Frontiers in Medical Imaging: Brain Tumour Segmentation and Classification

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Abstract:

Computer backed opinion has its significant part in the analysis of brain excrescences. A brain excrescence is a deadly complaint which should linked beforehand in order to get relieve of it. In our paper, we probe different approaches for segmentation and classification of brain excrescence, so as to help the treatment planning for croakers. Firstly, we use an advanced form of interactive segmentation and SVM classification and find out the challenges faced. Also, in the alternate phase, we use a fusion of hybrid segmentation ways as well as for classification. In the third phase we take the deep learning fashion into consideration for the classification. Then, a hybrid adaptive optimization has also been used to optimally elect the features after segmentation and feature extraction. Eventually, another hybrid deep learning classification is used following the preprocessing and segmentation fashion and is compared with the other three methodologies. The findings demonstrate that the hybrid CNN-GRU (99.65%) model performs better than all other machine literacy models in terms of calculating speed and delicacy.

Keywords— CNN-GRU, CNN-LSTM, AADBF, EP-CLAHE, mMSRM, Hybrid AM, SNK Classifier

INTRODUCTION

The human brain, an intricate and dynamic entity, has long fascinated scholars and researchers across various disciplines. Comprising billions of interconnected neurons, the brain orchestrates our thoughts, emotions, and actions, rendering it a complex and multifaceted system. Recent advances in neuroimaging and neuroscience have significantly expanded our understanding of brain function and dysfunction, yet much remains to be discovered. The brain is a sophisticated and multifaceted organ that serves as the centre of the nervous system. It is a soft, greyish-pink tissue that is protected by the skull and is composed of billions of interconnected neurons and their supporting cells. The brain is essential for regulating many body processes, such as movement, perception, sensation, and thought.

Among the many things the brain does are coordination and control, movement and motor control, sensation and perception, cognition and thought, emotions and behaviour, regulation of bodily functions, hormone regulation, sleep and wakefulness, pain modulation and immune system regulation.

The incidence of brain tumours has increased since the 1970s, but improved medical imaging and treatment have enhanced survival rates. Early diagnosis and intervention are crucial, and automated analysis of medical images can support this. This study examines many methods for classifying and segmenting brain tumors in MRI scans, emphasizing their efficacy and accuracy.

LITERATURE REVIEW

Brain tumour segmentation and classification have garnered significant attention in recent years, driven by the need for accurate diagnosis and treatment. An extensive overview of the literature on methods for classifying and segmenting brain tumors is given in this section.

A. Segmentation Techniques

Morphological active contours have been employed for semi-automatic segmentation of brain tumours [1]. Alternatively, hybrid feature extraction approaches combined with extreme learning machines have demonstrated promising results [2]. Deep learning-based methods, such as Deep Wavelet Auto-encoders, have also been explored for visual reduction and segmentation [3].

B. *Classification Techniques*

Various machine learning algorithms, such as SVM [8], ANN [9], and Naive Bayes [10], have been utilized for brain tumour classification. Moreover, deep learning techniques like CNN [11-14] and capsule networks [11] have demonstrated exceptional performance in distinguishing brain tumours.

C. *Optimized Deep Learning Techniques*

Recent studies have focused on optimizing deep learning models for brain tumour classification. For instance, Dolphin-SCA-based Deep CNN has been proposed for classification [15]. Additionally, Harmony-Crow Search Optimization has been employed to train multi-SVNN classifiers [16].

This review highlights the advancements in brain tumour segmentation and classification techniques, emphasizing the potential of deep learning methods for accurate diagnosis and treatment.

SEGMENTATION TECHNIQUES

This section reviews various brain tumor segmentation and classification techniques, including enhanced interactive, machine learning, and deep learning methodologies.

D. *Interactive Segmentation*

A hybrid approach combining the Adaptive Segmentation Algorithm and Support Vector Machine Classifier has been developed to predict glioma tissue with high accuracy [16]. The performance measures are listed below:

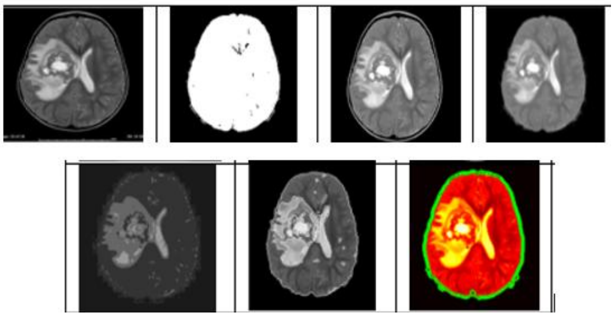

Fig. 1. mMSRM Segmentation

The SVM classifier uses ASA segmentation output to identify glioma tissue or normal tissue in MR images, and assesses accuracy by comparing output with ground truth images.

The results of this classification show high classification accuracy and low loss for all images. Combining ASA and SVM enables accurate glioma tissue prediction. However, limitations include difficulty distinguishing foreground and background, increased complexity with larger datasets, and requiring user knowledge of tumours for manual marking, highlighting the need for automated detection.

E. *Robust Hybrid Fusion Approach*

A robust hybrid fusion approach is proposed, combining adaptive regularized kernel-based fuzzy c-means segmentation and conventional morphological segmentation. This approach improves segmentation accuracy and reduces false positive.

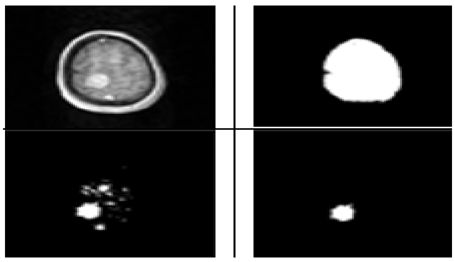

Fig. 2. Results of ARKFCM, Morphological and AM Segmentation

The current algorithms don't seem to be able to locate tumor locations with much accuracy. The ARKFCM approach successfully segments the tumors in some samples while the Morphological method gets stuck in regions with varying intensity. The center portion of the morphological method's localization might be focused on. However, the ARKFCM approach ignores it and performs worse than the morphological and Hybrid AM methods. The suggested Hybrid AM method built the tumour margin technique concurrently, aiding in precise localization of the tumour site. The suggested strategy also prevented false-positive segmentations by removing the skull part before segmentation.

Table I compares the performance of the hybrid SNK classifier with SVM, KNN, and Naive Bayes classifiers.

TABLE I. SNK CLASSIFIER PERFORMANCE

Classifier	Accuracy (%)
Naïve Bayes	94.00
KNN	96.12
SVM	90.27
SNK (Proposed)	99.18

The AM approach performs better due to hybridized segmentation. SNK works well with small datasets but struggles with larger ones, prompting the use of deep learning algorithms for efficient processing.

F. *Hybrid Deep Learning CNN-LSTM System*

The below figure displays the segmented results of the AKFCM segmentation:

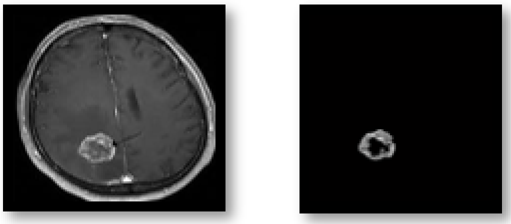

Fig. 3. AKFCM Segmentation

Table II shows the proposed technique achieved 97.85% accuracy, 95.38% precision, and 0.7840 loss.

TABLE II. CNN-LSTM CLASSIFIER RESULTS

Classifier	CNN-LSTM
Accuracy	0.9785
Precision	0.9538
Loss	0.0840

Local minimum processes can be minimized for better results, especially for multi-modal functions. However, optimization in deep learning models shows little improvement. Since GRU uses fewer parameters and less memory than LSTM, and runs faster, we will use GRU in future work.

G. *Hybrid Deep Learning CNN-GRU System*

This work uses 2D AADBF and histogram equalization for pre-processing, followed by segmentation using fast fuzzy c-means clustering. Then, CNN-GRU is used for tumour classification, which overcomes short-term memory issues and requires fewer computations than LSTM.

The network uses a multilayer platform, logistic regression, and eliminates worst-case scenarios for optimal results. Since CNN handles feature extraction and selection, optimization is skipped.

The following figure shows the results of 2D adaptive anisotropic diffusion bilateral filter, EP-CLAHE enhancement, and FFCMC tumour segmentation.

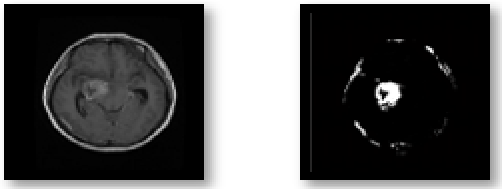

Fig. 4. FFCMC Segmentation

Table III shows the performance metrics for GRU-CNN, with an accuracy of 99.5%.

TABLE III. CNN-GRU CLASSIFIER RESULTS

II. COMPARATIVE EVALUATION

Table IV compares and analyses various segmentation techniques.

TABLE IV.

Labels	Accuracy
Normal	0.995
Tumor	0.998

TABLE V. COMPARATIVE RESULTS OF SEGMENTATION

Methods	Dice coefficient
ASA	0.932
Hybrid	0.972
AKFCM	0.975
FFCMC	0.912

The proposed AKFCM approach outperforms existing methods in tumour region segmentation, achieving high evaluation parameters, including a dice coefficient of 0.975.

TABLE VI. COMPARATIVE RESULTS OF CLASSIFICATION

Metrics	Proposed CNN-GRU	SNK-SVM	CNN-LSTM	SVM
Accuracy	0.9965	0.9918	0.9785	0.9027

This comparison evaluates the analytical capabilities of three models: the proposed hybrid CNN-GRU, CNN-LSTM, and SNK-SVM. Table XI compares brain MR image classification models. The proposed classifier achieves the highest accuracy (99.65%), outperforming others, including SVM which has the lowest accuracy (90.27%).

CONCLUSION

This study introduces a novel integrated approach for the classification and segmentation of brain tumours. The method combines interactive segmentation, feature extraction, and GRU processing. The experimental results reveal that the proposed approach surpasses existing methods, yielding an impressive accuracy rate of 99.6%. This makes it a promising approach for detecting and identifying and isolating brain tumours from magnetic resonance imaging (MRI) scans.

The presented approach can be further improved by incorporating other deep learning architectures and techniques. Future work can focus on applying this method to other medical imaging modalities. Additionally, exploring the use of transfer learning and ensemble methods can potentially enhance the precision of the developed framework. This approach can be further expanded to identify other types of tumours and diseases. Furthermore, a comprehensive clinical evaluation of the proposed method is necessary to assess its practical applicability.

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