MRI Brain Tumor Segmentation using Cuckoo Optimization and Ensemble CNNs

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Abstract: ***Early identification of brain tumors significantly increases patient survival rates. Traditional methods relying on specialist knowledge are time - consuming and prone to inaccuracies. This paper proposes an automated segmentation technique using Cuckoo - based optimization and Ensemble Convolutional Neural Networks CNNs to enhance the segmentation of MRI brain images. Experimental results on the Leaderboard and Brats Challenge datasets demonstrate that the proposed method achieves superior performance, with Dice Similarity Coefficients DSC, Positive Predictive Values PPV, and Sensitivity metrics outperforming existing methods for High - Grade Glioma HGG and Low - Grade Glioma LGG. The purpose of this article is to propose and validate an automated method for brain tumor segmentation in MRI images using Cuckoo - based optimization and Ensemble Convolutional Neural Networks CNNs.***

Keywords: Ensemble Convolutional Neural Networks (ECNN), Segmentation, High - Grade Glioma, Low - Grade Glioma, Dimensionality reduction, MRI.

1. Introduction

A tumor or neoplasm is a growth or expansion of abnormal tissue distinguishable from surrounding tissues by its structure. The development of a tumor within the skull often interferes with mental function. Malignant tumors, accounting for about 13% of all fatalities worldwide, may be life - threatening. It is a notable cause of death. There is an increasing incidence of malignant tumors worldwide. A significant fraction of the existing standard conclusion procedure relies on human involvement in interpreting an MRI test for the judgement; undoubtedly, this increases the risk of incorrect recognition and moreover the identifying evidence of brain tumor. [1]

Brain tumor is one of the real foundations for the expansion of analyzing mortality amongst youngsters and grown - ups. It fundamentally is a deformed development of cells inside mind that are likely to be destructive. Brain tumor is a standout amongst the highest in life threatening diseases in humans hence its recognition must be such so that its quick and exact. This can be accomplished by the execution of robotized tumor recognition procedures in pictures. Gliomas and meningiomas are those instances that are basically poor - quality tumors, named amiable tumors and glioblastoma and astrocytoma may be considered as being a grade of tumors that are high - grade types, which may be considered as being threatening or most often referred to as being malignant tumors [2]

In general, the standard system for determining brain tumor is through the process of reverberation imaging. MRIs are essentially a non - obtrusive system, which provides the basis to analyze and study tissue differentiating and is generally accessible in facilities. Basically MRIs makes it conceivable to deliver particularly unique kinds of tissue based differentiating by shifting excitations as well as through reiteration times, this makes it an exceptionally a form of flexible apparatus for distinctively determining imaging structures that are intriguing. The brain's architecture, the tumor's size, and its area were all visible on an X - ray. MRI and X - ray's utilization of radio frequency and aspects of magnetic based qualities result in identifying the picture's human body without ionized radiations. Imaging assumes a focal role while drawing conclusions on brain tumors. Currently, there are several clinical diagnoses, distinctive MRI groupings are utilized for analysis and outline of tumor compartments [3]. Also, MRI split the picture into various tissues White Matter (WM), Gray Matter (GM) and Cerebrospinal Fluid (CSF). In managing MRI pictures, a standout amongst the most difficult issues is to fragment tumor since tumor shows up in various size and in various force Due to the complexity of the brain's structure, brain tumor division is challenging. Image Restoration addressed rebuilding, including as Mathematic Morphology, Watershed Segmentation, consolidated grouping, and characterization components, were used in this case. It has also been suggested to create an information model of the MRI images. It was done at the cuboids level to determine the various pieces of information. These arrangement techniques allow for greater support and allow for the proper treatment of MRI images. In order to change or identify tumors from images, the Multi - Modality Framework consists of a few components and then examines the MRI and CT filter images. The problem of brain regions being influenced by various knowledge techniques is addressed by the half - and - half algorithm. With 110 anomalous and 62 typical key MRI images under examination, the various levelled self - organizing map achieves a precision of 92.41. The global thresholding of the images is done using Scalp EEG and Modified Wavelet - ICA. Identifying tumors and related issues from MRI Images. The PCA or Principal Component Analysis Based Reconstruction strategy has been deployed for CT Scans and MRI database that takes care of the issues related to assessment and investigation of information and basic leadership process. The information gathered from the information conveyed forms the basis for study and provides coordinated information, which is utilized with other information for examination reasons at that point and help in the process of obtaining substantial, pertinent data from databases [1].

To take care of this issue as of late tumors can be divided as being those that either engendered physically and naturally. Manual division is a costly, tedious and dreary task to undertake. Programmed identification of tumor encourages the doctors to discover injuries all the more precisely [4]. In this paper the programmed division is performed dependent on ECNNs also known as Ensemble Convolutional Neural Networks. The dimensionality decrease for the MRI pictures depends on the cuckoo seek calculation. Whatever point wherein the measurement diminishes the division gets expanded. The proposed technique evaluated on the Brats database which contains two datasets: Leaderboard and Challenge dataset. The outcomes are estimated utilizing Dice Similarity Coefficient (DSC), Positive Predictive Value (PPV) and Sensitivity. This work organized as literature review in 2, the proposed philosophy has been clarified in segment 3, results and dialog are acquired in segment 4, and lastly the end and future works are examined in segment 5.

2. Literature Review

Lisboa et al [5] examined about the blend of an Artificial Neural Network (ANN) classifier, a component choice process, and an innovative approach to direct dimensionality decrease strategy that gives an information projection to representation and which safeguards totally the class separation accomplished by the classifier, is connected to the examination of a global, multi - focus 1H - Management Research Services (MRS) database of mind tumors. When combined it results that are both instinctively interpretable and extremely exact. The strategy overall remains sufficiently straightforward as to permit its simple mix in existing medicinally based supportive networks.

Zacharaki et al [6] examined the utilization of example based arrangement strategies for recognizing distinctive sorts of brain tumors, for example, essential gliomas from metastases, and furthermore to review of gliomas. The proposed plan involves several stages, including defining the region of interest, feature extraction, selection, and classification. The highlighted aspects incorporate tumor shape and power qualities, just as pivot invariant surface highlights. Feature subset determination is carried out by utilizing bolster vector machines with a recursive component end.

According to Kharrat et al [7], brain tumors can be successfully identified from cerebral MRI images. Their approach comprises of three stages: improvement, division and order. To enhance the nature of pictures and limit the danger of particular areas a combination in the division stage and an upgraded procedure is connected. Additionally numerical morphology has been deployed here to build the difference in MRI pictures. At that point the Wavelet Transform is connected in the division procedure to break down the MRI pictures. Finally, the k - implies calculation is executed to separate the suspicious locales or tumors. Some of trial results on brain pictures demonstrate the achievability and the execution of the suggested technique here.

Ratan et al [8] have developed a brain tumor division - based strategy and approved division based on the 2D and 3D MRI Data. The division results are represented and subjected to quantitative evaluations, which demonstrate the suitability of this methodology. After identifying the tumor manually, it was examined if it would be possible to use MRI data to improve mental tumor shape guesses as well as 2D and 3D perception for meticulously arranging and inspecting the tumor. Currently, careful arrangement makes use of both 2D and 3D models to coordinate data from diverse imaging modalities, each containing at least one aspect of morphology or a unique set of capabilities. Initially, the focus of the study was on configuring the tumor's territory for a single cut of the MRI data collection. Later, the work was broadened to include determining the tumor's volume using several picture MRI informational indexes.

Badran et al [9] suggested a PC - based method to identify brain tumor using a using Brain MRI images. Prior to further putting an order into those tumors that are either benign or threatening, the mind is first grouped into a healthy brain or a brain that has a tumor. NN approach combines pre - handling, picture division, highlight extraction, and picture order projects. Finally, the locality of curiosity method is used as an affirmation stage to designate the tumor zone. To test and review the suggested calculation, a MATLAB GUI, or Graphical User Interface, programme has been constructed that is simple to comprehend and analyse.

El - Dahshan et al [10] have succinctly exhibited a half breed strategy for the characterization of the attractive resonance - based images and pictures (MRI). The proposed method has three phases such as highlight extraction, reduction in dimensionality and characterization. Important phase of the proposed method is to identify the tumor region based Discrete Wavelet Transformation (DWT). Next phase, the highlighted attractive resonance - based images and pictures have been reduced by deploying PCA. In the order organized here are two classifiers which have been created. Resultant outcome here clearly indicates that the proposed procedure optimizes its robust features and is effective in contrasted with recent work and study that have been conducted here.

Karpagam and Gowri [11] examined and presented an approach that helps in dealing with distinguishing the volume of brain tumor by deploying the breadth and chart - based strategy used to calculate the volume. The chart dependent on pixel esteem is drawn taking into consideration different concentrates from the tumor cells that are in the affected area's first position. Then, the influenced locale is considered as being oval in shape and the volumes have been determined on the basis of the same. In this framework the mean has been found from the volumes which have been developed in the influenced area. The trial results demonstrate that the brain tumor development and volume may be estimated by diagram and distance across the deployment of the effective strategy here.

Kharat et al [12] suggested two Neural Network to know the characterization of the Brian MRI Images. Strategy here that deploys the Neural Network comprises of three phases, specifically, feature extraction, reduction in dimensionality, and order. During the primary stage, acquired highlights are examined related with MRI pictures by deploying the DWT. The second stage highlights of the MRI have been diminished by deploying the PCA with respect the more essential highlights. The acknowledgment of the related objects and picture grouping is increasingly vital as it forms the basis for abnormal state handling, for example, brain tumor characterization. For picture division. Both feed - forward (cooperative) and input (auto - affiliated) systems can be created using these technologies.

Madhusudhana Reddy and Prabha [13] presented a Brain tumor discovery and characterization framework. The framework utilizes picture handling and neural system strategies to identify tumor and to order the sort of tumor. The histogram balance, picture change, thresholding capacities are utilized for identification of tumor. BW mark work is utilized for the assurance of centroid of the tumor. Expanded administrator is additionally used to determine the limits of the tumor look proceeds. The Neural system techniques are utilized for arrangement of tumor in MR pictures. In the neural system back engendering technique is utilized. Preparation and pre - processing of the two layer feed forward system is carried out using the back propagation for facilitating the process of characterization of tumors.

Introduced in a very novel and innovative manner in their study Rameshwar et al [14] introduced effective procedures for the grouping of the attractive reverberation mind pictures. Their strategy comprised of two phases. In the principal stage arrange, distinct wavelet change is utilized for dimensionality decrease and highlight extraction. Characterization is performed during the second stage while utilizing the probabilistic neural system. Deployment of the classifier helps to order genuine MR pictures as the non - cancerous or benign as well as the carcinogenic or the Malignant. PNN or the Probabilistic neural system along with the picture and information handling technique has been utilized to execute a robotized brain tumor order. The utilization of procedure deploying artificial intelligence has appeared as being quite productive and potentially effective for this particular study.

A key and specific programmed division strategy dependent on CNN was suggested by Pereira et al [15] that deploys the investigation of parts that are little and are basically 3 ×3. Gliomas are the ones that mostly well - known and known to be aggressive amongst brain tumors, that results in a comparatively short life - span. Here the vast spatial and auxiliary inconstancy amidst brain tumors make programmed division an issue that pertains to testing.

Chithambaram and Perumal [16] for facilitating further research and study presented one programmed mind tumor location strategy to expand the exactness and yield anyway it diminishes the finding time. The proposed strategy can be utilized effectively and connected to distinguish the shape of the tumor and its geometrical measurements. In view of finding vector quantization with that picture and information examination is researched despite the fact that a control method is intended to do a mechanized brain tumor arrangement utilizing MRI - filters. This examination presents two methods for the recognition reason; initial one is Edge identification and division moment is Artificial Neural Network capability. The pointed Neural Network method includes a few phases, specifically, highlight extraction, dimensionality decrease, location, division and grouping. In this examination, the proposed technique is increasingly precise and viable for the mind tumor identification and division.

3. Proposed Methodology

Programmed division has been performed here in this study that is dependent on convolutional neural systems. Decrease in the dimensionality for the MRI pictures depends on the cuckoo search calculation and algorithm. At whatever point the measurement diminishes the division gets expanded. The proposed technique was approved on the BRATS database contains two datasets: Leaderboard and Challenge dataset. The outcomes are estimated utilizing the measurements like DSC also known as Dice Similarity Coefficient, Positive PPV or the Predictive Value and Sensitivity. Figure 1 displays an outline of the proposed methodology. Three fundamental stages that have been proposed here are: pre - preparing, grouping by means of ECNN and post - handling.

Pre - processing

In pre - processing phase, MRI and X - ray images are preprocessed by twisting the predisposition field, due to this, the variance in the MRI Image is highlighted by the related tissues and their intensity within them based on N4ITK technique [18], [19], [20] and [21]. Thus, to make the power and complexity of the force standardization technique's patients and acquisitions increasingly comparable. In this force standardization strategy, a lot of power tourist spots PL= {cpu1, f10, f20. . . f90, cpu2} are took in for each grouping from the preparation set. cpu1and cpu2 are picked for every MRI arrangement as portrayed in [21]. f1 represents the force at the lth percentile. Subsequent to preparing, the force standardization is cultivated by directly changing the first powers between two tourist spots into the comparing learned milestones. In this way, each group's histogram is becoming increasingly comparable among participants.

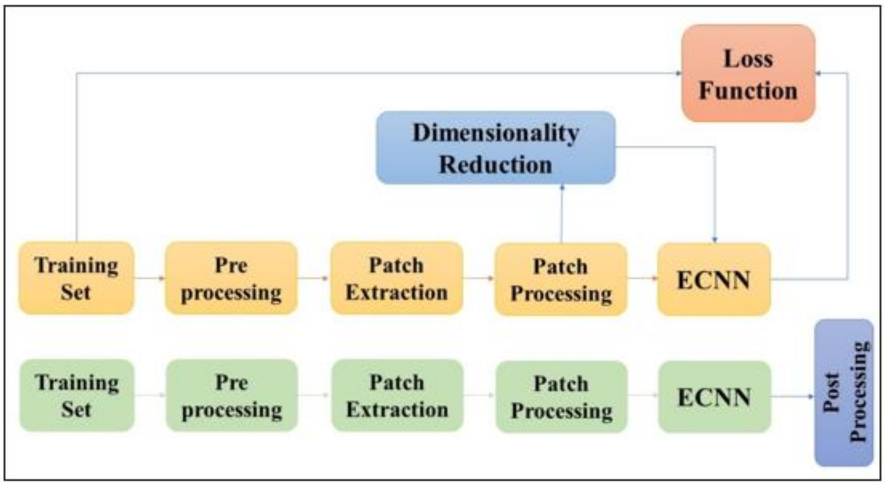

Figure 1: Overview of the proposed method

Dimensionality reduction method

At segmentation of an MRI image, a method known as decrease in dimensionality is typically used. In this method, a subset of the patches visible in the image is selected to help divide the image. The best subset eliminates the remaining, irrelevant measurements from it since it has the fewest measurements and hence is the most precise.

Cuckoo search

An epic CS or the commonly known Cuckoo Search has been utilized for determining the perfect tumor division rate. CS parameters assume a vital job in diminishing the components of patches in MRI mind tumor pictures. Cuckoo Search calculation execution profoundly relies upon the bones similitude esteems and finding the measurement decrease esteem necessitates learning of the issue explanation. In this work, the decrease of measurements is seen and it is utilized to discover the CS parameters. As a result for finding the decrease in dimensional estimation of the tumor division rate of BPTT or Back Propagation through Time is utilized. CS is a more or less a heuristic search calculation and algorithm propelled by the process of reproduction of cuckoos. Fundamentally, cuckoos lay their eggs in other host flying creatures' homes of various species. Here the host fowl may feel that the eggs may not belong to it or its own and either annihilate egg or forsake settle completely. Three glorified standards for Cuckoo Search are:

1) Every cuckoo lays a single egg, which is then placed in an arbitrary house;
2) The best houses continue to provide the next generations with eggs of extraordinary quality;
3) Here, the number of host residences that are reachable is assessed, and host poultry is likely to find a cuckoo egg laid by the bird. ∈ [0, 1].

The pseudo - code for CS algorithm is given:

Begin

Function g (x) =dice similarity, $x = (x_{ab},.....x_{nm})^T$

(a=1 to n number of patches, b =1 to m number of images)

1) Generating initial population of n host patches x_{ab} (a=1 to n number of patches, b =1 to m number of images)
2) While (t < Max Generations)
3) Move patches randomly via Lévy voyages
4) Evaluate its fitness F_i (segmentation accuracy)
5) Select nest k at random from the available n nests

If $(G_a>G_k)$

- Substitute the new, dimensionality - reduced vector for k.
- A fraction of the worst nests being abandoned, and new nests are being constructed;
- Hold the top suggestions or nests with the highest dice value;
- Sort the answers and determine the current top feature vector

6) End the while loop
7) Post Processing Results

End

For generating newly generated feature vector, Levy flight is used to and given by

$x_i (t + 1) = x_i (t) + \alpha \wedge \text{Levy} (\lambda)$

Where α is step size and ∧ is entry - wise multiplication. The Levy flight step lengths are distributed by Levy $u = t^{-\lambda}$, $1< \lambda \leq 3$. [22].

Ensemble Convolutional Neural Networks

Rotating layers of convolution and pooling make up an established convolutional arrangement. The first convolutional layer is used to differentiate samples found within close information picture districts. This is accomplished by converging channels across the information picture, calculating the channel's internal result at each position in the image, and producing the results as highlight maps. Then, each element outline is associated to a non - direct capacity g () as follows: a = g (c). The outcome enactments are applied to the pooling/subsampling layers. All such layers, entire data inside a lot of little neighborhood districts, 〖{Rj}〗 (j=1) ^n, delivering a pooled highlight delineate of littler size as yield. Pooling function sj = pool (f (ci)) ∀i∈Rj.

The two basic decisions to perform normal and max - pooling. The main takes the number - crunching mean of the components in each pooling locale, while max - pooling chooses the biggest component of the pooling district. There are a variety of capacities g () that can be used as non - linearities; the most well - known options are tanh, computed, softmax, and ReLu.

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In a convolutional organize display, the convolutional layers would be able to extract highlights that are gradually invariant to neighborhood changes of the information picture since they take the pooled maps as information. A fully linked layer with one yield unit for each class in the acknowledgement undertaking makes up the final layer always. The most well - known choice for the last layer is the implementation work softmax, which allows each neuron's yield initiation to be translated as the chance of a particular information picture fitting into that class.

Ensembles of CNNs

Here the blend enhances the execution of machine learning models. Averaging the forecasts of a few models is most useful when the individual models are not the same as one another, at the end of the day, to make them diverse they should have distinctive hyper - parameters or be prepared on the basis of various information.

In that display, the info picture is pre - processed by squares. The dataset is pre - processed before preparing, at that point, toward the start of each age, the pictures are contorted (square). A subjective number of CNNs can be prepared on sources of info pre - processed in various ways. The last forecasts are gotten by averaging singular expectations of each CNN.

Regularization

Recently, DropOut [23] and DropConnect [24]—two novel methods for regularising CNNs—have been presented. Sub - inspecting a neural network by eliminating units while using DropOut and DropConnect sums. The combination of a couple of these methods can result in gains because each of these techniques exhibits overfitting control in a unique way. This will be demonstrated in the following.

DropOut is related to the yields of a completely associated layer, where each yield layer component is maintained with likelihood p and often set to 0 with likelihood (1 - p). The output of a layer can be built as follows if we further anticipate a neural enactment work with a (0) = 0, for instance, tanh and ReLu:

$$p=x*c\ (Nw) \tag{1}$$

where x is a paired veil vector of size d with every component j coming freely from a Bernoulli dispersion xj~ Bernoulli (p), N is a network with loads of a completely associated layer and w are the completely associated layer inputs.

DropConnect is like DropOut, yet connected to the loads N. The associations are chosen haphazardly amid the preparation. For a DropConnect layer, the yield is given as:

$$p=c\ ((Q*N)\ w) \tag{2}$$

where Q is weight paired cover, and Qij~ Bernoulli (p). Every component of the cover Q is drawn autonomously for every model amid preparing.

Given some info design, the yield probabilities from all CNN are arrived at the midpoint of before making an expectation. For yield I, the normal yield Si is given by:

$$S_i = \frac{1}{n}\sum_{j=1}^{n} r_j\ (i) \tag{3}$$

where rj (i) is the yield I of system j for a given information design.

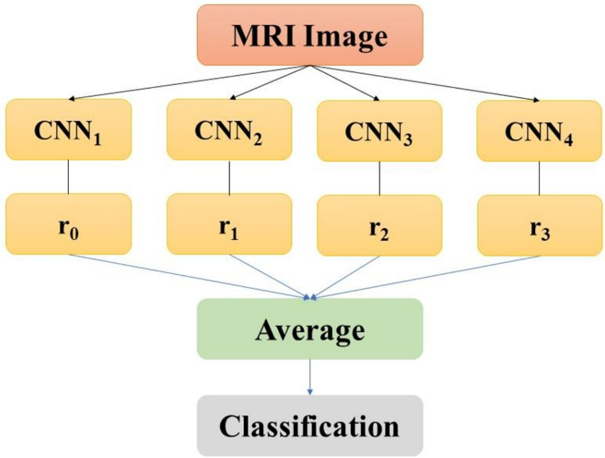

Figure 2: Ensemble Convolutional Neural Networks

The methodology comprises in applying an alternate load for each system. In the approval set, arranges that had a lower order mistake will have a bigger weight when joining the outcomes. Given some information design, the yield probabilities from all CNNs are increased by a load α before the expectation:

$$S_i = \sum_{j=1}^{n} \alpha_j r_j\ (i) \tag{4}$$

We utilize two unique ways to deal with figure the load α. The principal technique comprises on a weighted mean:

$$\alpha_k = \frac{A_k}{\sum_{i=1}^{n} A_i} \tag{5}$$

where Ak is the precision in the approval set for the system k, and I keeps running over the n systems.

In the second strategy, the load αk is picked by rank. The loads depend on the request of exactness in the approval set. This implies the loads are settled, freely on the estimation of the blunder:

$$\alpha_k = \frac{R\ (A_k)}{\sum_{i=1}^{n} R\ (A_i)} \tag{6}$$

where R () is a capacity that gives the situation of the system dependent on the approval precision arranged in expanding request. For instance, the system with biggest precision will have an R () estimation of n, the system with the next biggest exactness a capacity estimation of n−1, etc until the system with most minimal precision gets 1.

Post - Processing

Some little groups might be incorrectly delegated tumor. To manage that, we force volumetric compels by expelling groups in the division gotten by the CNN that are littler than a predefined edge T_{VOL}.

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Experimental Result Analysis and Discussion

Experimental analysis of the proposed method on the BRATS database of Leaderboard and Challenge dataset.

The assessment of the proposed method is evaluated using Dice Similarity Coefficient (DSC), Positive Predictive Value (PPV) and Sensitivity. The DSC estimates the cover between the manual and the programmed division. It is characterized as,

$$DSC = \frac{2TP}{FP + 2TP + FN'} \qquad (7)$$

where TP, FP and FN are the quantities of genuine positive, false positive and false negative recognitions, individually. PPV is a proportion of the measure of FP and TP, characterized as,

$$PPV = \frac{TP}{TP + FP'} \qquad (8)$$

Sensitivity is helpful to assess the quantity of TP and FN identifications, being characterized as

$$Sensitivity = \frac{TP}{TP + FN'} \qquad (9)$$

Leaderboard dataset

The Leaderboard dataset for the methods such as random forest, CNN and ECNN with grades HGG, LGG and Combined have been listed in table 1.

Table 1: Leaderboard dataset

Dataset	Method	Grade	DSC	PPV	Sensitivity
Leaderboard	ECNN	HGG	0.91	0.95	0.87
		LGG	0.72	0.70	0.93
		Combined	0.88	0.90	0.91
	CNN	HGG	0.89	0.92	0.87
		LGG	0.66	0.55	0.865
		Combined	0.85	0.86	0.88
	Random Forest	HGG	0.88	0.90	0.87
		LGG	0.35	0.30	0.64
		Combined	0.79	0.80	0.83

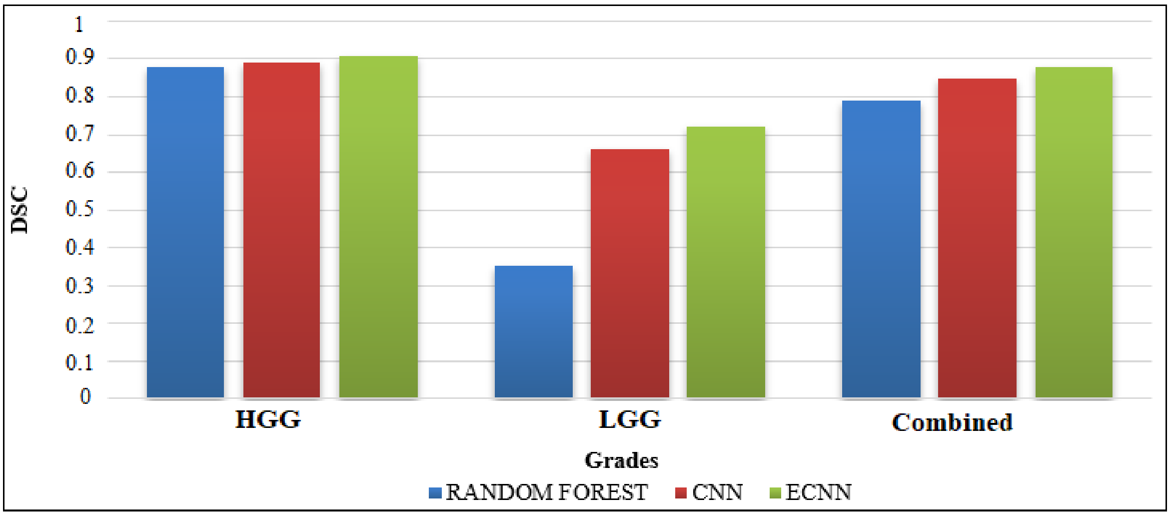

Figure 3: Leaderboard Dataset for DSC

The Leaderboard dataset for DSC is given in figure 3. The leaderboard dataset in DSC for the grade HGG in the proposed method ECNN is 0.03 greater than the random forest and 0.02 greater than the CNN. The leaderboard dataset in DSC for the grade LGG in the proposed method ECNN is 0.37 greater than the random forest and 0.06 greater than the CNN. The leaderboard dataset in DSC for the combined grade in the proposed method ECNN is 0.09 greater than the random forest and 0.03 greater than the CNN. The proposed method ECNN has higher values than the CNN and random forest method for all the three grades HGG, LGG and Combined.

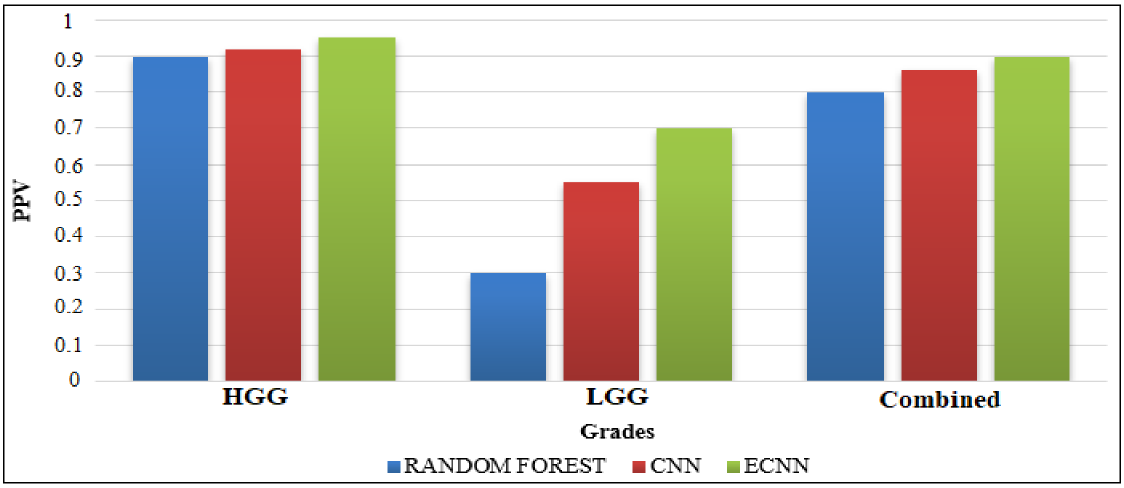

Figure 4: Leaderboard dataset for PPV

The Leaderboard dataset for PPV is given in figure 4. The leaderboard dataset in PPV for the grade HGG in the proposed method ECNN is 0.05 greater than the random forest and 0.03 greater than the CNN. The leaderboard dataset in PPV for the grade LGG in the proposed method ECNN is 0.40 greater than the random forest and 0.15 greater than the CNN. The leaderboard dataset in PPV for the combined grade in the proposed method ECNN is 0.10 greater than the random forest and 0.04 greater than the CNN. The proposed method ECNN has higher values than the CNN and random forest method for all the three grades HGG, LGG and Combined.

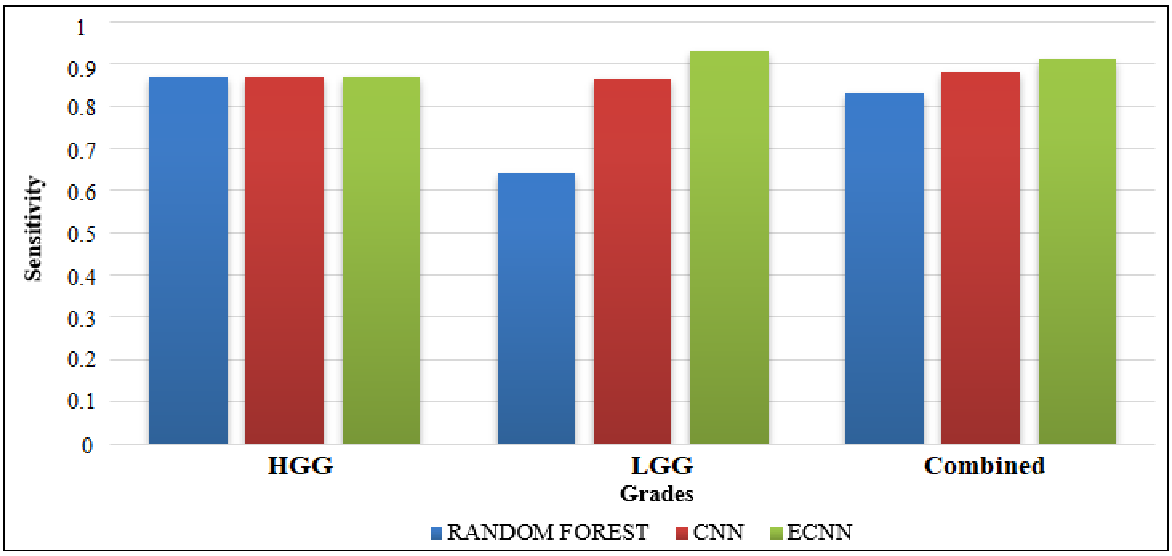

Figure 5: Leaderboard dataset for Sensitivity

The Leaderboard dataset for Sensitivity is given in figure 5. The leaderboard dataset in sensitivity for the grade HGG is same as 0.87 for all the three methods. The leaderboard dataset in sensitivity for the grade LGG in the proposed method ECNN is 0.29 greater than the random forest and 0.065 greater than the CNN. The leaderboard dataset in sensitivity for the combined grade in the proposed method ECNN is 0.08 greater than the random forest and 0.03 greater than the CNN. The proposed method ECNN has higher values than the CNN and random forest method for the grades LGG and Combined whereas for the grade HGG, all the three methods have the same value.

Challenge dataset

The CHALLENGE dataset for the methods such as random forest, CNN and ECNN for the grade HGG have been listed in table 2.

Table 2: Challenge Dataset

Dataset	Method	Grade	DSC	PPV	Sensitivity
Challenge	ECNN	HGG	0.92	0.93	0.95
		LGG	0.86	0.88	0.93
		Combined	0.85	0.89	0.92
	CNN	HGG	0.72	0.79	0.84
		LGG	0.59	0.63	0.8
		Combined	0.56	0.82	0.82
	Random Forest	HGG	0.70	0.75	0.78
		LGG	0.63	0.66	0.72
		Combined	0.53	0.62	0.69

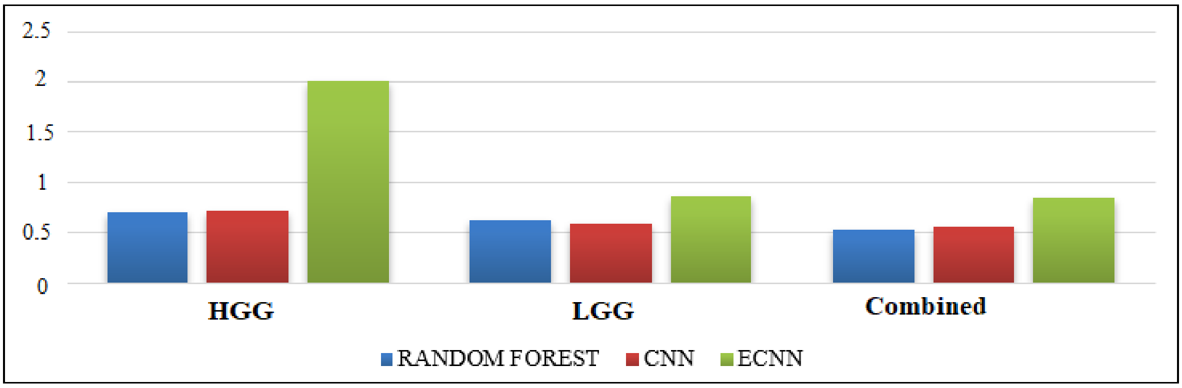

Figure 6: Challenge dataset for DSC

The Challenge dataset for DSC is given in figure 6. The Challenge dataset in DSC for the grade HGG in the proposed method ECNN is 0.22 greater than the random forest and 0.20 greater than the CNN. The Challenge dataset in DSC for the grade LGG in the proposed method ECNN is 0.23 greater than the random forest and 0.37 greater than the CNN. The challenge dataset in DSC for the combined grade in the proposed method ECNN is 0.32 greater than the random forest and 0.26 greater than the CNN. The proposed method

ECNN has higher values than the CNN and random forest method for all the three grades HGG, LGG and Combined.

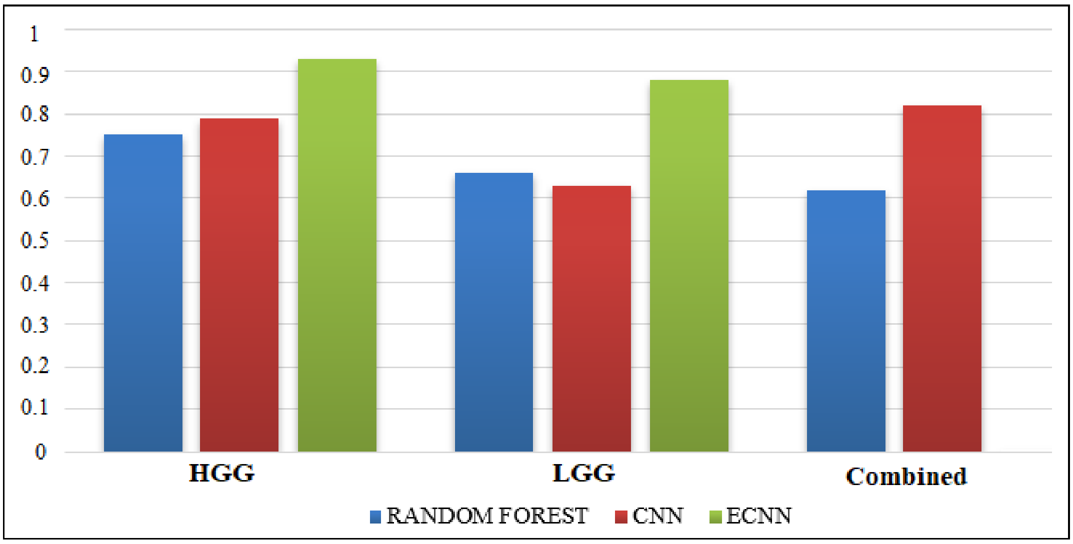

Figure 7: Challenge dataset for PPV

The Challenge dataset for PPV is given in figure 7. The Challenge dataset in PPV for the grade HGG in the proposed method ECNN is 0.18 greater than the random forest and 0.14 greater than the CNN. The Challenge dataset in PPV for the grade LGG in the proposed method ECNN is 0.22 greater than the random forest and 0.25 greater than the CNN. The challenge dataset in PPV for the combined grade in the proposed method ECNN is 0.27 greater than the random forest and 0.07 greater than the CNN. The proposed method ECNN has higher values than the CNN and random forest method for all the three grades HGG, LGG and Combined.

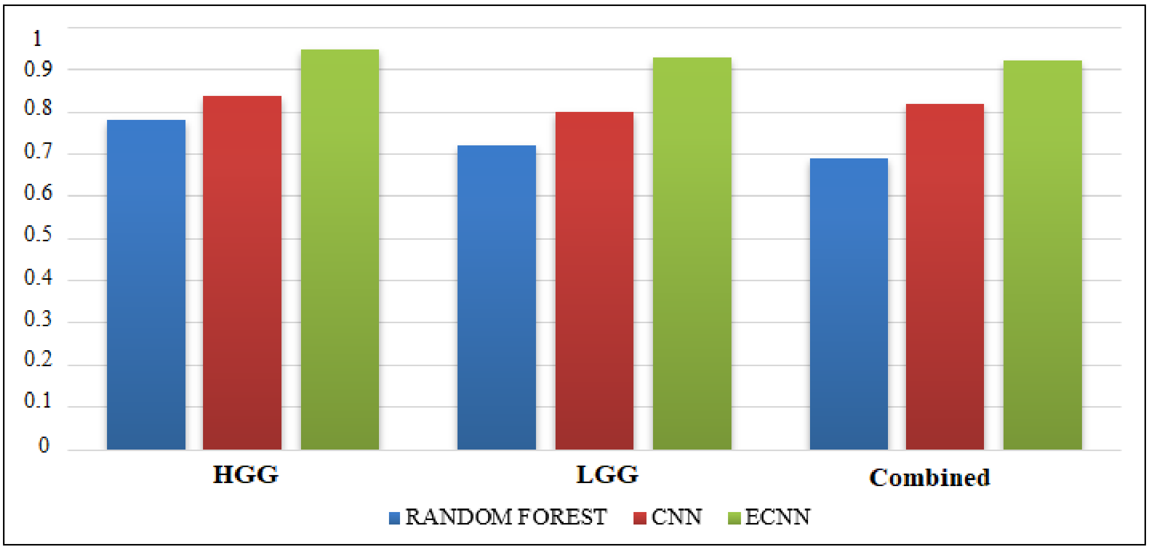

Figure 8: Challenge Dataset for Sensitivity

The Challenge dataset for sensitivity is given in figure 8. The Challenge dataset in sensitivity for the grade HGG in the proposed method ECNN is 0.17 greater than the random forest and 0.11 greater than the CNN. The Challenge dataset in sensitivity for the grade LGG in the proposed method ECNN is 0.20 greater than the random forest and 0.13 greater than the CNN. The challenge dataset in sensitivity for the combined grade in the proposed method ECNN is 0.22 greater than the random forest and 0.10 greater than the CNN. The proposed method ECNN has higher values than the CNN and random forest method for all the three grades HGG, LGG and Combined.

4. Conclusion

This study proposes an effective method for brain tumor segmentation using Cuckoo - based optimization and Ensemble CNNs. Experimental results on the Leaderboard and Brats Challenge datasets demonstrate superior performance metrics, highlighting the methods potential for improving diagnostic accuracy and efficiency in clinical settings.

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