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Batch Normalization Based Convolutional Neural Network for Segmentation and Classification of Brain Tumor MRI Images

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Abstract: The uncontrolled growth of cells in human brain can lead to the formation of tumors, which can occur in all age people. The tumor in brain can affect nerve cells, soft tissues and blood vessels. The early detection of brain tumor is necessary to aid doctors in treating cancer patients to increase their survival rate. For this various deep learning models are created and discovered for efficient brain tumor detection and classification. In this paper, the Convolutional Neural Network is proposed for efficient brain tumor classification in MRI images using BRATS 2019, 2020 and 2021 dataset. The min-max normalization is used in this research for data preprocessing and fed to the segmentation process. The mask region-based CNN is employed for segmenting brain tumors; Followed by that, Batch normalization is applied to enhance the training process and minimize the overfitting issues. The obtained result shows that the proposed CNN model achieves better accuracy of 99.55% on BRATS 2019, 99.80% on BRATS 2020 and 99.29% on BRATS 2021 dataset which ensures accurate classification compared with other existing methods like 3D U-Net and CapsNet + latent-dynamic condition random field (LDCRF) + post-processing.

Keywords: Batch normalization, CapsNet, Convolutional neural network, 3D U-Net, MRI images.

1. Introduction

In human body, the sensitive organ is a brain which manages nervous system and whole actions of body. In general, brain tumors are considered as harmful and life-threatening disease [1]. Irregular cells development leads the brain tumor that terminates brain structure and leads cancer. Blurred vision, strong headaches and seizures are brain disease indicators [2]. The 9.6 million peoples were diagnosed with cancer According to World Health Organization (WHO) records and died because of brain cancer in 2018 [3]. It can categorize in dual types, Benign and Malignant, the first one is low harmful that stays in a specific part in brain [4]. Malignant is life-threatening where cells are quickly developed and expanded to brain and spinal areas [5]. The ionizing radiation and genealogical are issues that leads cancer. Various treatments are there for brain tumor patient [6].

In medical field, numerous methods to diagnose brain tumors like CT scans, EEGs, and MRIs. Among them, magnetic resonance image (MRI) is extensively utilized as efficient method and exhaustive data of interior organs [7, 8]. MRI employed high magnetic field to scan interior regions. The medical field required few methods to categorize and identify diseases [9]. Subsequently, computer–aided diagnosis (CAD) method is utilized for perceiving tumor prior stage in absence of human intervention. It produces diagnostic data according to MRI images [10]. ML techniques are established for feature extraction, selection, and classification. Several extraction models like clustering, threshold and texture based are utilized for segmenting tumor regions [11, 12]. The DL models cannot contain any classification features. The CNN produce several convolutional layers which extract features from images in the absence of human intervention [13]. To identify infected tumor tissues from different types of

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medical imaging, segmentation is used [14]. Segmentation is essential in image analysis and the image is split into different blocks that have common and identical features including texture, grey level, brightness, color, and contrast [15]. The major contribution of this manuscript is as follows:

- The preprocessing is done by using mix-max normalization which improves the performance of the model and fed to the segmentation process.
- The mask region-based CNN is employed for segmenting brain tumors and Batch normalization is applied to enhance the training process and minimize the overfitting issues.
- After the segmentation, CNN features are extracted and these features are fed to CNN classifier, and the performance is estimated by utilizing accuracy, precision, recall and F1-score.

The rest of portion present in manuscript is organized as follows: section 2 presents the Literature review. The block diagram of the proposed model is presented in section 3. The experimental result of this proposed model is illustrated in section 4. Section 5 describes the conclusion of this paper and lastly, this paper finishes with the references.

2. Literature review

Naoual Atia [16] introduced a particle swarm optimization (PSO) and two-way fixed effect analysis of variance (ANOVA) based fitness function for effective brain tumor segmentation. The PSO method is utilized to detect the block that contains a lesion brain image. The two-way fixed ANOVA method-based fitness function was applied to determine the better candidate block that output in automatic brain tumor segmentation. The advantage of using the ANOVA method is that it is easy to implement, applied to compare more than two samples and utilized to group with various observations. The limitation of this model has maximum computational complexity and minimizes the observed brain tissue color.

Ahmet Ilhan [17] presented a brain tumor segmentation in MRI based on tumor improvement through the u-net model. The nonparametric tumor localization was utilized to localize the region and an improved model was employed to modify the localized area. The output images are given to U-net architecture for segmenting brain images. The performance was evaluated on the BRATS 2012, 2019 and 2020 dataset. The developed model improves the segmentation capability and provides better accuracy and low-cost segmentation with a huge success rate. The limitation of the model gives a high computational cost and it is established on images that contains numerous indistinct tumor region with a limited pixel.

Xinyu Zhou [18] developed an effective 3D residual neural network (ERV-Net) for tumor segmentation to acquire efficiency and greater performance. To decrease GPU memory and enhance ERV-NET efficiency, 3D shufflenetV2 is used as an encoder and to avoid degradation, residual blocks were used as the decoder. ERV-NET was an effective deep-learning method for achieving competitive performance not only huge achievement in detection and classification. However, spatial information was ignored in MRIs because it led to poor performance.

Sandeep Singh [19] introduced a convolutional neural network called 3D U-Net which is employed for segment various regions in MRI. The BRAST 2018, 2019, 2020, and 2021 dataset were utilized with 2240 studies. Every study has 5 series like T1, contrast-improved T1, Flair, T2, and segmented mask files all in NIFTI format. The developed model utilized a 3D u-Net which trained individually on all datasets by shifting weights crosswise. The method performance is endured as an output of lack of data and it takes a long time for training.

Mahmoud Elmezain [20] implemented an automated model for segmenting brain tumors by combining a deep capsule network (CapsNet) and latent-dynamic condition random field (LDCRF). In pre-processing, N4ITK procedure includes modifying every MR image's bias field previously standardizing concentration. During the segmentation process, the image utilized for train CapsNet. Lastly, simple threshold model is utilized to modify pixel labels and eliminate minor 3D-connected regions in segmentation results. Advantage of this model was easy implantation, low computational cost and showed potential for medical applications. This developed model maximizes the training cost and training difficulty.

Amran Hossain [21] suggested a lightweight MSegNet model for brain tumor segmentation and a BINet model for classification to classify the reconstructed microwave (RMW) images. The MSegNet model was developed and tested on RMW tumor images to segment both small and large brain tumors. To create the original dataset, primarily 300 image samples are obtained from sensor-based microwave brain imaging (SMBI). The developed model was lightweight, accurately segmenting the tumor with high-resolution images and low inference and training time. The limitation of this model only reconstructs the two tumor-based images and non-tumor images.

Ejaz Ul Haq [22] implemented a hybrid technique based on deep convolutional neural network (DCNN) and ML for segmentation and classification of tumors by utilizing MRI. The CNN is in the initial stage of learning the feature map from the space of image of MRI images into the region of the tumor marker. Next, faster region-based CNN was created for the tumor region localization by utilizing a region proposal network (RPN). Finally, DCNN and ML classifiers are combined in series for segmentation and classification. The method attained automatic segmentation and classification of brain tumors without user interface. The limitation of the method was it takes high computational time.

Pranjal Agrawal [23] introduced a 3D-UNet DNN for segmentation and classification of brain tumors by utilizing the Kaggle dataset. The introduced method depends on the 3D segmentation of MRI images. The MRI images of the brain in 3D volume are separated in 3D sub-volumes which are fed into segmentation and responded into 3D volume. The advantage of method was critical features directly from multiple-modal MRI brain tissues. However, delimited data accessibility and huge cost are limitations of using 3D DL in clinical imaging.

Arkapravo Chattopadhyay and Mausumi Maitra [24] developed an MRI-based deep learning technique for brain tumor detection through CNN. The developed model was utilized to segment brain tumor from 2D MRI images by CNN that is followed through conventional classifiers. The several MRI images are considered with various size, shape, location and intensity for train the model. Additionally, the SVM classifier and activation algorithms like sigmoid, softmax are utilized to cross-check the model. The developed CNN model learns difficult features in automatically from multi-modal MRI images. However, this model has limitations like time complexity and required weight optimization of various data fusion models.

Javeria Amin [25] presented an ensemble transfer learning and quantum variational classifier (QUC) for brain tumor detection technique. In this developed model, deep features are extracted from Inceptionv3 which was provided to QVR for discrimination among tumors. The classified images are transferred to developed Seg-network model in which the real infected area was segmented for examine the severity level. The developed model trained on tuned hyperparameter with ground mask which accurately segments the tumor region. However, this model necessitates large-dataset and consumes more time for training.

Muhammad Irfan Sharif [26] suggested an analysis of brain tumor using MRI based YOLOv2 and CNN technique. The developed technique comprises four various phases such as lesion enhancement, feature extraction and selection for classification, localization and segmentation. In this model, the homomorphic filter was employed for removing noise and send to an Inceptionv3 for feature extraction. Here, the optimal features are selected and classified. Then, the infected regions are localized depends on YOLOv2-Inceptionv3 here features are extracted through concatenation layer and send to YOLOv2 model. The developed model achieves better noise resistance than the existing methods. However, this model has limitations like time complexity and required weight optimization of various data fusion models.

Ajay S. Ladkat [27] implemented a DNN brain tumor segmentation using mathematical model. In this developed model every slice of 3Dimage was enhanced through mathematical model that is passes via 3D attention U-net for generate segmented tumor result. The developed model provides accurate tumor pixel segmentation findings from 3D brain images. The feature extraction types are accomplished as primary criterion. This model enhances human lifetime and reduces death amount through huge accuracy and low complexity. However, it has limited memory, false tolerance and required high computational time.

From the overall analysis, the mathematical model with 3D attention U-net has limited memory, false tolerance and required high computational time. The CNN model has limitations like time complexity and required weight optimization of various data fusion models. The SoftMax classifier has time complexity and required weight optimization of various data fusion models. The ensemble transfer learning and quantum variational classifier necessitates large-dataset and consumes more time for training. Hence, these limitations are considered and overcomes by proposed CNN classifier in this manuscript.

3. Proposed method

This proposed method is utilized for brain tumor segmentation by BRATS 2019, 2020 and 2021 dataset. The preprocessing is done by using mix-max normalization which improves the performance of the model and fed to segmentation process. The mask region-based CNN is employed for segmenting brain tumors and Batch normalization is applied for enhancing the training process and minimizing the

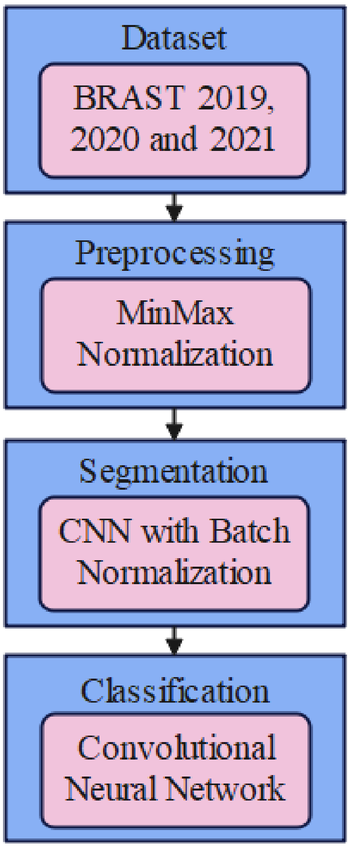

Figure. 1 Work flow of the proposed methodology

overfitting issues. After segmentation, CNN features are extracted and these features are fed to CNN classifier and the performance is estimated by utilizing accuracy, precision, recall and F1-score. The workflow of proposed method is represented in Fig. 1.

3.1 Dataset

In this manuscript, the proposed CNN method experiments were conducted on the three datasets such as BRATS 2019, 2020 and 2021. The BRATS 2019 dataset [28] has 335 cases in which 259 occurrences of high-grade LGG and 76 occurrences of low-grade LGG correspondingly. The validation and testing set contains 125 and 166 cases respectively. The BRATS 2020 dataset [29] employs pre-operative MRI scans and focus on segmentation. The training dataset includes 369 MRI scans in which 293 has attained from GBM/HGG and 76 from low-grade LGG with their segmentation. The BRATS 2021 dataset [30] which includes training, validation and testing datasets. The training comprises 1251 cases, with 4 modalities and 1 annotation. While validation comprises 219 cases with 4 modalities and no annotations. The output model annotation against validation is required to be sent the online validation tool to get performance. Semantic segmentation labels equivalent to the validation cases are not publicly accessible and this paper utilized 5-fold cross-validation with a ratio of 8:2.

3.2 Preprocessing

Data preprocessing is a process of converting the raw data into a desired format, the dataset from several resources may consist of incomplete data. So, for further analysis, this data is required to be filtered and normalized. Data normalization is the process of preprocessing the input data. The BRATS 2019, 2020 and 2021 datasets are standardized using min-max normalization method which improves the model performance. The highest score of the feature is transformed into 1, the smallest score of the feature is transformed into 0 and other values of the feature are transformed into an integer between 0 and 1. The mathematical representation of min-max normalization is shown in Eq. (1),

$$v' = \frac{v - min_A}{max_A - min_A}\left(new_{max_A} - new_{min_A}\right) + new_{min_A} \quad (1)$$

Where, v' is the respective min-max normalization attribute value, v is the primary attribute value, max_A is the highest score and min_A is the smallest score of the feature.

3.3 Segmentation

The pre-processed data is utilized for segmentation by using a CNN with Batch Normalization (BN). The segmentation stage is responsible for segmenting the brain tumor from medical images. The mask region-based CNN is employed for segmenting brain tumors and Batch normalization is applied for enhancing the training process and minimizing the overfitting issues.

3.3.1. Convolutional neural network

One of the instance segmentation methods named a mask region-based CNN is used for precise segmentation in brain tumors. This method is utilized to obtain pixel level segmentation. The mask region-based CNN exchanges region of interest (RoI) pooling with RoIAlign that identifies minor objects in the image. The procedure of mask region-based CNN is presented as below:

- The pre-processed image is taken as input that contains target objects and allows it to pre-trained CNN that provides a feature map for the image.

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- Allows the feature map over a Region Proposal Network (RPN) to achieve an object proposal with their object values.
- To enhance the proposal and produce segments the RoIAlign layer is utilized on the proposal.
- At last, the proposals are given to the FC layer to predict the bounding box, object mask and class label.

The loss function of mask region-based CNN relates to loss of segmentation, localization and classification are presented in Eq. (2),

$$L = L_{cls} + L_{box} + L_{mask} \quad (2)$$

Where, the L_{cls} , L_{box} and L_{mask} is the classification loss, candidate box regression loss and mask layer loss respectively.

The $m \times m$ dimension mask for each RoI and class is produced by the mask branch, total K classes are there. Hence, the total output size is $K \times m^2$. The L_{mask} is described as average binary cross-entropy loss, the region is related to ground truth class k which only contains kth mask. It is presented as Eq. (3),

$$L_{mask} = -\frac{1}{m^2}\sum_{i\leq j, j\leq m}\left[y_{ij}\, log\, \hat{y}_{ij}{}^{k} + \left(1 - y_{ij}\right) log\left(1 - log\, \hat{y}_{ij}{}^{k}\right)\right] \quad (3)$$

Where, y_{ij} is the cell label (i, j) in true mask for region $m \times m$ and $\hat{y}_{ij}{}^{k}$ is the predicted score of similar cells in the mask acquired for ground truth class k.

3.3.2. Batch normalization (BN)

Through the training of the CNN model, the input value distribution for a particular layer depends on the previous layer of the model. This inconsistency produces overfitting and minimizes the learning rates. In this manuscript, Batch Normalization [31] is utilized to enhance the training process and minimize overfitting by regulating the input vector in the same way that removes the noisy features that stabilize the training process. The BN is a deep neural network training method that creates sample data distribution in batch consistency. During the training process, the BN splits the sample data into numerous small sets, and then estimates the mean and variance of the feature map by a weighted average of small sets to obtain the mean and variance of all sample data. The normalization permits to utilization lesser dropout rates because it acts as standardized and the input is a vector. The BN is performed by using Eqs. (4), (5) and (6),

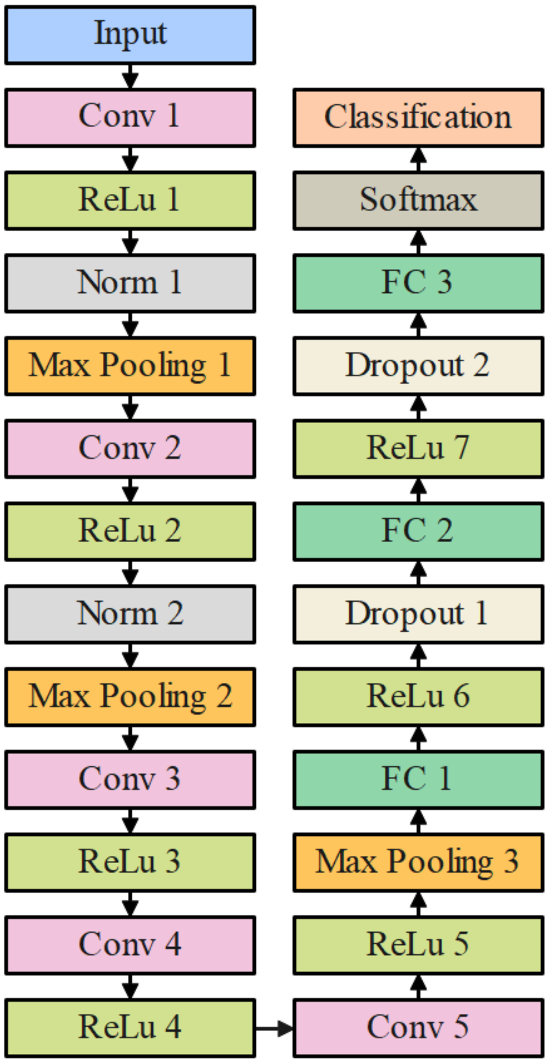

Figure. 2 CNN Architecture

$$M_{BN}(X) = \frac{1}{N}\sum_{i=1}^{N} X_i \quad (4)$$

$$\sigma^2{}_{BN}(X) = \frac{1}{N}\sum_{i=1}^{N}\left(X_i - M_{BN}(X)\right)^2 \quad (5)$$

$$Y_i = \frac{X_i - M_{BN}(X)}{\sqrt{\sigma^2{}_{BN}(X)}} \quad (6)$$

Where, M_{BN}, $\sigma^2{}_{BN}$ and N is the mean, variance and number of elements in the input vector X respectively. Y_i is the output of batch normalization.

3.4 Classification

After the segmentation, the CNN features are extracted and these features are fed to classification process. For a large number of images, the computational time and complexity increase. The CNN is used as the vectorized images by perceiving their features. The CNN architecture contains numerous layers such as input, convolutional, normalization, max pooling, fully connected, dropout, softmax and output layer [32]. The CNN Architecture is shown in Fig. 2.

In this paper, the input MRI images are resized to $256 \times 256 \times 1$, which denotes to image height, width and channel number. The convolutional layer is characterized for capturing the lower-level features, by maximizing layers to generate higher-level features from input images. The lower and higher-level features contain color, gradient orientation and edges. The conv layer includes a group of convolution kernels named filters, that convolved to input for generating output features. The kernel weights are initialized with random scores at training and at every epoch in training stage, the weights are adjusted and kernel learns to extract necessary features. The representation of discrete time for the convolution process and bi-dimensional cases are expressed as Eq. (7) and (8),

$$f_C(t) = (y \times k)(t) = \sum_{b=-\infty}^{\infty} y(b)\, k(t-b) \quad (7)$$

$$f_C(i,j) = (X \times W)(i,j) = \sum_n \sum_m X(i,j) \times W(i-n, j-m) \quad (8)$$

Where, $f_C(t)$ and $f_C(i,j)$ are represents convolution operation for single input y and two-dimensional input X correspondingly. The b and k are the shifting time and kernel filter respectively. i and j define the matrix range requisite after employing the convolution process.

For each convolution layer, the FC layer and non-linear activation function are applied to permit the network from difficulted features and permit the input non-linear mapping to the output. The Rectified Linear Unit (ReLU) is a generally utilized activation function for enhancing training time and overcoming vanishing gradient problems. The ReLU requires a minimum computational load to evaluate other functions. The activation functions like ReLU $g_1(x)$, sigmoid $g_2(x)$ and tanh $g_3(x)$ functions are presented as Eq. (9), (10) and (11),

$$g_1(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} \quad (9)$$

$$g_2(x) = \frac{1}{1+e^{-x}} \quad (10)$$

$$g_3(x) = \frac{2}{1+e^{-2x}} \quad (11)$$

For any convolution layer, the input size $a^{[L-1]}$ of layer has $n^{[L-1]}$ channels and $h^{[L-1]} \times w^{[L-1]}$ dimension, forward procedure of the convolution layer and output feature size $a^{[L]}$ from convolution process is determined as Eqs. (12), (13), (14) and (15),

$$X^{[L]} = W^{[L]} a^{[L-1]} + b^{[L]} \quad (12)$$

$$a^{[L]} = g\left(X^{[L]}\right) \quad (13)$$

$$h^{[L]} = \left\lfloor \frac{h^{[L-1]} - f^{[L]} + 2P^{[L]}}{s^{[L]}} + 1 \right\rfloor \quad (14)$$

$$w^{[L]} = \left\lfloor \frac{w^{[L-1]} - f^{[L]} + 2P^{[L]}}{s^{[L]}} + 1 \right\rfloor \quad (15)$$

Where, $W^{[L]}$ and $b^{[L]}$ are weight and bias of convolution layer, $h^{[L]}$ and $w^{[L]}$ represents the height and weight of the output feature map, $f^{[L]}$, $p^{[L]}$ and $s^{[L]}$ indicates the filter size, padding and stride of convolution process correspondingly. The computation cost (C) of CNN examines the network performance for every convolution layer is presented as Eq. (16),

$$C = f^{[L]} \times f^{[L]} \times n^{[L-1]} \times h^{[L]} \times w^{[L]} \times n_f \quad (16)$$

Where, $f^{[L]} \times f^{[L]}$, $n^{[L-1]}$ and n_f represents the kernel size, number of input channel and number of filters, $w^{[L]}$ and $h^{[L]}$ is the weight and height of the output conv layer correspondingly. After conv, max pooling revenues larger size feature maps and minimizes in small size to test the feature vector for reducing feature map width and height. Minimizing feature map size, preserves information with step of every pool is presented as Eqs. (17) (18),

$$w_p^{[l]} = \frac{w^{[l-1]} - f^{[l]}}{s^{[l]} + 1} \quad (17)$$

$$h_p^{[l]} = \frac{h^{[l-1]} - f^{[l]}}{s^{[l]} + 1} \quad (18)$$

Where, $w_p^{[l]}$ and $h_p^{[l]}$ are width and height of pooling layer output, $s^{[l]}$ and $f^{[l]}$ is the step number and filter size respectively. The final of CNN is the classification layer, which comprises the fatten, FC, and softmax layers. The fatten layer is the translation of 2D format to a single vector. The FC is responsible for calculating the volume size compared to the class value. It predicts the class label by understanding the vectorized input features. The softmax layer is a utilization of multi-class classification to select predicted value as input and produce result from range of 0 to 1 presenting class possibility. The decision result is selected depending on probability value which is presented as Eq. (19),

$$P(Y = j|X, W, b) = \frac{e^{x^T wj}}{\sum_{j=1}^{m} e^{x^T wj}} \quad (19)$$

Where, W and b are weight and bias vector. Cross-entropy loss is evaluated for multiclass classification by relating the true and predicted labels which are preferable for deep networks depending only on the output neuron instead of the activation function. The loss function is presented as Eq. (20),

$$L = -\sum_{c=1}^{m} y_{0,c} \log(P_{0,c}) \quad (20)$$

Where, y is binary indicator (0 or 1) if class label c is exact classification and p is predicted possibility for observation o in class c.

4. Result

In this paper, the proposed CNN is stimulated by utilizing a python environment with the system configuration: RAM:16GB, processor: intel core i7 and operating system: Windows 10. The parameters like accuracy, precision, recall and F1-score are utilized for estimate model performance. Mathematical representation of these parameter is shown in Eqs. (21), (22), (23) and (24),

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (21)$$

$$Precision = \frac{TP}{TP+FP} \quad (22)$$

$$Recall = \frac{TP}{TP+FN} \quad (23)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (24)$$

Where, TP, TN, FP and FN represents True Positive, True Negative, False Positive and False Negative correspondingly.

4.1 Quantitative analysis

The quantitative analysis of convolutional neural network (CNN) model is evaluated by utilizing metrics like accuracy, precision, recall and F1-score. Table 1 and Fig. 3 represents the performance of classification using BRATS 2019 dataset. Table 2 and Fig. 4 represents the performance of classification using BRATS 2020 dataset. Table 3 and Fig. 5 illustrates performance of classification using BRATS 2021 dataset. The accuracy, precision, recall and F1-score of Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF) and Naïve Bayes are measured and matched with the proposed CNN model. The obtained result shows that proposed CNN model achieves better accuracy of 99.29% on BRATS 2021, 99.80% on BRATS 2020 and 99.55% on BRATS 2019 dataset which is comparatively higher than the other existing methods.

Table 1. Performance of classification using BRATS 2019 dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	62	63	61	62
Decision Tree	86	85	86	85
Random Forest	78	76	76	78
Naïve Bayes	81	79	81	79
CNN	99.55	98	98	98

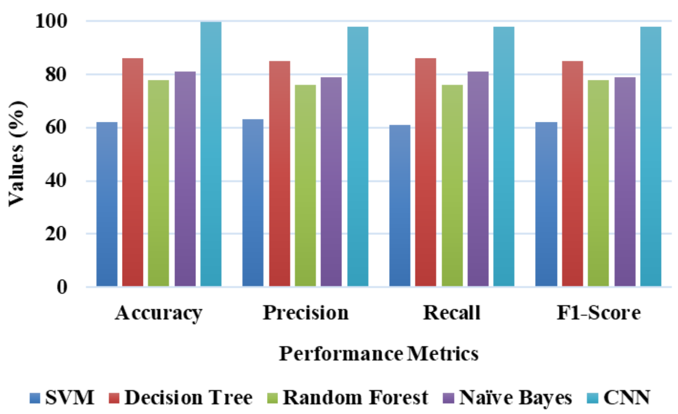

Figure. 3 Performance of classification using BRATS 2019 dataset

Table 2. Performance of classification using BRATS 2020 dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	70	73	71	72
Decision Tree	76	75	76	75
Random Forest	80	78	79	78
Naïve Bayes	83	81	81	81
CNN	99.80	99	99	99

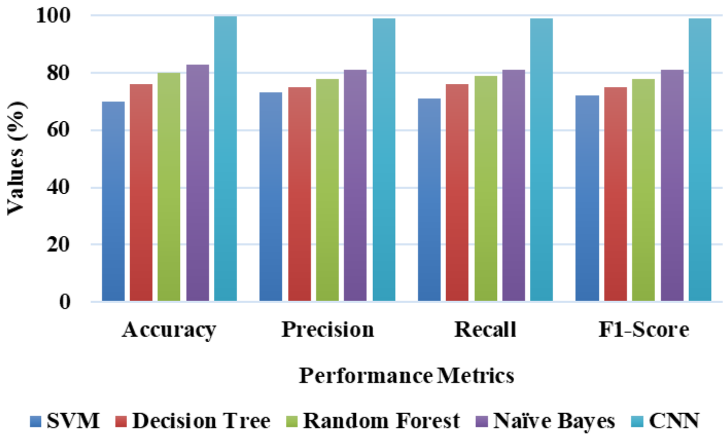

Figure. 4 Performance of classification using BRATS 2020 dataset

Table 3. Performance of classification using BRATS 2021 dataset

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	72	73	71	71
Decision Tree	68	68	68	68
Random Forest	80	80	78	79
Naïve Bayes	62	61	61	61
CNN	99.29	99.3	99.15	99.78

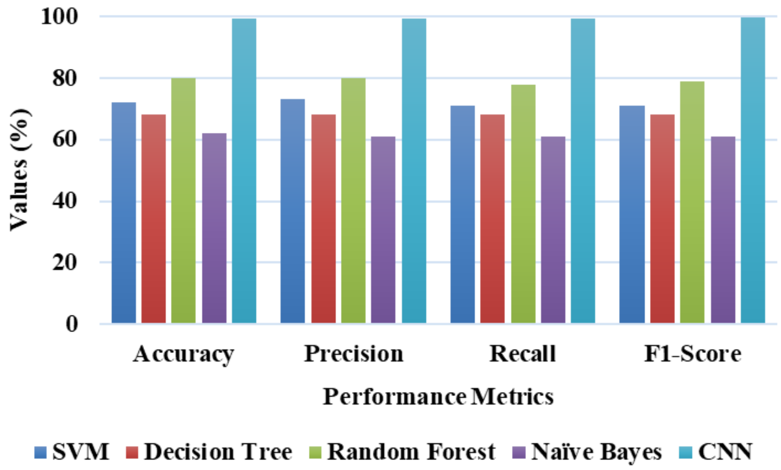

Figure. 5 Performance of classification using BRATS 2021 dataset

Table 4. Comparative analysis of the proposed method on BRATS 2019 dataset

Author	Technique	Dataset	Accuracy (%)	Precision (%)	Recall (%)
Muhammad Irfan Sharif [26]	Softmax classifier	BRATS 2019	99.2	N/A	N/A
Ajay S. Ladkat [27]	Mathematical model with 3D attention U-net		98.90	99	98
Proposed method	CNN		99.55	98	98

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Table 5. Comparative analysis of the proposed method on BRAST 2020 dataset

Author	Technique	Dataset	Accuracy (%)	Recall (%)
Arkapravo Chattopadhyay and Mausumi Maitra [24]	CNN	BRATS 2020	99.74	N/A
Javeria Amin [25]	Ensemble Transfer learning and Quantum Variational Classifier		99.70	N/A
Muhammad Irfan Sharif [26]	Softmax classifier		99.0	98
Proposed method	CNN		99.80	99

Table 6. Comparative analysis of the proposed method on BRAST 2021 dataset

Author	Technique	Dataset	Accuracy (%)	Recall (%)
Sandeep Singh [19]	3D U-Net	BRATS 2021	99.13	N/A
Mahmoud Elmezain [20]	CapsNet + LDCRF + post-processing		N/A	88
Proposed method	CNN		99.29	99.15

4.2 Comparative analysis

This section shows the comparative analysis of the CNN classifier with performance metrics like accuracy, precision and recall as shown in Table 4, 5 and 6. Existing methods like 3D U-Net [19], CapsNet + LDCRF + post-processing [20], CNN [24], Ensemble Transfer learning and Quantum Variational Classifier [25], Softmax classifier [26] and Mathematical model with 3D attention U-net [27] are used for evaluating the ability of this classifier. The proposed model is trained, tested and validated by using BRAST 2019, 2020 and 2021 dataset. The proposed method attains accuracy of 99.55% on BRATS 2019, 99.80% on BRATS 2020 and 99.29% on BRATS 2021 dataset which is comparatively higher than the other existing methods.

5. Conclusion

A group of abnormal cells that can infiltrate neighbouring tissues in brain is referred to as a brain tumor. The early detection of brain tumors is necessary to aid doctors in treating cancer patients to increase their survival rate. The BRATS 2019, 2020 and 2021 dataset are utilized in this research for effective segmentation and classification. The preprocessing is done by using mix-max normalization which improves performance of the model and fed to segmentation process. The mask region-based CNN is employed for segmenting brain tumors and Batch normalization is applied to enhance training process and minimize the overfitting issues. After segmentation, CNN features are extracted and these features are fed to CNN classifier. Performance of proposed CNN model is evaluated by utilizing accuracy of 99.55% on BRATS 2019, 99.80% on BRATS 2020 and 99.29% on BRATS 2021 dataset which ensures accurate tumor classification compared to existing methods. The future work is to enhance the performance of segmentation process by using several classifiers.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

The paper background work, conceptualization, methodology, dataset collection, implementation, result analysis and comparison, preparing and editing draft, visualization have been done by first author. The supervision, review of work and project administration, have been done by second author.

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