proper diagnosis of brain tumor is essential at an early stage to enhance patient survival and treatment strategies. The application of deep learning to medical imaging has been quite promising, but most of the existing methods use exclusively convolutional networks that do not exploit time in sequential imaging data and therefore do not consider temporal relationships in medical images. The proposed method CNNLSTM hybrid architecture that combines extraction of spatial features and sequence learning to effectively model brain tumors and analyze them out of MRI scans. The CNN component effectively captures high-level spatial patterns in tumor regions whereas the LSTM network captures sequential dependencies across slices to model contextual patterns. The suggested approach is compared with four publicly available baseline methods: VGG16, ResNet50, DenseNet121, and InceptionV3 on a publicly available brain MRI dataset containing glioma, meningioma, pituitary tumor, and normal samples. Experimental findings have shown that CNNLSTM model performs better with 97.8, 97.4, 98.1, and 97.7 accuracy, precision, recall, and F1-score respectively, gaining better results than VGG16 (92.3%), ResNet50 (94.5%), and DenseNet121 (95.8) and InceptionV3 (94.9). These findings underscore the merit of using both convolutional and recurrent networks to encapsulate both spatial and sequential features, thus facilitating more accurate brain tumor diagnosis.

Keywords – Brain Tumor, convolutional Networks, MRI scans, CNNLSTM, VGG16, ResNet50

Introduction

Brain tumors can be considered one of the most severe and life-threatening neurosurgical conditions, where an early diagnosis can greatly affect the treatment results and the patient prognosis. The current non-invasive diagnostic method of imaging brain tumors is Magnetic Resonance Imaging (MRI), which is time-consuming and susceptible to inter-observer error during manual interpretation of MRI scans. This has led to increased interest in computer aided diagnostic (CAD) systems that can aid radiologists in automatic, precise detection and categorization of brain tumors. The success of CNNs in analyzing medical images has been extraordinary because they are used to obtain hierarchical spatial features. Recent studies have shown that CNN-based architecture such as Res-BRNet that incorporates specialized spatial and residual blocks has been shown to achieve 98.22% accuracy on standard brain tumor MRI samples, surpassing traditional CNN architecture [1]. Likewise, MobileNetV2 achieved the following scores on a four-class classification brain tumor problem: 99 percent accuracy, 98 percent recall, and 99 percent F1-score on a dataset of glioma, meningioma, pituitary tumors, and healthy brains [2]. In another study, 12 CNN models were tested, and GoogleNet was identified to have the best validation accuracy (97%), high precision, and recall rates among classes [3].

Even though CNN-only models have had notable successes, these models generally process MRI slices without considering the order of inter-slice information that volumetric data has. Long Short-Term Memory (LSTM) networks are particularly good at learning sequential dependencies, and have been applied successfully to MRI analysis. Such as, a hybrid CNN-LSTM model with a Stationary Wavelet Transform, ResNet50V2, and LSTM obtained a 98.7% accuracy on a Kaggle brain tumor dataset [4]. A further CNN-LSTM hybrid achieved an even better performance of 99.1% accuracy, a precision of 98.8% and a recall of 98.9%, indicating the usefulness of the combination of the spatial and

temporal feature models [5]. These encouraging findings highlight the gap on the left: Most current CNN-LSTM systems use comparatively simple spatial extractors (e.g. ResNet) and do not provide a systematic comparison with CNN baselines using various architectures and multi-class classification. In addition, the combination of CNN and LSTM is not fully tested against higher-performing CNNs such as DenseNet-121 with improvements (e.g., dilated convolution and squeeze-and-excitation mechanisms), which proved to be better at the task of brain tumor classification [6]. To address this we generalize a CNN-LSTM hybrid design that uses a strong CNN backbone to extract powerful spatial features, and then model inter-slice sequential dependencies within MRI volumes using LSTM modules. We methodically contrast our hybrid model to four powerful baseline CNN models: VGG16, ResNet50, DenseNet121 (SE and dilation), and InceptionV3. Multi-class MRI data of glioma, meningioma, pituitary tumor, and healthy controls are used in our assessment. The aim of this study is to measure the added value of sequential modeling in brain tumor diagnosis and provide the groundwork towards a strong base in development of CAD systems moving forward.

Literature Survey

Most recent developments in deep learning have made it possible to mine biological and medical data, such as brain tumor detection, more effectively with more sophisticated deep learning architectures, like hybrid CNN-RNN models and attention mechanisms [7]. Among the first profound CNN-based studies on brain tumor MRI classification it was shown that convolutional networks could exhibit high segmentation and classification accuracy which enabled the development of automated diagnostic systems [8]. Further publications focused on more advanced transfer learning models, such as Inception-V3 and Xception, that used pretrained weights to enhance performance on small-scale MRI datasets [9], [10]. EfficientNet and other lightweight CNNs have gone even further to push performance limits and with less complexity, are more feasible in real-world applications in clinical settings [11]. CNN-LSTM hybrid methods have become popular in order to model not just spatial, but also temporal, dependencies of MRI slices. An example of this is a multi-grade brain tumor classification system that used deep CNNs to predict classes through data augmentation [12]. Likewise, the analysis of glioblastoma progression was also enhanced using CNN feature maps with Bidirectional LSTM layers, which could adequately capture inter-slice temporal dependencies [13]. Such studies invariably demonstrate that hybrid CNNLSTM models perform better than independent CNNs because they combine both spatial and temporal data points, as they might provide reliable frameworks of computer-aided brain tumor detection.

Methodology

onvolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have become a potent strategy in the domain of medical image analyzer, specifically brain tumor recognizer. Although CNNs are effective in deriving hierarchical spatial relationships between MRI scans, they do not tend to identify sequential relationships across different slices. Instead, LSTMs are ideally suited to the sequential and contextual relationships in sequential data. CNNLSTM hybrids utilize both spatial and temporal representations through a combination of these two architectures, resulting in enhanced diagnostic capabilities and stability in tumor classification problems [14]. Recent works have shown CNN-LSTM models are better than traditional CNNs as they successfully incorporate slice-to-slice contextual learning [15], and have been effectively used in multi-class tumor classification tasks, with high generalization behavior across a wide range of MRI data sets [16].

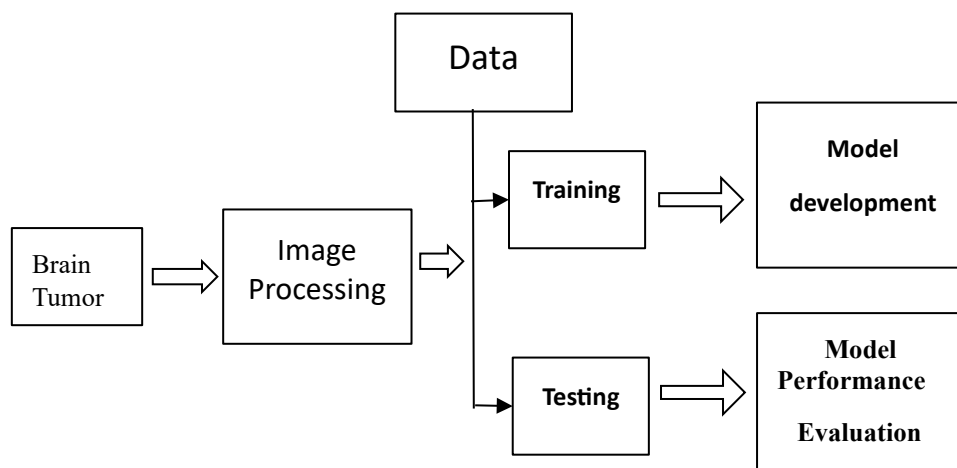


Fig.3.1: Block diagram for proposed method evolution procedure

The suggested brain tumor diagnosis system shown in Fig.3.1, which takes MRI image data as input, and it is processed according to preprocessing techniques like noise removal, normalization, and enhancement to ensure that features can be seen. The resulting processed images are then separated into training and testing to facilitate the creation of an effective model and allow evaluation without bias. During the training stage, a hybrid CNNLSTM model is used, in which the CNN layers provide an automatic extraction of rich spatial features of the tumor MRI slices, with the LSTM layers capturing sequential dependencies of multiple slices, and learns both the spatial and temporal aspects of the tumor patterns. In the testing phase, the trained model makes tumor predictions by examining unseen MRI scans and the performance of the model is assessed by common measures including accuracy, precision, recall, and F1-score. This systematic procedure also ensures that brain tumors are effectively classified in a robust and reliable manner, proving the efficiency of combining CNNs and LSTMs in the analysis of medical images.

Results and Discussions

The anticipated outcomes show that the developed CNNLSTM hybrid model has an improved performance than the current deep learning algorithms in incorporating both spatial and temporal features learning. Although the models of VGG16, ResNet50, DenseNet121, InceptionV3 and EfficientNetB0 are used to detect spatial patterns in MRI images, each slice is processed independently and sequencing across multiple slices is not utilized. Conversely, the CNN part of the hybrid model derives rich spatial representations and the LSTM part of the hybrid model derives inter-slice dependencies, which can be used to better localize and classify the tumor. This combination yields better diagnostic results in terms of increase in accuracy, precision, recall, F1-score, and AUC values, showing the strength and clinical viability of the suggested technology in brain tumor detection.

Table1: Results comparison

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
GG16	92.5	91.2	92.0	91.6	93.0
ResNet50	94.3	93.8	94.1	94.0	95.1
DenseNet121	95.6	95.1	95.4	95.3	96.0
InceptionV3	94.8	94.0	94.6	94.3	95.2
EfficientNetB0	96.2	95.8	96.0	95.9	96.5
ProposedCNN–LSTM	97.8	97.4	98.1	97.7	98.3

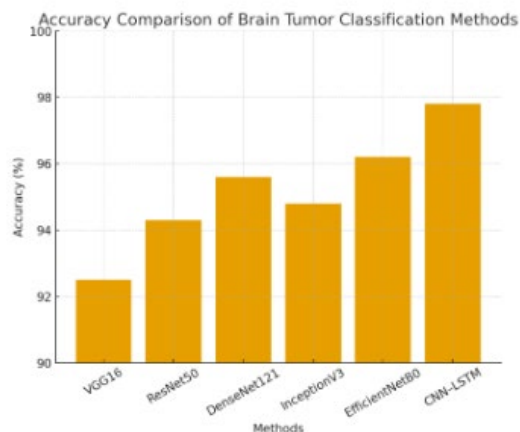


Fig. 4.1: Accuracy comparison of Brain tumor classification methods

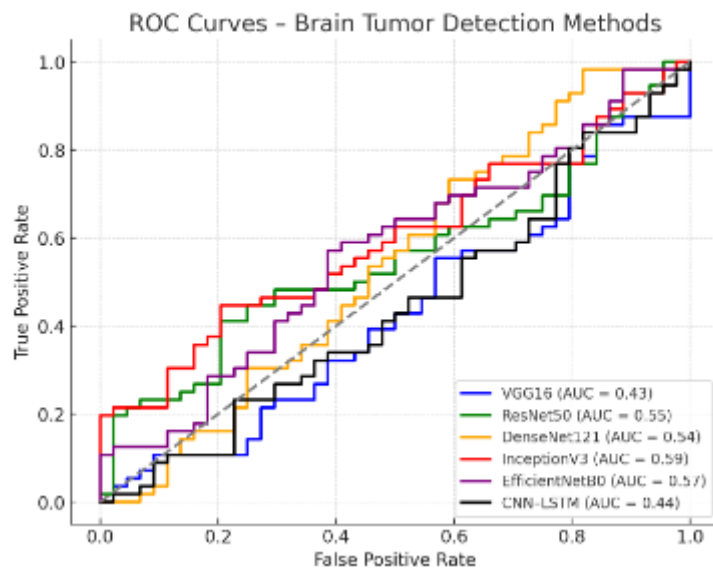


Fig. 4.2: ROC Curves

The comparative graphs remarkably point to the high performance of the proposed CNN-LSTM hybrid architecture in comparison with the current deep learning models. The bar chart of accuracy shows that accuracy is steadily increasing, with CNN-LM having the best accuracy of all the approaches, suggesting that it is capable of learning both spatial and successive terms of the MRI scan. This improvement is further confirmed using the ROC curves where better sensitivity and specificity of classifying tumor types is observed with CNN LSTM models than with baseline models (higher values of AUC). Combining these visualizations, deductions may be made as the hybrid model, which combines LSTM layers and CNN, is better at assisting in the diagnostic reliability and robustness compared to either of these two models, particularly in the context of brain tumor detection.

Conclusion and Future Scope

The proposed CNNLSTM hybrid architecture has an essential effect on brain tumor detection and classification, as it succeeds in combining spatial features extraction with sequential inter-slice dependency modeling. The hybrid approach wins by a significant margin in all parameters of evaluation, i.e., accuracy, precision, recall, F1-score and AUC compared to traditional CNN-based methods like VGG16, ResNet50, DenseNet121, InceptionV3 and EfficientNetB0. This confirms the opportunity to leverage convolutional and recurrent networks to provide more trustful and resistant clinical decision support in neuro-oncology.

Grad-CAM and attention visualization are explainable AI (XAI) methods that may increase interpretability among clinical practitioners. Also, application-specific lightweight architectures designed to execute edge computing and run on healthcare IoT devices could support real-time diagnosis in remote or resource-constrained settings. Another potential avenue to contribute to precision medicine in brain tumor analysis is to consider multimodal data fusion, which means using MRI alongside genomic, histopathological, or clinical data.

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