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Deep Learning for Brain Hemorrhage- A Study

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Abstract:
This research project aims to create and apply an optimal deep learning solution for automatically classifying brain hemorrhage from medical images using a CNN and Particle Swarm Optimization (PSO). The experiments have also justified the significant improvement that can be ensured if Particle Swarm Optimization approaches are combined with Deep Learning algorithms for diagnosis purposes.

Keywords: Brain hemorrhage, Deep Learning, PSO.

I.INTRODUCTION

Brain disorders affect brain-related functions involving cognition, movement, speech, and memories. Another form of brain disorder is brain hemorrhage, which is a severe form of a disorder affecting the brain. It is usually caused by the bursting of blood vessels, resulting in bleeding thus leading to a rise in intracranial pressure and damage to neurons in the brain. Symptoms include a severe headache, weakness, difficulties in speech, or loss of consciousness

Due to this fact, deep learning approaches are widely employed for efficient processing of vast biomedical data generated by IoMT technologies, since they automatically extract complex features and allow for fast analysis, thus enabling accurate, real-time clinical decision-making. Among various deep learning models, CNN-based models have shown high performance for spatial feature extraction as well as the identification of CT image slices as hemorrhage or non-hemorrhage to enhance the reliability of the process to identify hemorrhage. Convolutional Neural Networks (CNNs) pick out hierarchical image features that assist in identifying minute differences related to hemorrhage in CT scans to accurately detect hemorrhage in the brain. Within deep learning algorithms, high accuracy is achieved by CNN-based approaches to pick out spatial features as well as classify the CT scan into either hemorrhage or non-hemorrhage categories to increase.

Particle Swarm Optimization (PSO) is a metaheuristic technique that is triggered by the social behavior of swarms and is known to work efficiently for hyper parameter optimization in deep learning networks. In medical imagery problems, studies using PSO have been found to optimize deep learning CNN parameters automatically, thus improving performance as opposed to doing the optimization manually.

Convolutional Neural Network (CNN)

The proposed approach takes the help of the Convolutional Neural Network technique for automatic classification of brain disease through medical imaging. First, the medical images of brain CT/MRI are collected and pre-processed to enhance the quality of the data. These include resizing images to uniform dimensions, normalizing pixel value intensity, and noise removal operations. Besides, a few augmentations of data like rotation and flip operations are performed for better generalization of models to avoid overfitting.We shall select the proposal related to the implementation of the operations carried out by the CNN network, which consists of several convolution layers; the application of the ReLU function to extract the features; subsequently apply the max pool method to decrease the size of the extracted features; finally apply the fully connected layers to apply the SoftMax function with a view to attaining the probability values for the classes.The model is trained on the given data with a view to minimizing the cross-entropy loss function using the backpropagation algorithm with the aid of the optimizer. The effectiveness of the model is evaluated by considering parameters such as accuracy, precision, recall, and F1 measure values.

Convolutional Operation

$$Z_{i,j}^{(k)} = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} X_{i+m,j+n}\, W_{m,n}^{(k)} + b^{(k)}$$

$Z_{i,j}^{(k)}$ is Output feature map valueM,N is Height and width of the filter$i,j$is Spatial position of output$X_{i+m,j+n}$ is Pixel value at position $W_{m,n}^{(k)}$ is Weight at kernel position (m,n), $b^{(k)}$ is Bias of the kthfilter.

Activation Function (ReLU)

$$P_{i,j} = \max_{(m,n)\in R_{i,j}} A_{m,n}$$

$A_{m,n}$ is Activated feature map values $R_{i,j}$ is Pooling region (e.g., 2×2 window) $P_{i,j}$ is Pooled output.

Global Average Pooling Layer

$$G_{\boldsymbol{k}} = \frac{1}{H \times W}\sum_{i=1}^{H}\sum_{j=1}^{W} F_k\,(i,j)$$

$F_k(i,j)$ is activation at spatial location (i,j) of the k^{th} feature map H is height of the feature map W is width of the feature map

Fully Connected Layer

$y = f(\sum_{i=1}^{n} w_i x_i + b)$

x_i is Input feature w_i is Weight connected to input b is Bias n is Number of inputs $f(\cdot)$ is Activation function y is Output neuron value

Sigmoid Function

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

x is Input value e is Euler's constant $\sigma(x)$ is Probability output

Binary Cross-Entropy Loss

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_{i)} + (1-y_i)\log 1 - \hat{y}_i$$

N is Total samples y_i is True label (0 or 1) $\hat{y}_i$ is Predicted probability $\mathcal{L}$ is Loss value

Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is used in the proposed framework for optimizing the parameters of the model by means of simulating the social behavior of swarm intelligene. Each particle in the PSO approach symbolically defines a solution denoted by its position using their best position (gbest) of the swarm of particles. Optimization of the velocity update process of PSO uses the weight of inertia and acceleration constants for controlling exploration versus exploitation. For optimization of important CNN hyper parameters like the learning rate, filter number, and neuron number for improved classification accuracy, the PSO approach acts on important CNN hyper parameters, where the fitness of each particle for classification accuracy error rate will be used for termination of the process of optimization, contributing to a better-optimized model with high accuracy.

Velocity Update

$$v_t^{t+1} = \mathrm{w}v_i^t + c_1 r_1(pbest_i - x_i^t) + c_2 r_2(\mathrm{gbest} - x_i^t)$$

v_i^t is Velocity at iteration t, w is Inertia weight $c1$ is Cognitive coefficient $c2$ is social coefficient $r1, r2$ is Random values $(0-1)pbest_i$ is Particle's best position $gbest$ is Global best position $x_i^t$is Current position

Position Update

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

x_i^t is Current position $v_i^{t+1}$is Updated velocity $x_i^{t+1}$is new position

Fitness Function

$f(x)$=Validation Accuracy

$x$is Hyper parameter set (learning rate, neurons, dropout)

$f(x)$ is CNN performance

Boundary Constraint

$$x_i = \min(\max(x_i, x_{min}), x_{max})$$

x_{min}, x_{max} is Allowed bounds x_i is Particle position

CNN+PSO

The proposed CNN-PSO system integrates a convolutional neural network with a particle swarm optimization algorithm to enhance classification efficacy between hemorrhagia and non-hemorrhagia instances of the brain CT scans. The CNN has the capability of automatic learning of image features, and MobileNetV2 is employed as a pre-trained backbone model to rapidly reduce training efforts with prior knowledge of visual concepts acquired from previous learning experiences.Particle Swarm Optimization has been incorporated to optimize the critical hyperparameters of CNN, including learning rate, number of neurons, batch size, and dropout rate, which considerably affect the model performance. A particle corresponds to each possible combination of the candidate hyperparameters inside the PSO algorithm, and the fitness calculation of each particle is determined by the corresponding accuracy achieved by the CNN model trained using the validation sets. Its positions are updated by using both the best and the globally best solutions.This hybrid CNN–PSO approach results in enhanced classification accuracy by improving model generalization and reducing overfitting, making it a robust and effective framework for automated brain hemorrhage detection.

II. RESULT ANALYSIS

Convolutional Neural Network (CNN)

The proposed model uses two classification strategies: a custom convolutional neural network combined with a transfer learning approach using MobileNetV2, to support the accurate and efficient initial detection of brain hemorrhages from CT image data.This model is implemented using TensorFlow and Keras, which utilizes the concepts and models in `tensorflow.keras`. Moreover, within the transfer learning process, MobileNetV2 serves as a backbone feature extractor, which extracts high-level features in the brain CT images through the use of its pre-trained convolutional layers. These extracted features are further refined through the use of Global Average Pooling, then through fully connected (Dense) layers, which enable the process of brain hemorrhage classification. Batch Normalization helps in training and accelerating convergence, while Dropout layers, on the other hand, prevent overfitting. The proposed technique has proven to be of great benefit in achieving the goal of classifying hemorrhage in the brain based on the CT scan images provided.

The CNN vs Validation Accuracy Curve after running the CNN model code on the VS Code platform. As the CNN is trained for varied epochs, the train accuracy rose from 65% accurate in the initial epochs to almost 94-95% in the final epochs, signifying effective feature extraction mechanisms within the CNN model's convolutional layers. Conversely, the validation accuracy rose from 70% to 90-92%, signifying overall satisfactory performance in the validation datasets. A slight variability in the two accuracies is expected in the CNN model. This is due to the fact that the CNN model is being trained on the train datasets. A slight variability in the two accuracies signifies that there is minimal overfitting in the CNN model, which is an ideal sign in verifying that the CNN model is successfully executed on the VS Code platform, as evident in Figure 1 above.

Training & Validation Loss Curveobtained after **30 epochs**. The training loss varied from around **0.7** in the early epochs to close to **0.25** in the latter epochs, whereas validation loss decreased from values around **0.6** to approximately **0.3**. The very close behavior of both sequences proves sound completion of the learning procedure with little overfitting, hence successful CNN model training.

CNN+PSO

Particle Swarm Optimization (PSO) is used as a suitable hyperparameter tuning technique in the CNN model. Through the use of the NumPy and TensorFlow Keras libraries, PSO is used for iterations in obtaining optimal values of the respective parameters through modeling the social behaviors of the particles within the search space. In the current study, PSO optimizes critical parameters in the CNN model, such as learning rate, number of neurons, and dropout rate. PSO optimizes and adjusts these parameters in an intelligent manner such that faster convergent results and lower loss values are obtained for improved performance and increased robustness and generalization in the CNN model.

The accuracy of the CNN + PSO model during the training and validation phases for the 30 epochs. The accuracy in the train data goes from approximately 0.76 to 0.96, and the accuracy in the validation data goes from roughly about 0.78 to 0.93. The very close fit by both graphs implies that there is stable learning with very minimal occurrences of overfitting.

The CNN+PSO learning and validation loss on 30 epochs. The loss falls from 0.6 to 0.15, and the validation loss improves from 0.45 to 0.2. That the learning and validation loss curves progress similarly indicates that the learning process is stable with less overfitting, ensuring successful optimization with CNN+PSO.

Confusion Matrix of the CNN + PSO Method.The majority of the samples have been classified correctly by the classifier with 492 Normal images and 779 Hemorrhage images classified properly, while the incorrect classification samples-30 Normal images and 42 Hemorrhage images-indicate that classification with the help of PSO based optimization algorithm optimizes classification results and minimizes the incorrect classification of samples.

Performance analysis of the CNN + PSO model. The model performs well with an overall test accuracy of 94.64 percent with well-balanced precision, recall, and F1-score values for classes Normal and Hemorrhage. The high ROC-AUC value of 0.9861 indicates excellent separation between classes and overall performance.

III. CONCLUSION

A brain hemorrhage diagnosis system using deep learning has been successfully developed. A simple CNN network worked satisfactorily, but addition of Particle Swarm Optimization (PSO) proved to be of great help to improve results. Compared to pre-trained models such as ResNet50 and VGG16, the CNN+PSO network gave better or equally good results. From the obtained results, it is proved that the combination of CNN with PSO is a beneficial approach for improving the classification task.

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