A HYBRID ALGORITHM FOR SEGMENTATION AND CLASSIFICATION OF BRAIN MRI IMAGES.

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Abstract

Over a past decade many people are suffering from Brain tumour which leads to death because of not providing treatment at right time. Early detection of Brain tumour and providing proper treatment will improve the survival rate of the patient which can be possible with the radiologist. Tumour will arise due to aging of cells in the brain which are not destroyed in proper time will leads to Brain tumour. One of the Major technique to visualise this brain tumour by using Magnetic resonance imaging in order to identify in which area of the brain is located, where its shape and size is also identified. It can be analysed with the help of machine learning, deep learning and Convolution neural network, in this paper we are using AASSD Algorithm for segmentation and fully CI dense net to classify Brain tumour. Here we are using 3064 T1 MRI images of 233 patients where 60% of this images are going for training and remaining 40% for testing. Here we are comparing different segmentation algorithms with different techniques in order to provide better Accuracy of 96%, specificity of 96%, sensitivity of 96%, precision of 93%, F1 score of 0.94.

Keywords: Brain tumour segmentation, AASSD, classification, Fully CI Dense net.

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INTRODUCTION

Brain tumor becomes the most hazardous disease in human beings, which leads to death when it is not treated properly. Over the past few years, most scholars are focusing to develop the automation model for segmentation and classification of brain tumour. Yet, all the existing models have some challenging issue to further improve the performance. The challenges for improvement are given in Table. I, which is regarding traditional classification approaches. CNN-U-Net [1] determines the weight value for balancing the image features and obtained the edge features. Since the middle layers are in deeper in nature, the learning process becomes slow. Dark-Nets [2] reduce the over fitting issue and also increase the classification rate and dice index value. Due to transformation of images, the intensity of image pixel may get reduced. CNN-AE [3] effectively identifies the tumour region and its corresponding grades. On the other hand, due to structural burden, it could not have the strength to achieve more results. DeepLabV3+ [4] offer the global accuracy value and less loss function. However, it reduces the semantic features since it process the down sampling the images. Alex and Google Net [5] increase the positive prediction value for rapidly diagnose the brain tumors and also attains more dice coefficients among the images. But, it does not have the capacity to classify the tumors in saggital and coronial way of representation. FCM-BAT[6] acquires the higher learning activities to produce the desired outcome. Yet, it could not meet up the required robustness of the system. ELM [7] precisely segments the tumor regions and enhances the detection level regarding various measures. Nevertheless, computational and time complexity occurs since it trains the model with most number of images. CNN-SVM [8] maximizes the efficiency and accurately provides the location information of tumour region in brain. However, it does not support to employ optimization algorithms and occurs with dimensionality issue. To provide the optimal results, these challenges are motivated to develop the efficient tumour classification model. We are using Artificial Alage Social Sky Driver (AASSD) Algorithm for segmentation and Improved fully Convol dense net to classify Brain tumour. Here we are using 3064 T1 MRI images of 233 patients where 60% of this images are going for training and remaining 40% for testing. Here we are comparing different segmentation algorithms with different techniques in order to provide better Accuracy of 96%, specificity of 96%, sensitivity of 96%, precision of 93%, F1 score of 0.94.

Literature review

In Jiang *et al.* [1] uses two optimisation techniques in order to achieve better segmentation of lesion in brain where first method Novel edge Extraction Algorithm is used to reduce the features of edges which are irrelevant and second method self-adaptive method is used for improving loss function in Back Propagation above methods achieved better results on BraTs-2017 and 2018 data sets.

In 2022, Ahuja *et al.* [2] uses BraTs-2018 data set T1 weighted MRI contrast enhanced images which are classified into 80%, 10%, 10% such as 1070 images of training data, 793 images of testing data and 793 image of validation data in order to improve dice coefficient as well as over fitting problem and multilevel classification of brain tumour using DarkNet-19 and DarkNet-53.Dice coefficient has improved with 2 Dimensional segmentation technique.

In 2021, Bashir-Gonbadi and Khotanlou [3] have used BraTs-2017 data set in order to categorize brain tumour into six levels such as glioma into two grades (i) High-grade glioma (ii) Low-grade glioma, (iii) Meningioma (iv)Astrocytoma (v) pituitary and (vi)No tumour by using convolution auto encoder neural network.in order to achieve better accuracy convolution auto encoder neural network is implemented on cheng data set.

In 2022, Shoushtari *et al.* [4] have used BraTs-2020 data set which consists of T1c and flair images of 293 patients, and developed Deep-Net method to locate glioblastama tumor in MRI images which can be implemented with the help of semantic segmentation using deeplabV3+ architecture in order to accomplish better Accuracy.

In 2019, Amin *et al.* [5] have proposed a model for segmentation and classification of brain MRI images into two classes such as beningn and malignant tumors. This classification has implemented with the combination of Google net and Alex net on MICCAI challenge data sets such as BraTs – 13,14,15,16 and ISLES – 2018 data sets.

In 2020, Alhassan and Zainon [6] have designed a model for tumor segmentation with the combination of BAT Algorithm and Fuzzy clustering means Algorithm with these Algorithms tumour area and non-tumour areas are identified then performance metrics are calculated with enhanced capsule network method.

In 2019, Gumaei *et al.* [7] have developed a Regularized extreme ML Algorithm for extracting features of brain tumour images in order to classify the tumor region and it will be compared with different state of art methods.

In 2021, Khairandish *et al.* [8] have implemented a method which is a combination of Convolution neural network and support vector machine in order to classify benign and malignant tumour. In order to extract features traditional methods are used which improves classification accuracy compare to different methods.

Author [citation]	**Methodology**	**Features**	**Challenges**
Jiang *et al.* [1]	CNN-U-Net	• Determines the weight value for balancing the image features. • Features from edges are obtained.	• Since the middle layers are in deeper in nature, the learning process becomes slow.
Ahuja *et al.* [2]	Dark-Nets	• It reduces the overfitting issue. • It increases the classification rate and dice index value.	• Due to transformation of images, the intensity of image pixel may gets reduced.
Bashir-Gonbadi and Khotanlou [3]	CNN-AE	• Effectively identifies the tumor region and its corresponding grades.	• Due to structural burden, it could not have the strength to achieve more results.
Shoushtari *et al.* [4]	DeepLabV3+	• Offers the global accuracy value and less loss function.	• Reduces the semantic features since it process the down sampling the

			images.
Amin *et al.* [5]	Alex and GoogleNet	• Increases the positive prediction value for rapidly diagnose the brain tumors. • It also attains more dice coefficients among the images.	• It does not have the capacity to classify the tumors in saggital and coronial way of representation.
Alhassan and Zainon [6]	FCM-BAT	• Acquires the higher learning activities to produce the desired outcome.	• It could not meet up the required robustness of the system.
Gumaei *et al.* [7]	ELM	• Precisely segments the tumor regions. • Enhances the detection level regarding various measures.	• Computational and time complexity occurs since it trains the model with most number of images.
Khairandish *et al.* [8]	CNN-SVM	• Maximizes the efficiency. • Accurately provides the location information of tumor region in brain.	• It does not support to employ optimization algorithms and occurs with dimensionality issue.

Methodology

In the initial stage, the medical images will be gathered from the publically available sources. These acquired images will be applied to the pre-processing stage, where the image scaling, contrast enhancement and anisotropic diffusion filtering methods will be utilized for this purpose. In order to do the proper recognition of the spatial location of a tumor, the tumor segmentation phase will be done here with the help of Attention based ASUN (Adaptive Swin UNet) where the parameters in ASUN will be optimized using a newly recommended Artificial algae Social ski-driver (AA-SSD) algorithm with the combination of Social ski-driver (SSD) [1] optimization and Artificial algae algorithm (AAA) [2]. Then, the segmented images will be subjected to the tumor classification phase, where the Cascaded Fully Convolutional Improved Dense Net will be designed with the adoption of AA-SSD algorithm for promoting the precise tumor classification by tuning the parameters in Fully Convolutional and Dense Net networks. The results from the experimental analysis will demonstrate the proposed model can facilitate the automatic detection of brain tumors.

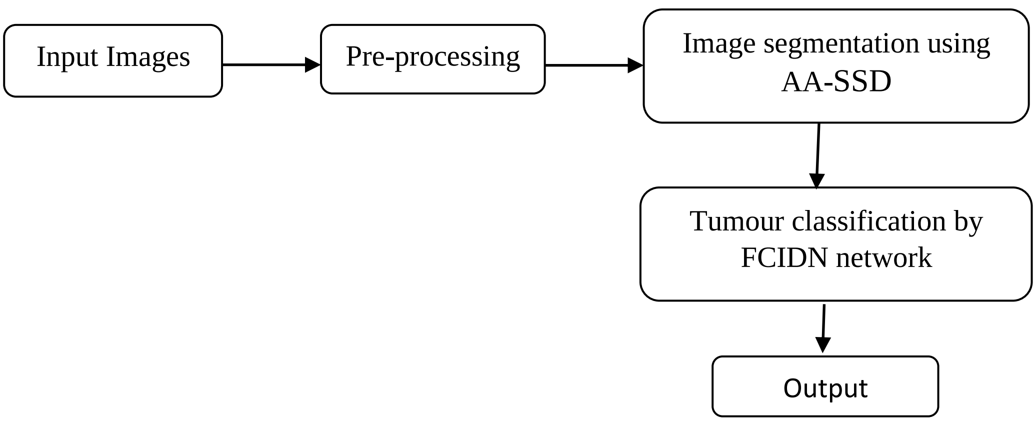

Fig 1. Shows the block diagram of Brain Tumour classification using FCIDN.

Results

The above proposed brain tumour classification model presents the results in terms of confusion matrix of proposed algorithm with other algorithms and proposed classification model with other classification model in terms of accuracy, precision, specificity, sensitivity, F1score, negative predictive rate, Mathew correlation coefficient, false positive rate, false negative rate, false discovery rate.

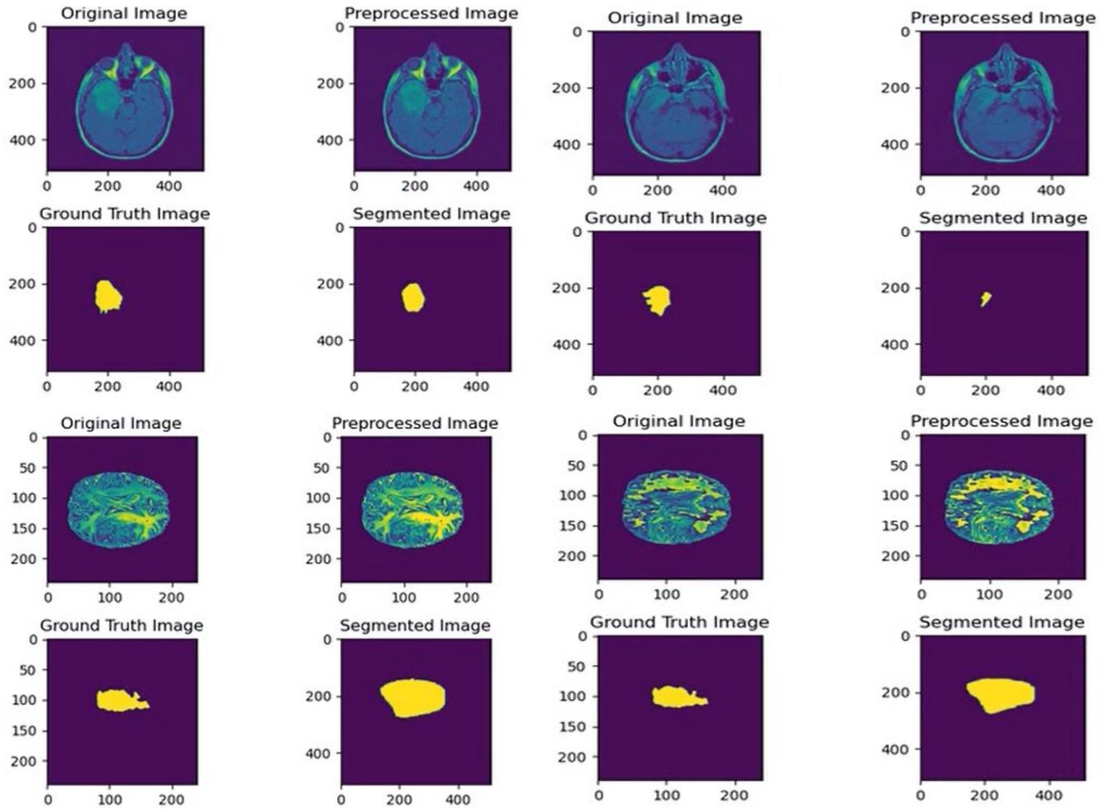

Fig 1. Shows Segmented images of proposed Algorithm

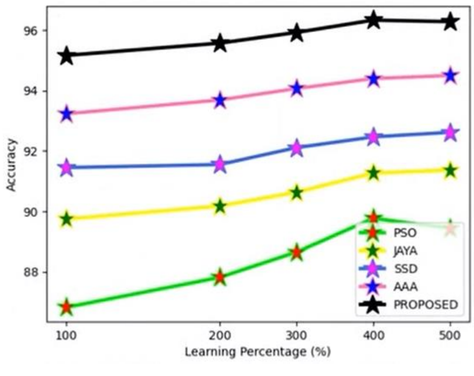

Fig 2. Shows accuracy of proposed Algorithm

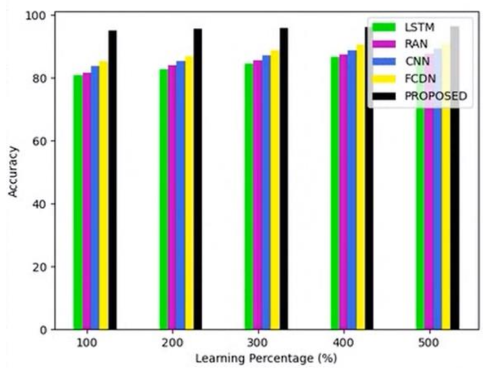

Fig 3. shows accuracy of proposed classification model

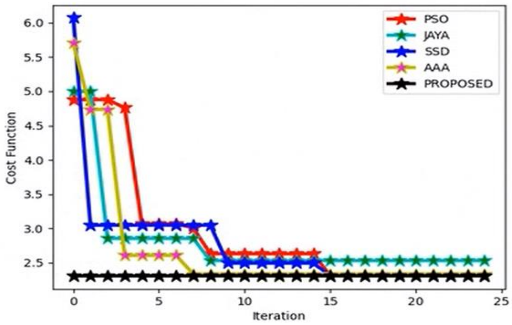

Fig 4. Shows cost function of proposed algorithm

Table 1. Comparison of confusion metrics with different Algorithms with AA-SSD

Parameters	PSO	JAYA	SSD	AAA	PROPOSED
Accuracy	0.89	0.91	0.92	0.94	**0.96**
Sensitivity	0.89	0.91	0.92	0.94	**0.96**
Specificity	0.89	0.91	0.92	0.94	**0.96**
Precision	0.81	0.84	0.87	0.98	**0.93**
FPR	0.18	0.88	0.87	0.85	**0.83**
FNR	0.18	0.88	0.87	0.85	**0.83**
NPV	0.94	0.95	0.95	0.96	**0.97**
FDR	0.18	0.15	0.12	0.89	**0.86**
F1Score	0.85	0.85	0.89	0.92	**0.94**
MCC	0.77	0.81	0.84	0.88	**0.91**

Table 2. Comparison of confusion metrics with different Data classifiers with FCIDN

Parameters	LSTM	RAN	CNN	FCDN	PROPOSED
Accuracy	0.86	0.87	0.89	0.98	**0.96**
Sensitivity	0.87	0.88	0.89	0.98	**0.96**
Specificity	0.86	0.87	0.89	0.98	**0.96**
Precision	0.77	0.79	0.81	0.84	**0.93**
FPR	0.13	0.12	0.10	0.91	**0.83**
FNR	0.12	0.11	0.10	0.92	**0.83**
NPV	0.92	0.93	0.93	0.94	**0.97**
FDR	0.22	0.20	0.18	0.15	**0.86**
F1Score	0.82	0.83	0.85	0.87	**0.94**
MCC	0.72	0.74	0.77	0.88	**0.91**

Conclusion

This paper achieved better results with the hybridisation of two different methods while performing segmentation AA-SSD algorithm is implemented and while performing classification another model such as FCIDN is implemented, with combination of these two methods has improved confusion metrics in accuracy, precision, sensitivity, specificity, negative predictive rate, F1 score, Mathew correlation coefficient, false positive rate, false negative rate, false discovery rate.

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