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Federated learning for brain tumor segmentation and classification : A statistical approach

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Abstract

Enhancing the chances of survival for cancer patients requires early brain tumour identification. This study suggests a federated learning-based method to deal with classification problems caused by overfitting. With the use of the BRATS 2019 and 2020 datasets, the method successfully divides and categorises brain tumours. Data preprocessing involves min-max normalization, followed by CNN segmentation from MRI images. Extracted features undergo shape, texture, and Resnet-50-based feature extraction. These features are then inputted into an LSTM classifier, utilizing Federated Learning for improved classification. Findings indicate that the suggested FL utilizing the CNN-LSTM model

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outperforms other techniques like U-net and ensemble models, achieving high accuracy: 99.59% on BRATS 2019 and 99.61% on BRATS 2020 datasets.

Subject Classification: *68T07, 92C20.*

Keywords: *Brain tumor, CNN, Federated learning (FL), LSTM, Magnetic resonance images, Statistical approach, Applied statistics.*

I. Introduction

The human brain, central to the nervous system, governs daily life activities. Brain tumours, a collection of uncontrolled cancer cells, pose significant diagnostic challenges. Various imaging systems like CT, EEG, and MRI provide crucial information about tumour characteristics. Deep learning methods aid in accurate tumour segmentation from MRI images, overcoming noise challenges. Feature selection enhances classification performance.

The paper proposes a federated learning approach using CNN and LSTM for effective segmentation and classification, addressing overfitting and class imbalance issues. Performance evaluation on BRATS 2019 and 2020 datasets incorporate measures such as f1-score, recall, accuracy, precision, and specificity. Related study, the suggested methodology, the findings, and the conclusion are covered in Sections 2 through 5.

II. Literature review

By utilising CNN and MRI-based YOLOv2 approaches, Sharif et al. [1] created a brain tumour analysis model that demonstrated enhanced noise resistance but limited time complexity. Rao et al., [2] implemented a KSVM-SSD model for tumour detection, employing feature fusion and optimization algorithms for high relevancy and less redundancy. Ilhan et al. [3] introduced a tumour localization and development method using U-net, enhancing visual appearance but not suitable for real-time data fusion. Sankaran et al. [4], integrate adaptive clustering and optimization techniques to minimize time complexity but facing memory limitations. Milan Decuyper et al. [5] developed an automatic classification and segmentation model using a 3D U-Net and CNN, achieving high accuracy but facing challenges in predicting individual classes. While Agrawal et al. [6] leveraged important features straight from MRI scans to create a 3D-UNet model for segmentation and classification, there were constraints in terms of available data and computational expense. Hossain et al., [7] suggested a lightweight MSegNet model for segmentation, accurately segmenting tumors with high resolution but limited to two tumor-based images. Akter et al. [8] used a CNN and U-Net for automatic segmentation and classification, which produced segmentation masks that were accurate but had mixed results when applied to real-world MRI data. Zebari et al. [9] proposed a DL fusion method for tumour classification, enhancing accuracy through feature extraction and fusion but facing complexity and feature extraction requirements.

III. Proposed methodology

The proposed methodology employs FL with CNN and LSTM for brain tumor segmentation and classification. BRATS 2019 and 2020 datasets are utilized. Pre-processing involves min-max normalization, and CNN is used for segmentation. Features are extracted using shape, texture, and ResNet-50 [10]. FL-based CNN and LSTM model enhance classification and ensure privacy, scalability, and real-time updates. Figure 1 displays the methodology's block diagram.

IV. Top of Form

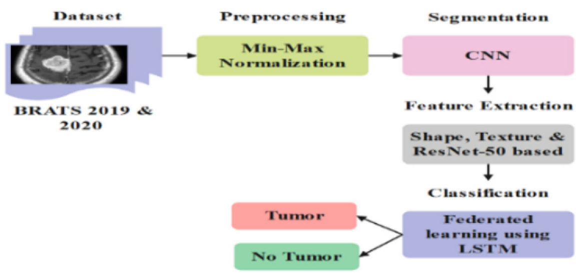

Figure 1

Block schematic illustrating the suggested approach

- **Dataset**

  The proposed FL using CNN-LSTM model experiments were conducted on the BRATS 2019 [11] and BRATS 2020 [12] datasets.

- **Preprocessing**

  The process of transforming raw data into a desired format is known as data pre-processing. A dataset sourced from multiple sources may include incomplete data.

- **Segmentation**

  In image processing, the neural network is the most powerful method to perform the segmentation. The primary imaging method for obtaining images of the brain is MRI.

The following are the concepts that are significantly utilized in the CNN segmentation:

Initialization: Initialization is significant to attain convergence. By utilizing the initialization, the activations and gradients are managed in the control stages or else the back-propagated gradients can disappear.

Function of Activation: For the non-linearly changing data, the activation function is controllable.

Pooling: It combines the dimension of the nearest features in the feature maps and the possible unnecessary features are compact and consistent for small changes of image like unwanted information that also reduces the estimation load of next phases. To merge features, it is general to utilize max-pooling.

Regularization: Regularization is utilized to minimize overfitting. The layers that are fully connected make use of the dropout. At every training phase, it eliminates potentially useful nodes from the network.

Loss Function: The loss function is utilized during the training of the CNN model to calculate an error between the prediction and the desired outputs.

- **Extracting features**

  Shape, texture, and ResNet50-based feature extraction are utilized to extract the characteristics following the segmentation procedure. The BRATS 2019 and 2020 dataset has been made significantly more informative by employing this method. Surface patterns are accounted for by texture, geometric aspects are captured by form, and deep learning features are captured by RsNet50.

Shape-oriented Feature Deletion

Shape properties like region, moment, and border in an image are the main purposes of shape-based feature extraction. The extraction makes it easier to transmit, identify, recognise, and compare shapes. Features based on shapes must withstand scaling, rotation, and conversion.

Texture-based Feature Extraction

The technique for texture-based feature extraction is called the Grey Level Co-occurrence Matrix (GLCM).

ResNet50-based Feature Extraction

The ResNet utilized the residual block for solving gradient vanishing and degradation problems that occur in the CNN model.

- **Classification**

The federated learning is a newly established ML procedure, that attempts to address issues of strict rules about data secrecy and restricted supply of accessible datasets as shown in Figure 2. In FL, there are two ends: one is a global server the other is a local server. The global server contains a global method and the local server comprises local information [13][14].

Figure 2

Federated learning

The LSTM model receives the extracted features as input. Figure 3 shows how the LSTM is structured.

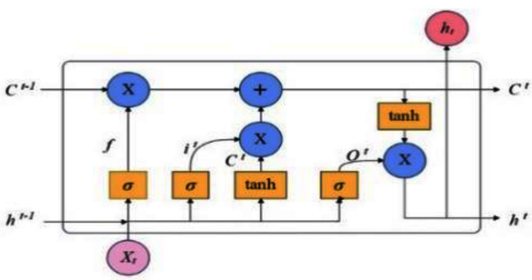

Figure 3

Architecture of LSTM

The second stage is the input gate which is used for processing the data.

V. Results

In this work, an environment powered by Python with one of the following system configurations is used to stimulate the proposed model: System software: Intel Core i7 CPU, Windows 10; 16 GB of RAM.

- **Quantitative and Qualitative Analysis**

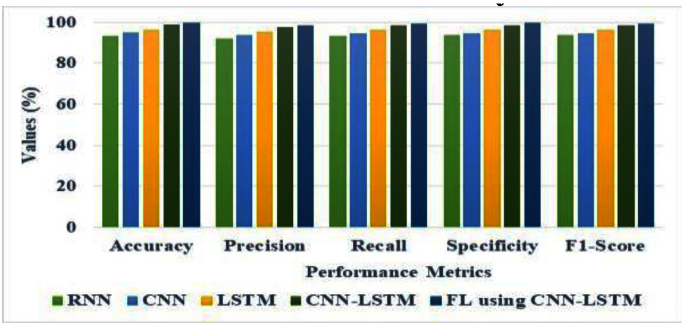

Figure 4

The classification performance with the BRATS 2019 dataset

Figure 4 shows the proposed FL using CNN-LSTM model performance on the BRATS 2019 dataset

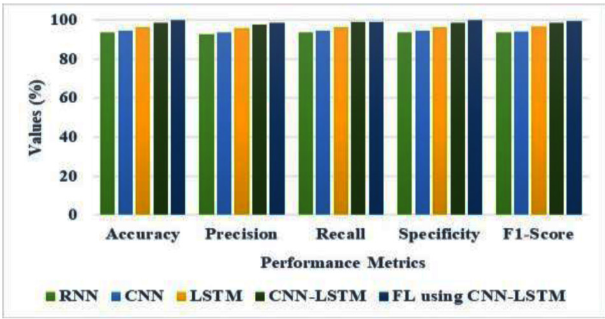

Figure 5

Classification results using the BRATS 2020 dataset

Figure 5 shows the recommended FL using CNN-LSTM model performance using the dataset from BRATS 2020.

- Comparative Analysis

In this, a comparison study of the proposed FL is shown using the CNN-LSTM model with the performance measures; these include precision, recall, precision, specificity, and f1-score, which are demonstrated in Tables 1, and 2.

Table 1

The relative study of the proposed model using the BRATS 2019 dataset

Reference	**Dataset**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**Specificity (%)**	**F1-Score**
[15]	BRATS 2019	97	97	96	98	-
[16]		99.36	-	99.0	-	98.6
[17]		99.38	92.60	83.01	99.82	-
Proposed		99.59	98.38	99.25	99.87	99.12

Table 2

The suggested method's comparative study with the BRATS 2020 dataset

Method	**Dataset**	**F1-Score**	**Accuracy (%)**	**Specificity (%)**	**Recall (%)**	**Precision (%)**
[15]	BRATS 2020	-	95	95	95	94
[16]		98.4	99.15	-	98.53	-
[17]		-	99.40	99.83	83.62	92.94
Proposed		99.23	99.61	99.86	98.71	93.57

VI. Discussion

The benefits of the suggested approach over current methods are described in this section. Existing methods like the Ensemble Method have time complexity and require weight optimization. KSVM-SSD has lower computational complexity and achieves high feature relevance with optimization. However, Tumor Localization and Enhancement +U-net isn't suitable for real-time data fusion. In contrast, the proposed FL using CNN-LSTM overcomes these limitations, minimizing overfitting, enhancing classification, preserving privacy, and providing real-time updates.

VII. Conclusion

Early detection of brain tumors contributes significantly towards enhancing the survival rate of a cancer patient. Overfitting in classification is addressed with a transfer learning-based approach proposed here. The datasets used for segmentation and classification are from the BRATS 2019 and 2020. Min-max normalization is employed for data pre-processing, followed by CNN segmentation of MRI images. Features are extracted using shape, texture, and Resnet-50 techniques. These features are then inputted into an LSTM classifier, leveraging Federated Learning (FL) for effective classification. The FL using the CNN-LSTM model accomplishes a high accuracy of 99.59% on BRATS 2019 and 99.61% on BRATS 2020 datasets, outperforming methods like the U-net ensemble model. Future work may include hyperparameter tuning to further enhance classification efficiency.

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