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Brain tumor detection from MRI images with using proposed deep learning model: the partial correlation-based channel selection

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Abstract: A brain tumor is an abnormal growth of a mass or cell in the brain. Early diagnosis of the tumor significantly increases the chances of successful treatment. Artificial intelligence-based systems can detect the tumor in early stages. In this way, it could be possible to detect a tumor and resolve this problem that may endanger human life early. In the study, the partial correlation-based channel selection formula was presented that allowed the selection of the most prominent feature that differs from the other studies in the literature. Additionally, the multi-channel convolution structure was proposed for the feature network phase of the Faster R-CNN architecture. In the proposed model, the most prominent features were obtained from the multi-channel selection structure in the feature network phase with the channel selection formula in the channel selection layer. The architecture was applied for the early detection of possible brain tumors, which are a severe risk for human life. Within the present study, the brain tumor was classified applying the proposed multi-channel Faster R-CNN based model with three different open-access datasets. VGG-16, faster region-based convolutional neural network (Faster R-CNN), DenseNet-201, Resnet-50, and SRN models, which are popular deep learning architectures, were applied to the same problem to compare the results and demonstrate the efficiency of the proposed model. Accuracy, sensitivity, and processing times of the applied methods were measured to demonstrate the models' performance and efficiency. As a result, the highest accuracy rates were obtained using the proposed model as 98.31%, 99.6%, and 99.8% for three datasets. In addition, it was compared with related studies in the literature to demonstrate the proposed model's applicability. The proposed model's accuracy and performance proved to be higher than in the other studies.

Key words: Artificial intelligence, proposed channel selection layer, partial correlation, deep learning, Faster R-CNN, brain tumor

1. Introduction

The tumor is an abnormal growth of tissues in a certain part due to extreme segmentation of cells in the body. Although some tumors may not cause fatal consequences, there is an exceptional case for brain tissue. A benign tumor may be fatal because the brain is protected in the skull. Therefore, all kinds of malignant or benign brain tumor treatment should be started early, and the tumor should be brought under control with correct intervention. More than 150 different brain tumors have been described in the literature [1]. However, two most cited brain tumor groups are primary and metastatic. The tumors originating from cells and structures in the brain are called primary brain tumors. Metastatic brain tumors are tumors that spread to the brain after forming in any part of the body. Notably, lung, breast, colon, pancreatic, kidney, and skin cancers spread through arterial circulation and cause the metastatic brain tumor [2]. Primary brain tumors include

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tumors that originate from the brain's tissues or this tissue's immediate area. Primary tumors develop either glial or non-glial forms. Based on cell origin, the tumors are classified either as benign or malignant. In the United States, in addition to approximately 700000 primary brain tumor patients, around 80000 new cases are diagnosed annually, and among nearly 70% have benign and 30% have malignant tumors [3]. Metastatic brain tumors include tumors that occur in another part of the body. In general, it has been transported to the brain via the bloodstream. Metastatic tumors are recognized as cancer. About 25% of patients with cancer disease have been affected by the brain metastatic tumor formation. For example, it has been seen that the cancer tissue in the lungs affects the formation of a metastatic brain tumor in 40% of patients with lung cancer. In the past, the survival time in patients diagnosed with such tumors was observed to be only a few weeks. More sophisticated diagnostic tools, innovative surgical and radiation-based approaches have provided patients with increased long-term survival rates [4].

The importance of unprocessed data has increased considerably with the development of technology and the emergence of data benefits. Data analysis uses data to make predictions and solve many real-life problems. This situation increased the popularity of artificial intelligence methods, which perform with high accuracy by analyzing data. Also, the time efficiency of these methods is significant, along with a high accuracy rate. Deep learning is defined as architecture with multi-layer neural networks in each layer. It uses the parallel computing and processing power gained by artificial neural networks even more powerfully using technologies that may increase hardware efficiency. Developments in artificial intelligence and image processing have accelerated with the widespread use of deep learning methods.

One of this study's contributions is that the proposed faster region-based convolutional neural network- (Faster R-CNN) based deep learning model was applied with high accuracy and effectiveness for diagnosing brain tumors that represent, a significant risk to human health. Another contribution of the study is to propose a model with channel selection layers that select the most important feature. Due to the applicability of deep learning methods in image processing, it was chosen as a method in the study. Three different brain magnetic resonance imaging (MRI) datasets were used in the study to demonstrate the success of the proposed method. The first dataset was the open-access brain MRI dataset [5], which was used by Cheng et al. [6] in their study. The second dataset was the brain tumor MRI images that can be accessed from the open-access Kaggle data repository [7]. Lastly, BRATS 2018 brain tumor MRI dataset [8–10] was chosen.

This research consists of two parts as a deep learning-based training model and a brain tumor diagnosis model. The diagnostic model is used to predict whether individuals have a brain tumor. Then, the deep learning models applied in the study are compared in terms of performance measurement parameters. The brain tumor prediction system can support doctors in determining the risk in patients with brain tumor onset. In the proposed model, which is Faster R-CNN based, a novel channel selection formula is presented in the study to select the most prominent feature filters.

Faster R-CNN architecture consists of three units. A feature map is created with the feature network, which is the first unit of the architecture. In the proposed model, multi-channel convolution structures are used for the feature network unit in Faster R-CNN. While each channel creates its feature network, it is aimed to reveal the most effective feature network through the channel selection layer with the proposed channel selection formula.

Contributions of the study include the following:

- A multi-channel structure has been proposed for the feature network unit of the Faster R-CNN architecture, providing a more effective use.

- A novel channel selection formula has been proposed, which has partial correlation-based channel selection to select the most prominent feature in the proposed channel selection layer in the architecture.
- A new model with high-performance values has been developed. Besides, the applicability of the model has been demonstrated.

The study consists of four sections. In the first section, the literature survey is presented. The second part is devoted to information about the applied methods and the dataset. In the third section, experimental studies of detecting brain tumors with the proposed model and other applied methods are shown and compared. In the last sections, the obtained results are shown and discussed.

1.1. Related works

In this section, studies in the literature that is related were summarized. Classification and detection stages are required to help predict tumor tissues. Deep learning architectures with their strength properties are more suitable for solving the such prediction problems than other approaches. Among the deep learning approaches, it has been evaluated that CNN architecture was most applied in the studies. Kakarla et al. [11], in 2021, used average-pooling CNN to classify brain magnetic resonance images. The proposed average-pooling CNN model was applied with eight-layer for three-class brain tumor classification in the study. The applied dataset consists of 3064 brain tumor magnetic resonance images (MRI). As a result, the accuracy rate of the proposed model has been obtained as 97.42%. Saranya et al. [12], in 2021, detected brain tumor using the deep learning method. The main purpose of their study was to segment MRI images depending on the direction. Karayegen et al. [13], in 2021, applied the CNN deep learning method to predict brain tumor on MRI. In their study, the BRATS dataset was used. They reached as 91.72% tumor prediction accuracy and 99.75% background prediction accuracy.

Grovik et al. [14], in 2020, applied the CNN method to demonstrate the automated detection of brain metastases on multisequence MRI. A total of 156 patients MRI with brain metastases were used in the study. As a result, the area under the curve (AUC) for the applied method was found to be 0.98. Sharif et al. [15], in 2020, used CNN-based Inception-v3 architecture for brain tumor segmentation. BRATS 2013, BRATS 2014, BRATS 2017, and BRATS 2018 datasets were used to evaluate the study's success. As a result, the average accuracy rate was obtained as 92%. Hollon et al. [16], in 2020, studied brain tumor diagnosis using stimulated Raman histology and deep CNN. The overall accuracy rate of the proposed model achieved 94.6%. Rehman et al. [17], in 2020, used CNN-AlexNet, GoogLeNet, and VGGNet architectures to detect brain tumors. For this goal, Figshare brain tumor MRI dataset was used. In the study, the highest accuracy rate was obtained using VGG16 architecture and reached 98.69%. Khan et al. [18], in 2020, utilized CNN architectures to predict brain tumor from MRI. Within the study, to increase the success, data augmentation and canny edge detection methods were applied. VGG-16, ResNet-50, and Inception-v3 architectures were used to compare the performances. The highest accuracy was obtained with VGG-16 model and achieved 96%. Mehrotra et al. [19], in 2020, applied five different CNN architectures such as AlexNet, GoogLeNet, ResNet50, ResNet101, and SqueezeNet to detect brain tumors. The proposed model achieved the highest accuracy as 99.04%.

Malathi et al. [20], in 2019, used the CNN method for brain tumor segmentation. In the study, BRATS 2015 dataset with high-grade gliomas data was used. In addition, the TensorFlow library has been utilized to implement high-level mathematical functions. Sajjad et al. [21], in 2019, proposed a model with data augmentation, which was applied to the CNN method for brain tumor classification. As a result, 87%

accuracy rate was achieved before the data augmentation. However, the accuracy rate was 90% after the data augmentation process. Özyurt et al. [22], in 2019, applied the CNN deep networks with the fuzzy systems (NS-CNN) to classify brain tumors. The accuracy rate achieved 95%. Alqudah et al. [23], in 2019, split brain tumors into three classes: glioma, meningioma, and pituitary tumor using the CNN method. The results varied for different lesions. While the proposed CNN classifier achieved an accuracy rate of 98.93% and a sensitivity rate of 98.18% for cropped lesions; for uncropped, it showed a 99% accuracy and 98.52% sensitivity rate; for segmented lesions, its accuracy rate was 97.62%.

Widhiarso et al. [24], in 2018, presented a brain tumor classification model using CNN and GLCM (gray level co-occurrence matrix). The study extracted energy, correlation, contrast, and homogeneity features from four different angles for each image. These features were applied to the CNN model. The best accuracy for the test results was found with two feature sets as 82%. Seetha et al. [25], in 2018, implemented a CNN-based deep learning model for brain tumor detection. In the study, a fuzzy c-means method was used for segmentation. These segmentation features were applied to support vector machines (SVM) and deep neural network classifiers. For the applied models, the highest accuracy rate was 97.5%. Wang et al. [26], in 2018, proposed CNN based model for automated medical images. The applicability of the proposed model was shown in the study. Cui et al. [27], in 2018, presented CNN based method for brain gliomas segmentation.

Khawaldeh et al. [28], in 2017, submitted a model for grading brain tumors from MR by using a modified version of the CNN-AlexNet architecture. As a result, it achieved an accuracy rate of 91%. Havaei et al. [29], in 2017, proposed a CNN model for brain tumor segmentation. BRATS dataset, which contains low and high-grade MRI images, was applied in the study. Hussian et al. [30], in 2017, proposed a segmentation model using the CNN method for brain tumor detection. In the proposed model, a preprocessing method was invoked to remove noises, and two sub-networks were used for stepwise modelling. The first network was utilized for tumor localization. After this process, the second network classified the tumor. The BRATS 2015 dataset with 220 high-grade and 54 low-grade glioma cases was applied in the study. Dong et al. [31], in 2017, presented a U-Net CNN-based model for identifying brain tumors without radiation effect. The study used the BRATS 2015 dataset, which includes 220 high-grade and 54 low-grade glioma tumor cases. The applicability of the proposed method has been shown in the study. Chinmayi et al. [32], in 2017, offered the Bhattacharya coefficient method for tumor detection on brain MR images. In the study, the highest accuracy rate attained 99.1%.

Isin et al. [33], in 2016, used the CNN method for brain tumor segmentation. The study showed that the CNN-based method, which was trained with multimodal MRI brain images, achieved successful results. Pereira et al. [34], in 2016, studied gliomas, one of the aggressive types of brain tumors. In the study, CNN based segmentation method was applied to the BRATS 2013 dataset. In addition, density normalization together with CNN helped to achieve more effective segmentation. Konstantinos et al. [35], in 2017, studied a segmentation of the brain lesion using the 3-dimensional CNN method. It was applied to lesions for detection as traumatic brain injury or brain tumor in multi-channel MR images. In the study, it was emphasized that successful segmentation results were obtained with the applied method.

It should be mentioned that other deep learning architectures and different methodologies are also utilized to model similar detection problems in the literature. Xue et al. [36], in 2021, proposed a model using DenseNet to extract the features of magnetic resonance images. In the study, the proposed two-branch DenseNet prediction model has achieved an accuracy rate of 94%. Deepak et al. [37], in 2021, used the siamese neural network (SNN) with three layers for brain tumor classification. Radiopaedia, Harvard, and Figshare datasets, which have open-access, were used to evaluate the model. As a result, the accuracy rates obtained were 92.6%, 98.5%, and 92.6%, respectively. Ismael et al. [38], in 2020, classified brain tumors using residual network (ResNet50). Vertical and horizontal data augmentation techniques were applied to extend the dataset. They achieved 99% accuracy on image-level. Nazir et al. [39], in 2019, detected brain tumors from MRI images using multilevel wavelets. They utilized discrete cosine transform for selecting high variance features and neural networks for classification. The accuracy rate attained 99.7%. Mohsen et al. [40], in 2017, used deep learning with discrete wavelets for brain tumor classification. In the study, wavelet transform was applied for tumor segmentation. The features taken from the segmentation were applied to feed deep learning. The model revealed in the study had an accuracy rate of 96% and a sensitivity rate of 97%. Cheng et al. [6], in 2015, proposed a model to improve performance with segmentation methods for brain tumor classification. They applied different feature extraction methods such as density histogram. As a result, the accuracy rate for the density histogram reached 71%. Then, a 78% accuracy rate was achieved by increasing productivity with related methods. Sasikala et al. [41], in 2008, classified brain tumors using a genetic algorithm-based feature selection method. The genetic algorithm-based model has suggested 4 of 29 features. Ninety-eight percent of accuracy rate was achieved with these suggested features.

In literature, studies have generally been on using standard deep learning architectures. There are only few works that are focused on different custom architectural approaches. In addition, classification or detection methods are widely used in images for feature extraction. In particular, different points of view or the custom network architecture usage have not been observed for selecting the best feature extraction. Furthermore, models have generally applied a single dataset. Different from the related studies, the multi-channel Faster R-CNN based architecture model and channel selection layer were proposed and their applicability was shown. In the proposed model, a channel selection formula was presented to select the most prominent feature. Besides, three different datasets were applied to show that the proposed architecture was applicable. In addition, data augmentation method was utilized for MRI to observe the behavior of different data. The proposed model was applied for brain tumor segmentation from MRI images to increase diagnostic accuracy, and its diagnostic results and statistical performance were compared to other applied models.

2. Materials and methods

2.1. Data preparation and preprocessing

Data is the most crucial factor for methods such as artificial intelligence and machine learning. The reason for this, it is the basis for learning and adapting the problem in these methods. Training data is selected from a dataset that represents the problem space homogeneously.

In the study, three different datasets were used to demonstrate the applicability of the proposed method. Firstly, the open-access figshare brain tumor dataset [5], which Cheng [6] studied, has been used in the model. There are 3064 MRI images, including glioma, meningioma, and pituitary, in the related dataset. In total, 1426 glioma, 708 meningioma, and 930 pituitary tumor MRI images are labeled. Secondly, the brain MRI image dataset in the Kaggle repository has been applied [7]. The dataset includes a total of 253 MRI images, 155 of which are labeled as a tumor and 98 of which are healthy. BRATS 2018 brain MRI dataset, which was studied by [8–10], was also used. The dataset includes a total of 285 MRI scans that are composed of 210 high-grade gliomas, 75 low-grade gliomas. Sample MRI images that were used in this work are shown in Figure 1.

The images from three datasets were preprocessed. Firstly, the images were resized into the same size as 128x128 to provide a more adapted and faster process in the system. Besides, data augmentation method has

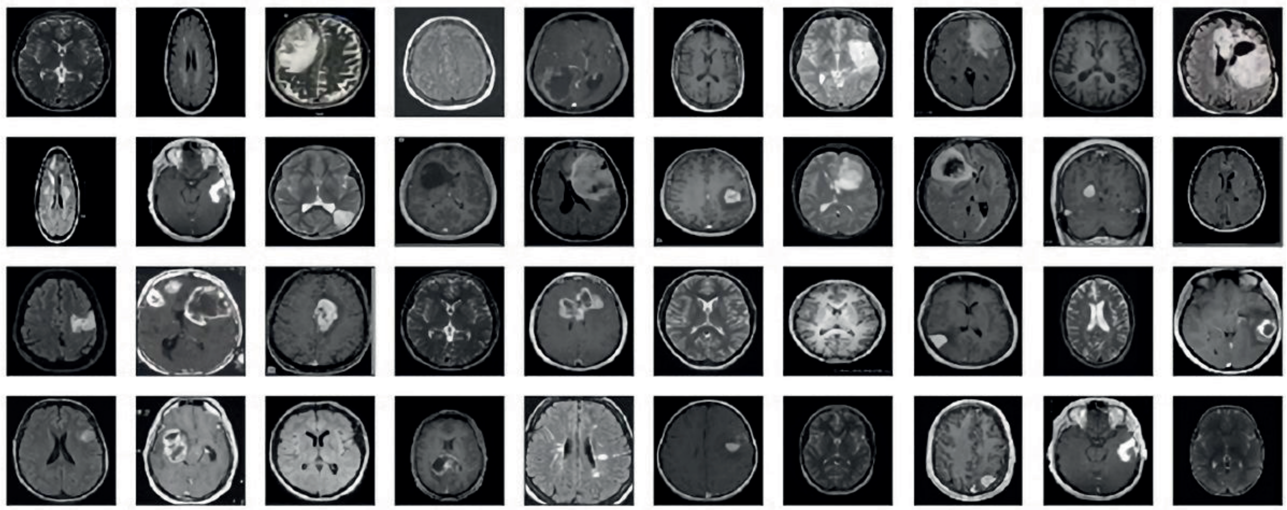

Figure 1. Sample MRI images.

been applied to increase the MRI images and decrease the risk of overfitting. Data augmentation was applied in the study with horizontal flipping technique in the images. In horizontal flipping augmentation technique, each row and column of an image pixels are reversed. In this way, a mirror image is obtained, which is equivalent to rotating the original image by 180°. Different images occurred with the applied data augmentation techniques. In this way, the training set was increased with synthetic data.

2.2. Deep learning & Faster R-CNN

Artificial neural network is artificial intelligence method that aims to learn and adapt like human brain. Deep learning can be defined as an architecture with multilayered artificial neural networks in each layer [42]. The difference in the deep learning method from other artificial intelligence and machine learning methods in the literature is that it can respond to data and complex problems since it contains many processing units [43]. In other machine learning methods, attribute information should be given to the system beforehand, but the attributes are came out by the method's skills in deep learning.

Ren et al. in 2015 [44], presented an object detection architecture called Faster R-CNN. The architecture uses convolutional neural networks such as YOLO (You Look Only Once). Faster R-CNN consists of 3 neural network layers. These layers are the feature network, region proposal network, and detection network (Figure 2). The function of this featured network is to generate the essential features from images. The shape and structure of the original image are not changed in the output of the feature network [45].

2.3. Proposed model with the approach of partial correlation-based channel selection

The diagram of applied models' working principles is shown in Figure 3 in three phases. In the first step, 5-fold cross-validation is used to prepare training and validation sets after the preprocessing, and data augmentation method is applied to the dataset. In the second phase, the method is applied to the problem, and the initial values of the learning parameters are assigned. Finally, the applied model's training process is completed. As a result of this process, optimum weights and parameters are determined.

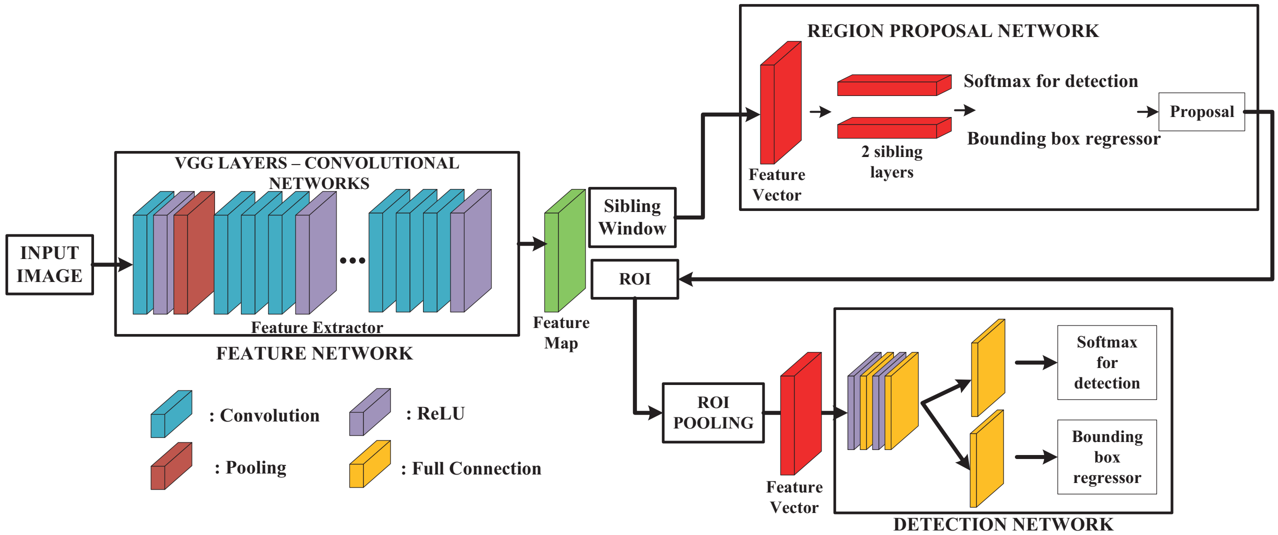

Figure 2. The architecture of Faster R-CNN.

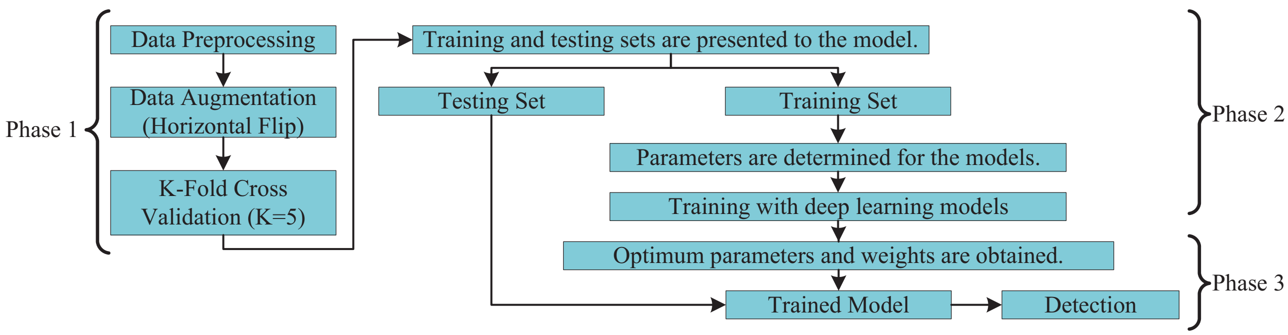

Figure 3. Working principles of the applied models.

Selective search is applied for the region proposal found in R-CNN and Fast R-CNN methods. Nevertheless, selective search is not fast enough for the processing time. Therefore, Ren et al. [44] proposed using a separate network to predict the region proposals in Faster R-CNN. Faster R-CNN consists of three layers. The first layer is the feature network layer, a separate network to find the essential features. In this study, the proposed 5-channel architecture is used as the feature network layer. It aims to obtain the most effective and essential features among the 5-channel convolutional neural networks and transmit them to the region proposal network (RPN), the second layer in Faster R-CNN using the proposed partial correlation-based channel selection formula. The primary aim in considering the multi-channel architecture in the feature selection layer is to reach the most effective and prominent feature of different feature extractions. Therefore, the multi-channel structure was used in the feature selection layer to guarantee the optimum generalizability and better detect complex patterns in MRI. The reason for choosing the number of channels as 5 is that it has the most appropriate process time and accuracy rates in the experimental studies. The proposed 5-channels Faster R-CNN model is shown in Figure 4. The proposed model aims to reach the best among the feature vectors obtained by using the multi-channel convolution structure in the feature network unit. The most effective feature map selected is transmitted to the region proposal network and detection network in the architecture to obtain a more accurate and efficient classification.

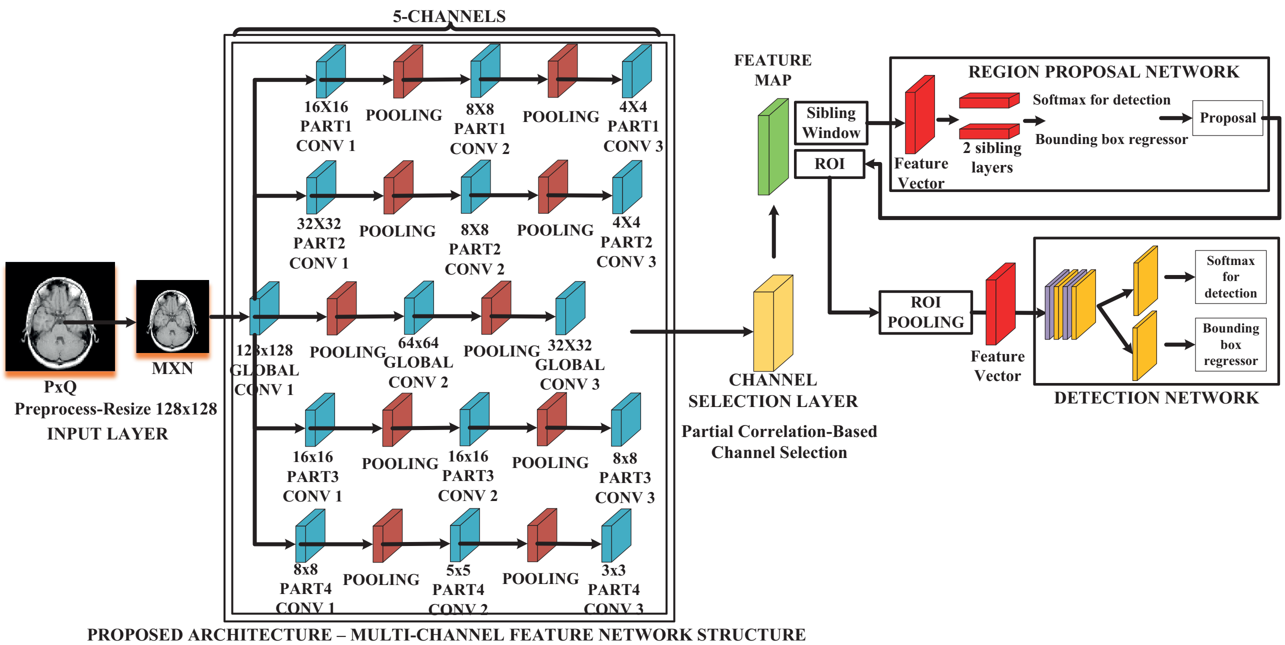

Figure 4. Proposed Faster R-CNN model's architecture.

In this section, a novel channel selection formula that is partial correlation-based is presented for selecting the most prominent features. The partial correlation coefficient is applied by controlling one or more variables to find the relation between variables. In the presented architecture, a convolution operator gives the possibility of all classes for each pixel. In Equation 1, all channels' feature extractors are multiplied to achieve the possibility score(ps). In Equation 1, x is the property of the map's output, w is the convolution core, and P is the set of pixel positions.

$$ps_k = \sum_{i=1,j=1}^{P} x_{i,j} * w_{i,j} \tag{1}$$

Partial correlation calculation was used in the channel selection formula to extract the most prominent features. A partial correlation was calculated of each pixel concerning other pixels in the kernel during the image filtering in the convolutional layer. The formula, which is used to find prominent features in the feature map is shown in equation 2. In the equation, $ps_{1,2,3}$ gives the probability of prediction with the partial correlation result of the pixel. $ps_{1,2}$ represents the correlation between 1 and 2, $ps_{1,3}$ represents the correlation between 1 and 2, $ps_{2,3}$ represents the correlation between 2 and 3.

$$ps_{1,2,3} = \frac{ps_{1,2} - ps_{1,3} * ps_{2,3}}{\sqrt{(1 - ps_{1,3}^2) * (1 - ps_{2,3}^2)}} \tag{2}$$

The notation that expresses feature selection by channel selection formula is given in Equation 3. As shown in Equation 3, a parameter was added to change the accurate label information's highest probability value.

$$Feature_{Score} = \begin{bmatrix} \max(ps) * hyperbolic - tangent(x_1, w_1) * w_1 \\ \max(ps) * hyperbolic - tangent(x_2, w_2) * w_2 \\ .... \\ .... \\ \max(ps) * hyperbolic - tangent(x_N, w_N) * w_N \end{bmatrix} * \begin{bmatrix} x_1 \\ x_2 \\ .... \\ .... \\ x_N \end{bmatrix} \quad (3)$$

In statistics, partial correlation is the measure of the relationship between an independent variable and a dependent variable when the other independent variables remain constant. The reason why a partial correlation-based formula is proposed for the channel selection formula in the study is to reveal which of the channels in the multi-channel structure in the feature network layer has the strongest correlation. The channel with the most important feature is selected by ordering the degrees of the relationship with the proposed formulas. In the channel selection formula, the hyperbolic tangent activation function is used due to its derivative being steeper than the Sigmoid activation function. It increases the performance of the model because it provides faster learning and classification with a wider range. The selective part (the channel selection layer) automatically provides the most considerable feature selection to the RPN among the five channels in the feature network layer using a partial correlation-based channel selection formula through the defined function (Figure 4). Figure 5 shows a sample of use of the proposed partial correlation-based channel selection formula.

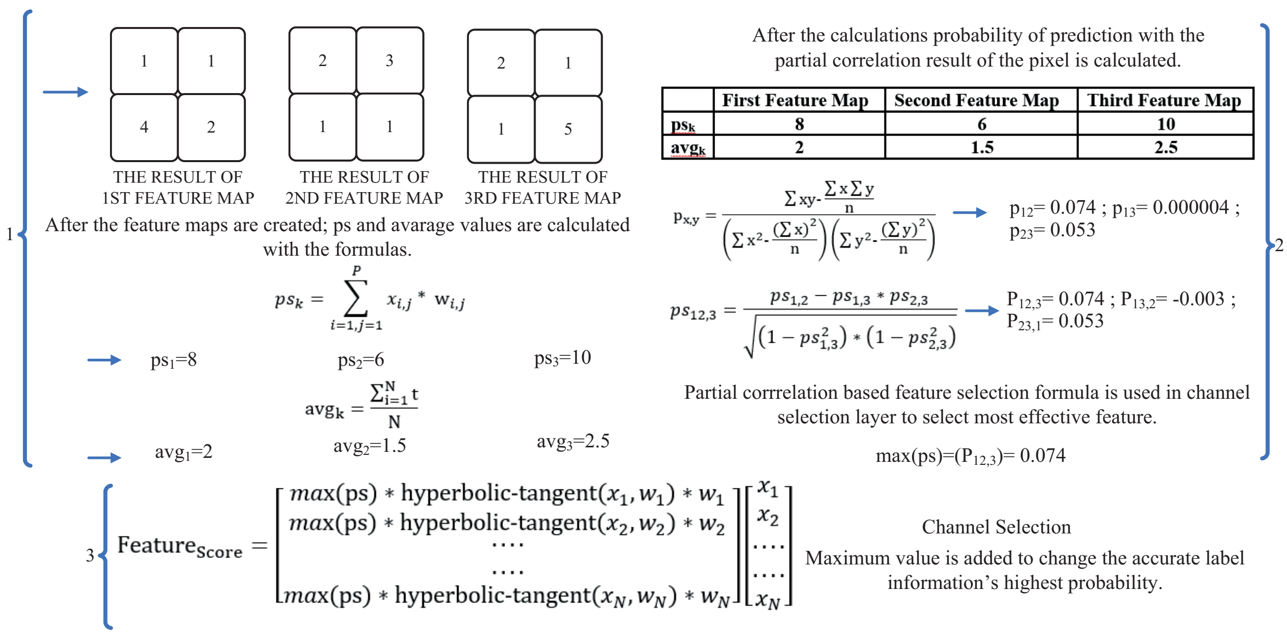

Figure 5. Specific sample calculation with the proposed formula.

2.4. Experimental studies – application

In the proposed model, multi-channel Faster R-CNN based deep learning architecture was used for classification. Also, VGG-16, DenseNet-201, ResNet-50, Standart Faster R-CNN, and SRN architectures were implemented to the same problem for comparison with the proposed model. Initial parameters were taken as the standard for all applied methods. All the models were applied in the 'Jupyter Notebook' platform using the Python programming language. Also, Keras, Tensorflow, OpenCV, and matplotlib libraries were used for modeling. The applied methods were carried out on a computer with a 3.50GHz processor, 16 GB Ram, NVIDIA GeForce 8GB graphics card.

Choosing the most suitable hyper-parameter group for modeling is one of the critical situations. The dataset is divided into small groups called mini-batches, and the learning process is carried out on these groups in deep learning applications. In the study, the mini-batch size was selected to be 16. The learning rate has a critical role in the training process. In the study, the learning rate value was obtained with the Adagrad optimization method that makes further updates for each parameter by using different learning coefficients at each step for each parameter. Thus, the learning rate was not adjusted manually. Weights were selected randomly in the first step, and they were calculated analytically using the least square method. The training process was completed at the 500th epoch for all the applied models since the error rate decreased substantially after the 500th epoch. The size of the convolution layers was tried as two, three, and four layers. In the study, the optimal hyper-parameters were obtained with three convolution layers. Increasing the number of convolutional layers does not affect a point because the effect of the back-propagation reaches the first layers to a lesser extent [46].

Data augmentation was implemented to the MRI before the training set was served up to the model. In the study, all of the datasets' size was enhanced by double with flipping the MRI images 180°. Afterwards, the images were brought to same size (128x128) by preprocessing.

In this work, K-folds cross validation method was utilized to identify the training and test set. In K-folds cross-validation, a dataset is splitted into K dissimilar subsets. For each unique group, K-1 subsets are used as the training set, and the rest of the group is used as the test set. Evaluation scores are obtained and retained during the training and testing processes. Finally, these evaluation scores are used to summarize the model's skill. The performance of a K-fold cross-validation can be assessed to include a measure of the variance with the standard deviation of evaluation scores. The selection of the low variance model skill was obtained through experimentation. Firstly, the K value was experimented as 10 and 15. When the cross-validation value was selected as 10 and 15, the training time increased considerably [47]. Besides, the accuracy rate did not increase significantly. The best result and performance were obtained with 5-fold cross-validation. The proposed model's cross-validation average accuracy results were given in Table 1 for K = 5, 10, and 15. Therefore, the K value was determined as 5 in the study to evaluate the performances of the models. After the learning processes of the models finished, the models' accuracies were verified with the test set. The detection of the tumor from a sample image by a trained proposed model is shown in Figure 6.

Table 1. Cross-validation average accuracy results.

K-Fold Value	1st Dataset Avg. Accuracy(%)	2nd Dataset Avg. Accuracy(%)	3rd Dataset Avg. Accuracy(%)
5	0.98211	0.99289	0.99298
10	0.98226	0.99308	0.99386
15	0.98225	0.99302	0.99391

The proposed multi-channel Faster R-CNN model has a 5-channel selection layer for the feature network phase on Faster R-CNN architecture (Figure 4). Convolution filter size, the convolution filter number and pooling size were determined based on extensive experiments. All input images were resized to 128x128 before feeding into the model. After preprocessing, the proposed multi-channel model starts with the global convolution

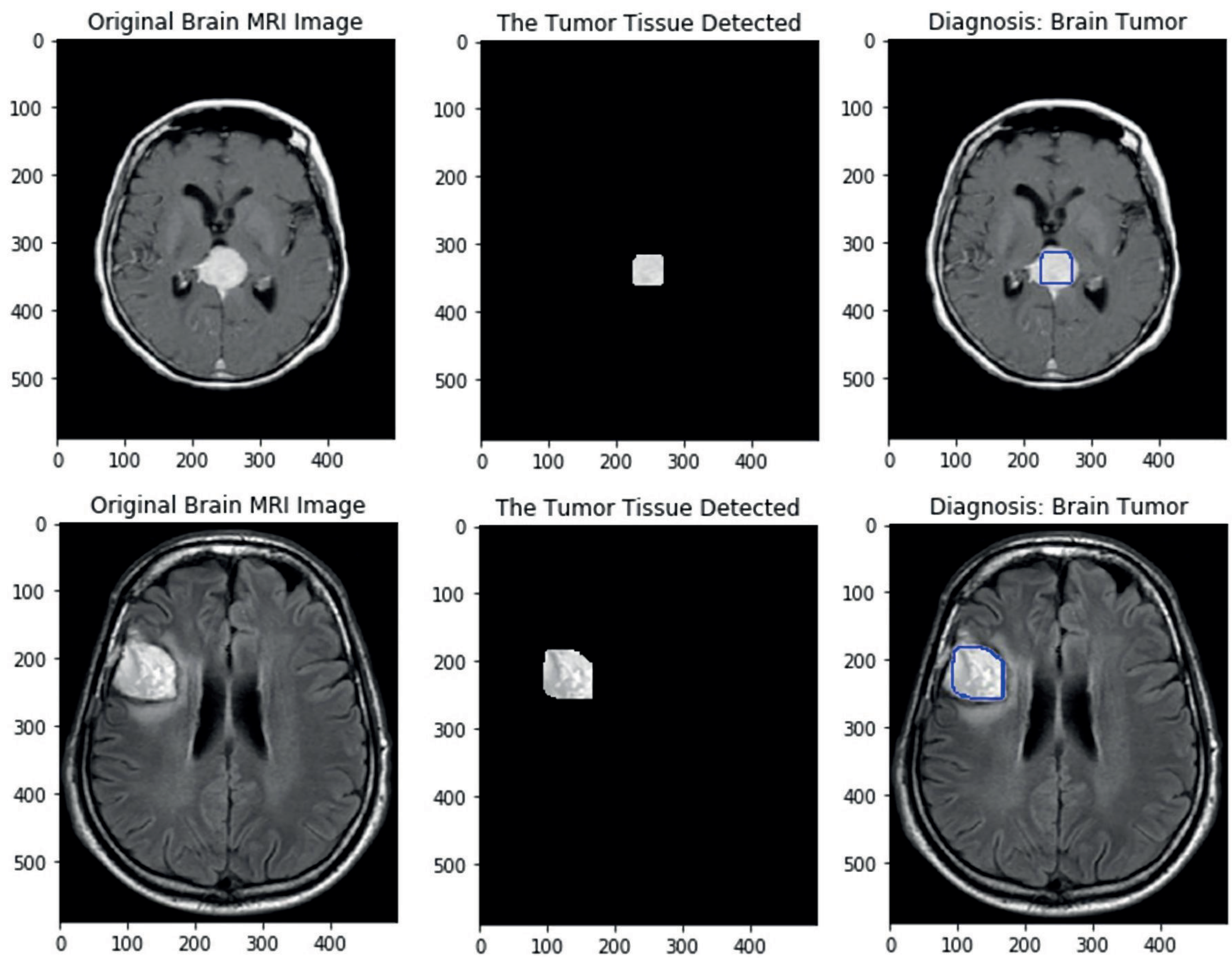

Figure 6. Detection of the 'Tumor' by the model.

layer feeding four different convolution layers. It is contrived as five channels in total in the feature network phase. Each channel has three convolution layers, two pooling layers and a ReLU unit. The global channel has a 128x128x1 convolution kernel in the first convolution layer, 64x64 convolution kernel in the second, and 32x32 convolution kernel in the last convolution layer. The second channel, fed from the global channel, has 16x16 convolution kernel in the first convolution layer, 8x8 in the second, and 4x4 in the third convolution layer. There are 32x32 convolution kernel in the first convolution layer in the third channel, 8x8 in the second convolution layer, and 4x4 in the third convolution layer. There are 16x16 convolution kernel in the first convolution layer in the fourth channel, 16x16 in the second convolution layer, and 8x8 in the third convolution layer. There are 8x8 convolution kernel in the first convolution layer in the fifth channel, 5x5 in the second layer, and 3x3 in the last convolution layer. Outputs from all channels are computed over the channel selection layer to obtain the best feature map of the proposed multi-channel Faster R-CNN architecture with the formulas given in Section 2.3. After the channel-selection layer is linked to the feature map, Softmax activation and Bounding box regression are performed to determine the classification possibilities. The model has performed with a total of 323388 parameters. The training process of the models was completed in approximately 40000 s and 500 iterations.

Performance metrics such as accuracy, sensitivity, precision, specificity, F_1 score, AUC, MAE, MSE and RMSE have been calculated for all applied methods. The F_1 score is the harmonic mean of precision and sensitivity. It can take values between a maximum of 1 (excellent precision and sensitivity) and a minimum of 0. The mean absolute error (MAE) is the difference between the predicted values and the target values. Mean squared error (MSE) represents the mean square loss per sample in the entire dataset. Root mean square error (RMSE) is the standard deviation of the estimation errors. MAE is not as sensitive to outliers as MSE. Generally, it provides more effective observation with continuous variable data. MSE is a more useful metric when it contains outliers or unexpected values. But, when the dataset contains a lot of noise, it might not be so useful. RMSE is a performance metric that succeeds when large errors are present due to the mean calculation done after the errors are squared. The statistical indices have been applied from the confusion matrix to evaluate the proposed classification system's performance [48].

3. Results

In this study, the multi-channel Faster R-CNN-based model with a novel channel selection formula was proposed to detect brain tumors that constitute a significant risk for human life. Three different datasets were used in the study. First, the dataset including MRI images was obtained via the internet, which was studied before in the literature. The other dataset was taken from the Kaggle repository, and the third dataset was selected as BRATS 2018. The classification performances of different classifiers and feature groups for brain tumor images were compared and applied to three different datasets. In the study, 3064 images from the first dataset, 253 images from the second dataset, and 285 images from the third dataset were used with six different classifier and data augmentation approaches. By applying data augmentation with the horizontal flip method, all datasets' size was increased twice. Also, in this way, the reactions of the classifiers were seen for different MRI images. The K-fold cross-validation method was applied to ensure that the most accurate performance results were received. The most optimum result was obtained with the K value 5. The most widely used deep learning architectures were performed to solve the same problem and the proposed model was used to compare their performances. Brain tumor detection statistics for the applied models to the first, second, and third datasets are presented in Table 2, Table 3 and Table 4.

Table 2. Comparison of applied models' performances for the 1st dataset.

1st Dataset	Proposed Model	Faster R-CNN	VGG-16	DenseNet-201	ResNet-50	SRN
Best Accuracy	0.9831	0.9750	0.9693	0.9577	0.9647	0.9489
Average Accuracy (k=5)	0.9821	0.9692	0.9611	0.9462	0.9488	0.9329
Sensitivity	0.9938	0.9853	0.9872	0.9814	0.9869	0.9773
Specificity	0.006	0.014	0.012	0.018	0.012	0.022
Precision	0.9851	0.9840	0.9743	0.9657	0.9707	0.9605
F_1	0.9894	09847	0.9807	0.9735	0.9787	0.9688
MSE	0.36	1.59	3.06	6.12	4.59	12.25
RMSE	0.60	1.26	1.75	2.47	2.14	3.50
MAE	0.82	1.82	3.64	6.82	5.03	13.24
R^2	0.9819	09706	0.9642	0.9504	0.9594	0.9392
AUC	0.983	0.961	0.954	0.927	0.947	0.905
Training Time (s)	45243	39521	40183	41632	40642	42537

Table 3. Comparison of applied models' performances for the 2nd dataset.

2nd Dataset	Proposed Model	Faster R-CNN	VGG-16	DenseNet-201	ResNet-50	SRN
Best Accuracy	0.996	0.9822	0.9683	0.9762	0.9486	0.9288
Average Accuracy (k=5)	0.9928	0.9782	0.9652	0.9739	0.9462	0.9256
Sensitivity	0.9975	0.9902	0.9828	0.9876	0.9729	0.9605
Specificity	0.002	0.009	0.017	0.012	0.026	0.039
Precision	0.9975	0.9878	0.9779	0.9851	0.9634	0.9512
F_1	0.9975	0.9890	0.9803	0.9864	0.9681	0.9558
MSE	0.12	0.75	1.77	1.26	2.40	5.31
RMSE	0.35	0.87	1.33	1.12	1.55	2.30
MAE	0.18	0.92	1.98	1.52	2.84	6.12
R^2	0.9954	0.9785	0.9624	0.9688	0.9412	0.9208
AUC	0.988	0.962	0.931	0.945	0.903	0.86
Training Time (s)	4592	4192	4344	4473	4310	4524

Table 4. Comparison of applied models' performances for the 3rd dataset.

3rd Dataset	Proposed Model	Faster R-CNN	VGG-16	DenseNet-201	ResNet-50	SRN
Best Accuracy	0.9982	0.9859	0.9771	0.9614	0.9561	0.9438
Average Accuracy (k=5)	0.9936	0.9785	0.9712	0.9561	0.9442	0.9291
Sensitivity	0.998	0.9919	0.9898	0.9795	0.9775	0.9732
Specificity	0.002	0.008	0.010	0.020	0.022	0.026
Precision	1	0.991	0.9839	0.9756	0.9715	0.9613
F_1	0.999	0.991	0.9869	0.9775	0.9745	0.9672
MSE	0.08	0.31	0.91	1.19	1.71	2.56
RMSE	0.29	0.55	0.95	1.09	1.30	1.60
MAE	0.21	0.39	1.27	1.42	2.04	3.06
R^2	0.9966	09802	0.9694	0.9564	0.9428	0.9311
AUC	0.996	0.98	0.965	0.957	0.936	0.92
Training Time (s)	4752	4352	4602	4692	4574	4718

According to these results, the proposed model was applied more successfully than other applied methods. The proposed model is more successful because the work presents a structure that makes feature network formation better. Each of the 5-channel convolutional feature network units used in the study creates a feature map. The best feature map was selected through the channel selection layer using the proposed partial correlation-based channel selection formula. The channel selection layer chooses the most effective and important feature map. This selected best feature map was transmitted to the region proposal network and detection network in the last step. The proposed method also was compared with the applied studies devoted the same problem in the literature. As a result of this comparison, the proposed method's performance was observed to be higher (Table 5).

The accuracy rates for the applied three datasets achieved 98.31%-99.6%-99.82% with the proposed model, 96.93%-96.83%-97.71% with VGG-16, 97.50%-98.22%-98.59% with Faster R-CNN, 95.77%-97.62%-96.14% with DenseNet201, 96.47%-94.86%-95.61% with ResNet, and 94.89%-92.82%-94.38% with SRN (Figure 7). In Figure

Table 5. Comparison of applied models' performances in literature.

Reference Study	Classifier	Dataset	Accuracy (Best %)
Proposed Model (3rd dataset)	Faster R-CNN	BRATS	99.8
Nazir et al. [39]	Multilevel Wavelet	Harvard	99.7
Proposed Model (2nd dataset)	Faster R-CNN	Kaggle	99.6
Chinmayi et al. [32]	CNN	TIMIT	99.1
Mehrotra et al. [19]	CNN	TCIA	99.04
Ismael et al. [38]	ResNet	Figshare	99
Rehman et al. [17]	VGG-16	Figshare	98.69
Proposed Model (1st dataset)	Faster R-CNN	Figshare	98.31
Grovik et al. [14]	CNN	156 patient MRI	98
Kakarla et al. [11]	CNN	Figshare	97.42
Mohsen et al. [40]	DNN	66 patient MRI	96.97
Khan et al [18].	VGG-16	Kaggle	96
Hollon et al. [16]	CNN	SRH images	94.6
Xue et al. [36]	DensetNet	TCIA	94
Deepak et al. [37]	SNN	Figshare	92.6
Sharif et al. [15]	CNN	BRATS	92
Karayegen et al. [13]	CNN	BRATS	91.72
Cheng et al. [6]	CNN	Figshare	91.28
Khawaldeh et al. [28]	CNN	TCIA	91.16
Widhiarso et al. [24]	CNN	Figshare	82.27

7, as the number of iterations increases, accuracy increases linearly. When the curve reaches a certain saturation, the accuracy increase is greatly reduced. This situation is monitored from the graph, and it is understood that the accuracy rate will not increase. From the graphs in Figure 7, it has been observed that the accuracy rates would not increase after 500 iterations. Moreover, the excessive number of iterations prolongs the training process and may lead to overfitting. ROC (receiver operating characteristic) curve has the false-positive ratio in the X-axis and the true positive ratio in the Y-axis. In order to determine the best cutoff point with the ROC curve, the point where the curve is closest to the upper left corner of the graph is taken as the cutoff point to the coordinate (0,1). The area under the curve (AUC) affects classification performance with the correct diagnosis. The AUC value and ROC Curve show the success of the model. ROC analysis of all applied models was evaluated to illustrate models' diagnostic ability (Figure 8). The ROC curves and AUC values of all applied models shown in Figure 8 revealed that the proposed model is the most successful. All applied models' AUC values were obtained as 0.9827-0.9876-0.9959 for the proposed model, 0.9605-0.9619-0.9805 for Faster R-CNN, 0.9543-0.9310-0.9648 for VGG-16, 0.9271-0.9454-0.957 for DenseNet-201, 0.9465-0.9028-9363 for ResNet-50 and 0.9049-0.8596-0.9196 for SRN.

4. Discussion

In this study, segmentation was applied to MRI images to determine tumor prediction using Faster R-CNN-based multi-channel architecture. Therefore, three different open-access MRI datasets were applied to six different

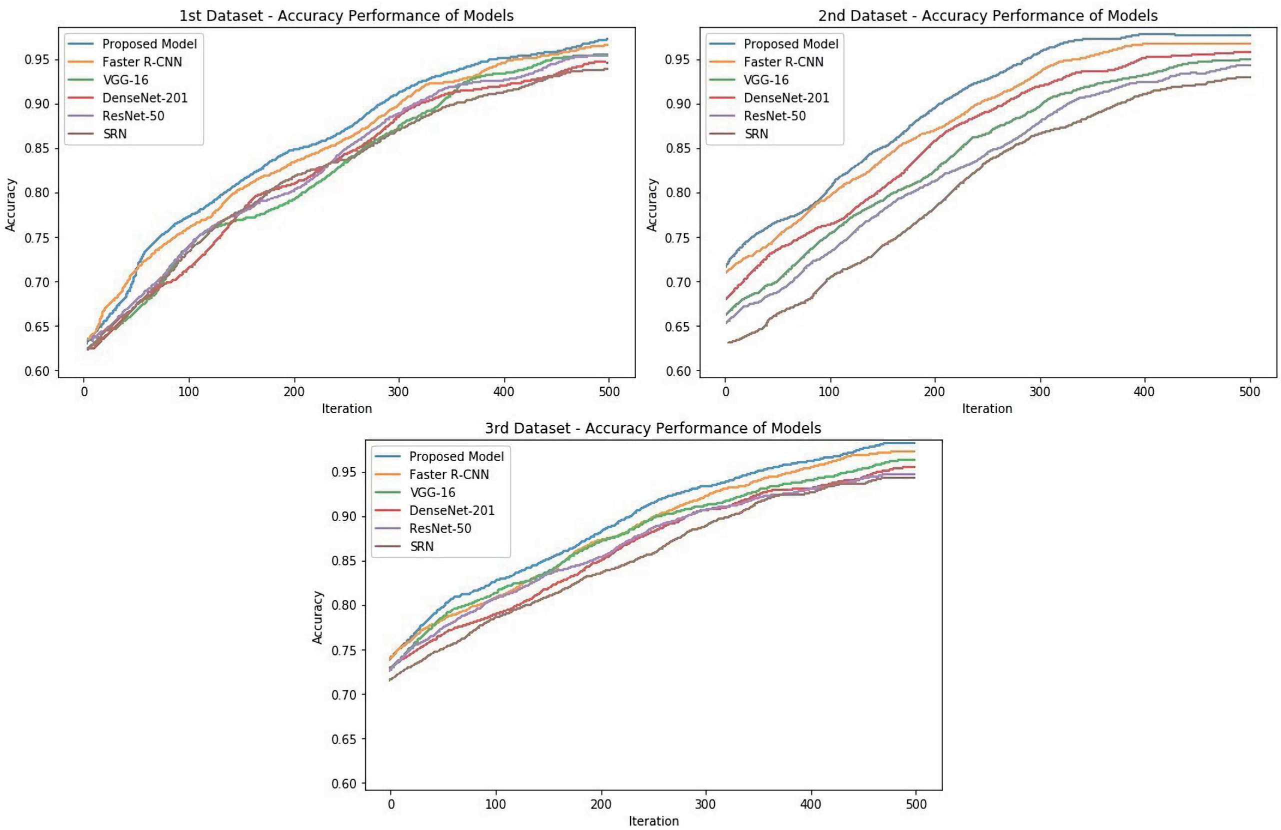

Figure 7. Accuracies of applied models.

deep learning network models and were trained for each dataset. Compared to other related studies, more reliable and successful results were obtained for performance criteria such as accuracy rate, F_1 score and ROC analysis. More effective and successful results were obtained in the study with the proposed model in terms of all performance assessment metrics compared to Faster R-CNN, VGG-16, DenseNet-201, ResNet-50, and SRN architectures. The outcomes of the performance metrics and processing times are presented in Table 2, Table 3 and Table 4.

However, more effective results can be obtained with the use of external GPU devices in future studies. Also, it may be necessary to increase the number of samples and classes to increase classification success. In the study, the accuracy rate of the model can be increased with the success of the training by obtaining different types of brain tumors MRI.

The proposed method stands out with a custom architecture instead of the classical model. A custom architecture has a channel selection layer to select the prominent and essential features in multi-channels. It is aimed to predict the presence of brain tumors from MRI using the proposed model. Evaluation criterias clearly show that the model can detect brain tumors with high sensitivity and accuracy.

5. Conclusion

In this work, Faster R-CNN-based multi-channel architecture was proposed to detect brain tumors from MRI. Early diagnosis of brain tumors is critical as it will reduce the risk of death. Robust feature selection method and

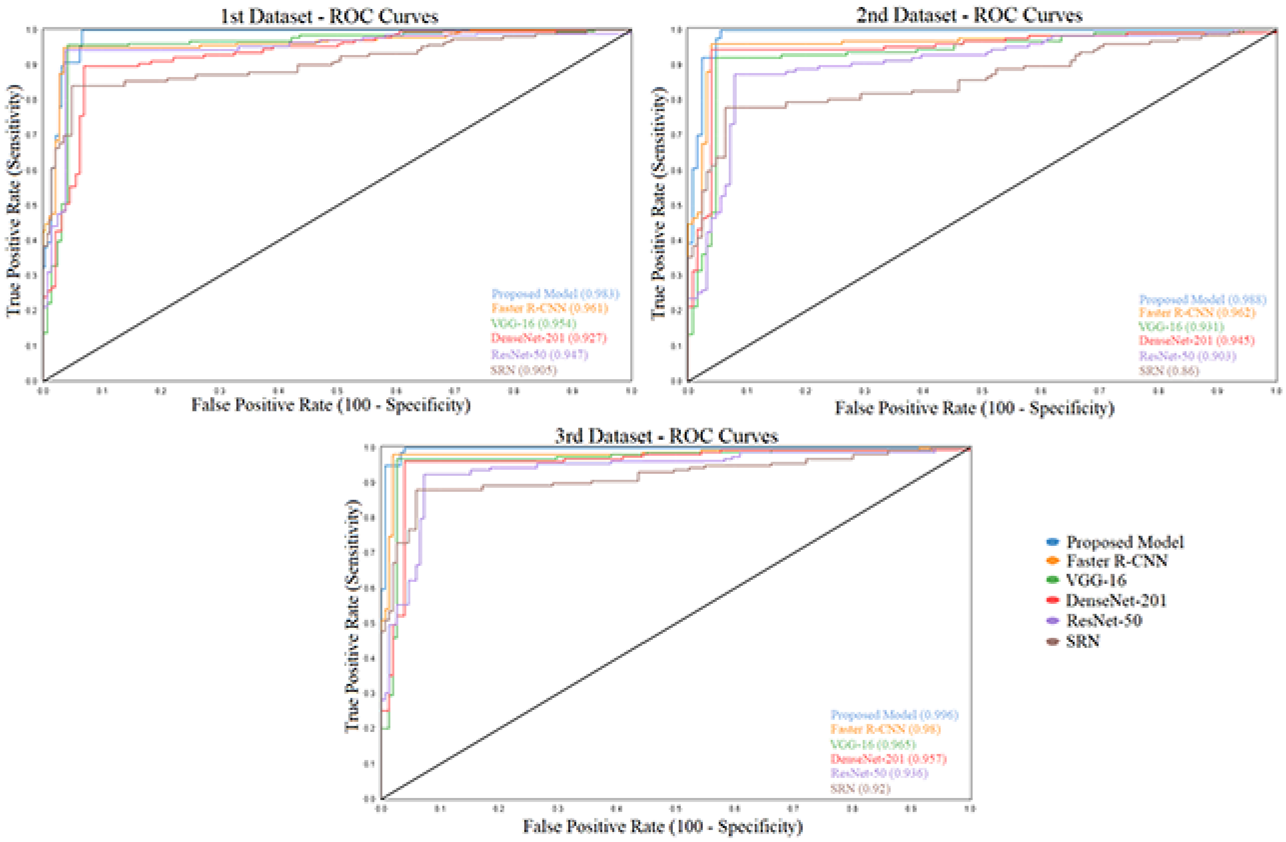

Figure 8. ROC curves for all applied models.

deep learning architecture could help detect the tumor image more accurately for early diagnosis. Therefore, a partial correlation-based channel selection formula was used to extract functional features and the multi-channel Faster R-CNN-based deep learning model to learn the features and do the classification. In the study, different from studies in literature, the channel selection formula was presented to select the most prominent feature filters with the Faster R-CNN based model. The novel formula obtains the determination of the most prominent among each features extractions in feature network phase.

Three different datasets, which include brain MRI images were applied in the study. The statistical results of all applied models were compared to show that the proposed method was applicable. When the results were analyzed, it was presented that the proposed model is applicable with regard to both performance metrics and computational time. In addition, the accuracy rate decreased for all applied models as the number of samples increased in the dataset.

The success of the proposed model is achieved thanks to the partial correlation-based channel selection layer used in the feature network phase. The channel selection layer achieves the most effective and important features using the proposed selection formula from the multi-channel convolutional layers. The standard Faster R-CNN architecture was also applicable and modeled to verify this success.

Besides, in this study, it has been shown that, with using deep learning methods, brain tumor cases, which are one of the leading causes of death in the world, can be detected before the tumor grows. Thus, the risk of death for patients could be reduced with early diagnosis.

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