OPTIMAL EPOCH SELECTION METHOD FOR ENHANCED CNN ALGORITHM

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Abstract

Convolutional Neural Networks (CNNs) have shown remarkable performance in image processing tasks, including image segmentation and feature extraction. However, training CNNs can be challenging when dealing with uneven data distribution, leading to biased predictions and overall poor performance. To address this issue, this research proposes an "Enhanced CNN" algorithm that incorporates a method called "Balanced Batch Normalization." This method applies batch normalization between the feature extraction stage and the convolutional layer, allowing the network to normalize activations within each mini-batch. This adaptive normalization facilitates efficient learning from all classes, effectively addressing the impact of uneven data distribution. Additionally, the proposed approach incorporates "optimal Epoch using cross-validation" to enhance training. By utilizing cross-validation, the algorithm selects the ideal number of epochs for model training, ensuring higher performance across different folds of the dataset. The upgraded CNN algorithm specifically targets imbalanced data issues, aiming to improve accuracy and reliability in brain tumor segmentation by combining balanced batch normalization with optimal epoch selection. The proposed approach enables the model to effectively segment tumor regions while maintaining a balanced representation of both tumor and non-tumor pixels, resulting in precise and robust segmentation results for brain tumor analysis.

Keywords: *Image Segmentation, Epoch Selection, Cross validation*

1. Introduction

CNNs have revolutionized image processing by exhibiting impressive performance in various tasks, such as image segmentation and feature extraction. However, training CNNs is significantly complicated by the issue of uneven data distribution (Shah et al., 2019). In this situation, the training dataset may underrepresent some classes or patterns, which could lead to biassed model predictions and poor overall performance (Zhao et al., 2019). In order to address this problem, this paper offers a "Enhanced CNN" algorithm that uses a method termed "Balanced Batch Normalisation." This method applies batch normalisation between the feature extraction stage and the convolutional layer.

The network may adaptively address the impacts of uneven data distribution by normalising the activations inside each mini-batch, enabling efficient learning from all classes. Additionally, the suggested approach improves training by the addition of "optimal Epoch using cross-validation." By utilising cross-validation, this method chooses the appropriate number of epochs for model training, assuring higher performance across various folds of the dataset. The upgraded CNN especially addresses the problems caused by imbalanced data, intending to improve accuracy and reliability in brain tumour segmentation by combining balanced batch normalisation with optimal epoch selection.

The proposed approach enables the model to effectively segment tumor regions while maintaining a balanced representation of both tumor and non-tumor pixels, leading to more precise and robust segmentation results in brain tumor analysis.

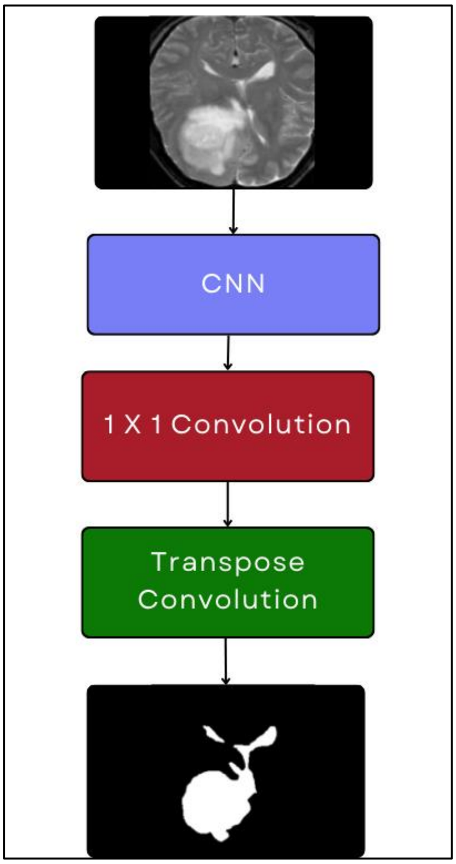

Figure 1: Existing CNN Flow Diagram

As seen in Figure 1, this model initially employs a CNN to extract image features, followed by a convolutional layer that converts the number of channels into the number of classes, and a transposed convolution that changes the height and breadth of the feature maps to match those of the input picture.

The figure 2 shows the existing FCN algorithm. The FCN consists of a down sampling path, used to extract and interpret the context, and an up-sampling path, which allows for localization. FCNs also employ skip connections to recover the fine-grained spatial information lost in the down sampling path. This algorithm first uses a CNN to extract image features, then transforms the number of channels into the number of classes via a 1×1 convolutional layer, and finally transforms the height and width of the feature maps to those of the input image via the transposed convolution.

Input: MRI image

Output: Segmented Image

Step 1: Pass through convolutional layer with 1x1 convolutions

Step2: Add up-sampling layers:

Insert transpose convolutional layers to increase the spatial resolution

Combine low-resolution feature maps with up-sampled feature maps

Step 3: Apply pixel-wise classification:

Add a 1x1 convolutional layer for prediction: P = Conv(F)

Apply softmax activation: Y = softmax(P)

Step 4: Train the network:

Optimize the parameters using cross-entropy

Fine-tune on a labelled dataset for the target task

Step 5: Inference:

Obtain the prediction map: P = FCN(image)

Step 6: Perform post-processing (thresholding, filtering)

End

2. Related Work

The decision to use of an optimal number of epochs plays a crucial role in training Convolutional Neural Network (CNN) algorithms to achieve improved performance. The appropriate amount of epochs must be chosen in order to avoid overfitting or underfitting, both of which might produce less-than-ideal outcomes. Numerous strategies have been put out to deal with this issue and enhance CNN algorithms' functionality. To find the best epoch selection strategy, a lot of creative strategies have surfaced in recent research.

Li et al. (2020) established one such technique by putting forth a dynamic epoch selection strategy based on validation loss patterns. By taking into account the validation loss curve, their method dynamically modified the number of epochs while monitoring the training process. The system stopped training when the validation loss hit a plateau in order to avoid overfitting [3].

Wang et al.'s (2019) adaptive epoch selection method was used early stopping criteria along with a dynamic learning rate adjustment approach. Based on the effectiveness of the network, the algorithm continuously adjusted the learning rate while monitoring the learning process. The algorithm stopped training when the accuracy improvement stalled [4]. A recent epoch selection approach based on network uncertainty assessment has been presented by Zhang et al. in 2021. To measure the degree of confidence in the network's predictions during training, their method made use of approaches for estimating uncertainty. The algorithm found the ideal number of epochs to avoid overfitting or premature halting by keeping an eye on the uncertainty values [5].

Cui et al. (2016) indicates that a patch-based approach that utilizes a convolutional neural network (CNN) for automatic brain MRI segmentation [6].

An epoch selection strategy based on adaptive regularisation was put out by Yang et al. (2018). In their method, the loss function included an adaptive regularisation term that dynamically changed the regularisation strength throughout training. The programme chose the ideal number of epochs and effectively avoided overfitting by optimising the regularisation term [7]. Additionally, employing both validation loss and model complexity indicators, Park et al. (2017) presented a hybrid epoch selection strategy for CNN training. In their method, the epoch selection process was integrated with measurements of model complexity, such as the quantity of parameters or activations. The programme chose the best stopping point by weighing the trade-off between validation loss and model complexity [8].

3. Optimal Epoch Selection

Optimal epoch selection with cross-validation plays an important role for achieving better performance in the ECNN model. The number of times the full training dataset is run through the learning algorithm during training is referred to as the epoch. In order to ensure that the model operates at its peak while averting problems like overfitting or underfitting, it is critical to choose the ideal number of epochs carefully. On the other hand, cross-validation entails splitting the given dataset into a number of folds, where each fold functions as both a training and validation set.

The training dataset is first divided into K folds of equal size. The model is trained on K-1 folds and evaluated on the remaining fold for each candidate number of epochs. For each fold, this process is repeated, and the accuracy is noted. The average performance metric for the current number of epochs is then computed for all folds. The number of epochs that produced the best average performance measure across all folds is then chosen as the optimal epoch.

```
Input: Classified Training dataset
Output: Optimal number of epochs
        Step 1: Split the training dataset:
                Divide the training dataset into K equal-sized folds
                Let D be the training dataset.
                Divide D into K folds: D = {D₁, D₂, ..., D_K}
        Step 2: For ∀ candidate epoch E:
                Let E be the number of epochs to train the model
                a. Initialize list for each fold
                        Let M = []
                b. For each fold (k):
                        For k = 1 to K:
                        i. Train model on K-1 for E
                                Let D_train = ∪{D_j : j ≠ k}
                                Train D_train for E
                        ii. Evaluate fold (k) metric.
                                Let D_val = D_k
                                Evaluate D_val
                c. Calculate mean (M) ∀ epochs (E)
        Step 3: Select the optimal epoch
                idx = argmax(mean (M))
                optimal_epoch = E[idx]
End
```

The figure 3 shows that, the algorithm divides the dataset into K equal-sized folds, resulting in K subsets (D_1, D_2, ..., D_K). Each fold represents a distinct subset of the data. then proceeds with iterating over different candidate numbers of epochs (E) to train the model. For each candidate E, it initializes an empty list (M) to store the performance metric (e.g. accuracy) for each fold. Next step is, the algorithm enters a loop for each fold (k). The model is trained on the remaining K-1 folds (D_train) for E epochs. The union operation (∪) is used to combine all the folds except for the current fold (k). The model's performance is evaluated on the validation fold (D_val), and the desired performance metric is calculated. This metric represents how well the model performs on the validation data. After iterating over all the folds and obtaining the performance metric for each fold, the algorithm calculates the average performance metric by taking the mean of the metric values stored in the list M. The final stage selects the optimal number of epochs by finding the index (idx) of the maximum average performance metric.

This index corresponds to the candidate number of epochs that resulted in the best performance. The optimal number of epochs (optimal_epochs) is then determined as E[idx].

Evaluation

The evaluation of the segmentations considered on accuracy and Jaccard index.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Accuracy is a measure of how well a model can correctly classify or segment an image into different regions or classes. where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives [9].

Jaccard index is a measure of how well a model can segment an image into different regions or classes by comparing the similarity between the predicted and actual regions [10][11].

$$Jaccard\ Index = \frac{A \cap B}{A \cup B}$$

where A is the set of pixels belonging to the predicted region and B is the set of pixels belonging to the actual region.

4. Experimental Results

The experiment done on brain MRI images taken from the BraTS 2015 dataset, consisting of multimodal magnetic resonance imaging (MRI) scans of brain tumor patients. It includes preoperative MRI scans of 220 patients, with each patient having four different MRI sequences: T1-weighted, T1-weighted with gadolinium contrast enhancement (T1Gd), T2-weighted, and fluid-attenuated inversion recovery (FLAIR). The dataset provides both high-resolution (1 mm^3) and low-resolution (2 mm^3) versions of the MRI scans. These images given input for the proposed algorithm, the results are shown in the table 1.

MRI Image **Segmented Image**

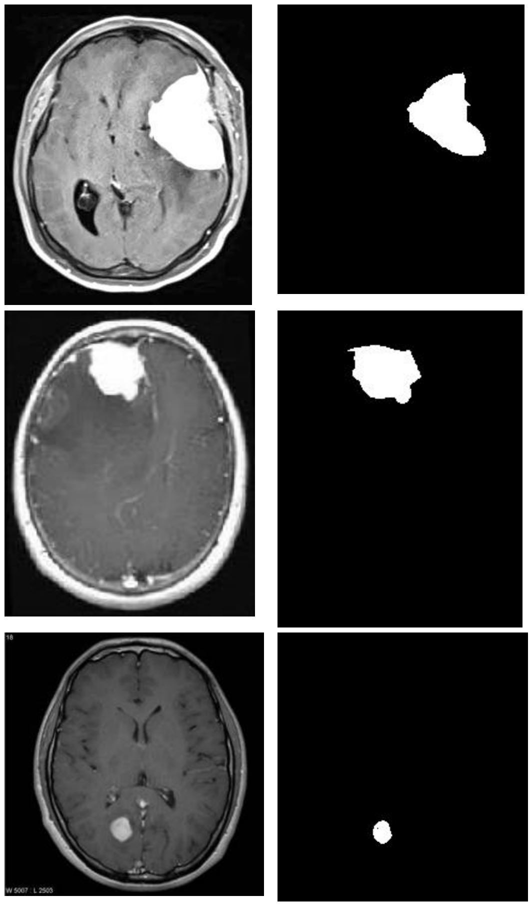

Table 1: Image Results

Table 2: Segmentation Results

Image ID	Accuracy (%)	Jaccard Index
01	**91.34**	**0.89**
02	**93.07**	**0.92**
03	**89.20**	**0.83**

The Proposed optimal epoch selection-CNN model achieved an average accuracy of approximately 91.87% across all the images. This indicates that, on average, the model correctly classified around 91.87% of the pixels within the segmented regions.

5. Discussions

The average Jaccard Index across all the images was approximately 0.88. This indicates a good overall overlap between the segmented regions and the ground truth. The results suggest that the CNN model performs well overall in segmenting the brain tumor regions, with higher accuracy and Jaccard Index values indicating better performance. The average accuracy and Jaccard Index values suggest a high level of accuracy and similarity between the segmented regions and the ground truth.

6. Conclusion

Based on the results and discussions, it can be concluded that the Proposed optimal epoch selection-CNN model demonstrates promising performance in brain tumor segmentation. With an average accuracy of approximately 91.87%, the model effectively classified a significant proportion of the pixels within the segmented regions correctly. Moreover, the average Jaccard Index of approximately 0.88 indicates a substantial overlap between the segmented regions and the ground truth, highlighting the model's ability to accurately delineate tumor regions. These findings suggest that the CNN model achieves high levels of accuracy and similarity with the ground truth, indicating its potential for reliable and precise brain tumor segmentation.

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