Improving Multi-class Brain Tumor Detection Using Vision Transformer as Feature Extractor

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Abstract. Accurate brain tumor subtypes classification is significant for prognosis and treatment. The aim of this research is to improve the multiclass brain tumor classification using vision transformer as feature extractor. In this study, we first optimized and employed deep learning ResNet101 for feature extraction and fed to machine learning classifiers for multi-class classification. We then optimized and employed vision transformer and fed these features to machine learning decision classifier. We measured the performance with standard performance metrics. The Artificial Intelligence vision transformer with decision tree classifier yielded highest multi-class classification performance with 99.89% accuracy and 1.00 AUC to detect pituitary followed by 97.69% accuracy and AUC of 0.96 to detect meningioma. The results are compared with ResNet101 with transfer learning. ResNet101 deep features by utilizing KNN yielded detection of pituitary tumor (98.80% accuracy, 0.99 AUC), glioma (93.47% accuracy, 0.93 AUC). The results revealed that proposed approach with vision transformer and decision tree features extractor are more robust in detecting multiclass brain tumor prediction. The proposed approach can be better utilized for betterment of treatment and prognosis to obtain improved clinical outcomes.

Keywords: deep learning Brain tumor · types · convolution neural network · vision transformer

1 Introduction

The brain tumor is one of the most commonly diagnosed diseases in humans without discrimination of any age group and sex. Generally, a brain tumor is separated into various stages (1, 2, 3.. etc.), a higher stage means higher severeness of the tumor, and earlier stage tumors have more probability of recovery. So, diagnosing the tumor initially is very important in order to initiate a fruitful treatment [1]. However, at earlier stages tumors are so small to detect for radiologists even from the quality magnetic resonance imaging (MRI). MRI technology gives more in-depth information about the tumor and is more efficient compared to old techniques. Thus, the chance of human error and competence

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(knowledge and health issues, etc.) compels researchers to take advantage of computers. Various computer-aided studies are suggested in the past to assist radiologists to detect brain tumors from MRI images [2–6]. Few researchers used Machine learning-based methods for classification purposes. Most of the machine learning-based methods are based on handcrafted features [7–12]. The key part of Machine Learning based classification tasks is features extraction which produces discriminant information of an image. Feature extraction techniques such as Scale-invariant Fourier transform (SIFT), Morphology, Texture, entropy and elliptic Fourier descriptors (EFDs) can be employed to extract features from medical raw images [12]. In the past, these methods were used separately and in a hybrid way along with various Machine Learning (ML) classification algorithms. For brain tumor classification there are a variety of Machine learning classification algorithms were reported [13–27]. Other studies such as [28] performed some morphological operations on the segmented part of an image and employed features extraction technique Space Pyramid Matching (SPM). Then, for the classification task, features were passed to ML classifiers such as Support vector Machine, (SVM), K-nearest neighbor (KNN), and Sparse Representation Classification (SRC). The researchers [3] purposed shape-based features extraction approach and for the classification task, random forest, and Support Vector Machine are used. In the literature, it was observed the performance of the ML classification methods heavily depends on the features extraction methods. Making the choice of appropriate features for supervised Learning tasks is a fatiguing and time-consuming process.

Among many of the mentioned above, hand-crafted features are not robust. It can be observed that lots of hand-crafted features are not robust and usually their discriminative power is low [29–31]. Unlike these proposed methods our goal is to build a model based on Vision Transformer (ViT) [32] which is a very popular method in various areas of computer vision in recent times. The success of the Transformers [33] in Machine translation gives an idea of convolution-free models that basically depend on transformer layers, which makes this method interesting in the computer vision area. Moreover, Vision Transformer [32] models show potential to achieve higher accuracy equal to or even higher than convolutional neural networks-based models. Recently, there are various types of vision transformers-based methods are proposed such as pyramid structures like convolutional neural networks (CNNs) [34], data-efficient vision Transformer [35], and all-to-all self-attention [36]. In our proposed method, we used the vision transformer model as a feature extractor in order to take leverage of powerful machine learning classifiers. In the first step, Otsu's Thresholding technique was utilized to remove noisy part of image. Then denoised training images are passed to the vision transformer for training and testing images features are extracted from this model. Where training of the machine learning classifier (decision tree) is done using extracted features from ViT model.

The Fig. 1 indicates the flow of work to detect the multiclass classification. We input the multiclass (glioma, meningioma and pituitary) data, segmented the images partitioned the data with 70% for training and 30% for testing. The vision transformer is used for training and extracted features from vision transformer along with decision tree. The final model provides the multiclass classification results based on the vision transformer and vision transformer-decision tree (Fig. 2).

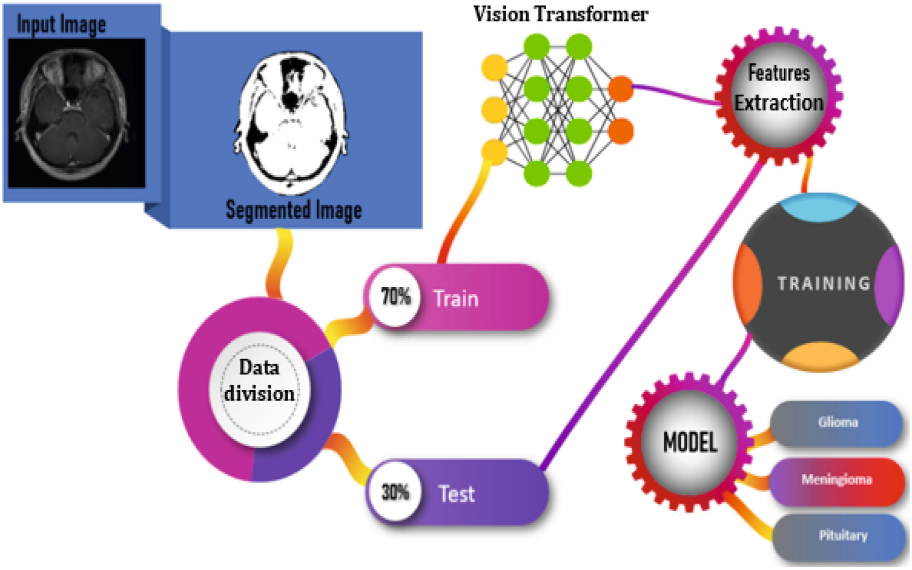

Fig. 1. Schematic diagram

2 Materials and Methods

2.1 Dataset

A publicly available dataset from (https://github.com/chengjun583/brainTumorRetrieval) was utilized in our study as described in [28, 37]. There were 233 patients from 3064 T1-weighted contrast enhanced images of three subtypes i.e. gliomas (1426 slices), pituitary tumor (930 slices) and meningiomas (708 slices).

2.2 Vision Transformer

Transformer were proposed originally in [38]. The main objective to design transformer is to allow the modeling of dependencies irrespective to their distance in input sequence. The transformers due to the parallel computing capability are also more robust than the recurrent neural networks (RNNs) by removing recurrent connection. There are several encoder and decoder layers of transformer. An input to the high-level encoding is transformed by encoder whereas the decoder transforms an embedding to output. An encoder contained several encoding layers. For all encoded layers, the input is denoted as a tensor x to the encoder layer with a shape of $T \times C$, here time steps are denoted by T and channels by C. Moreover, W^Q denote the query transform matrix, W^K represent the key transformed matrix and W^V denote the value transform matrix. Likewise, $C \times d_k$ shows the shape of W^Q and W^K and W^V shape is $C \times d_v$, here d_k and d_v denote the integers. The query (K), key (K) and value (V) are obtained using:

$$Q = xW^Q$$

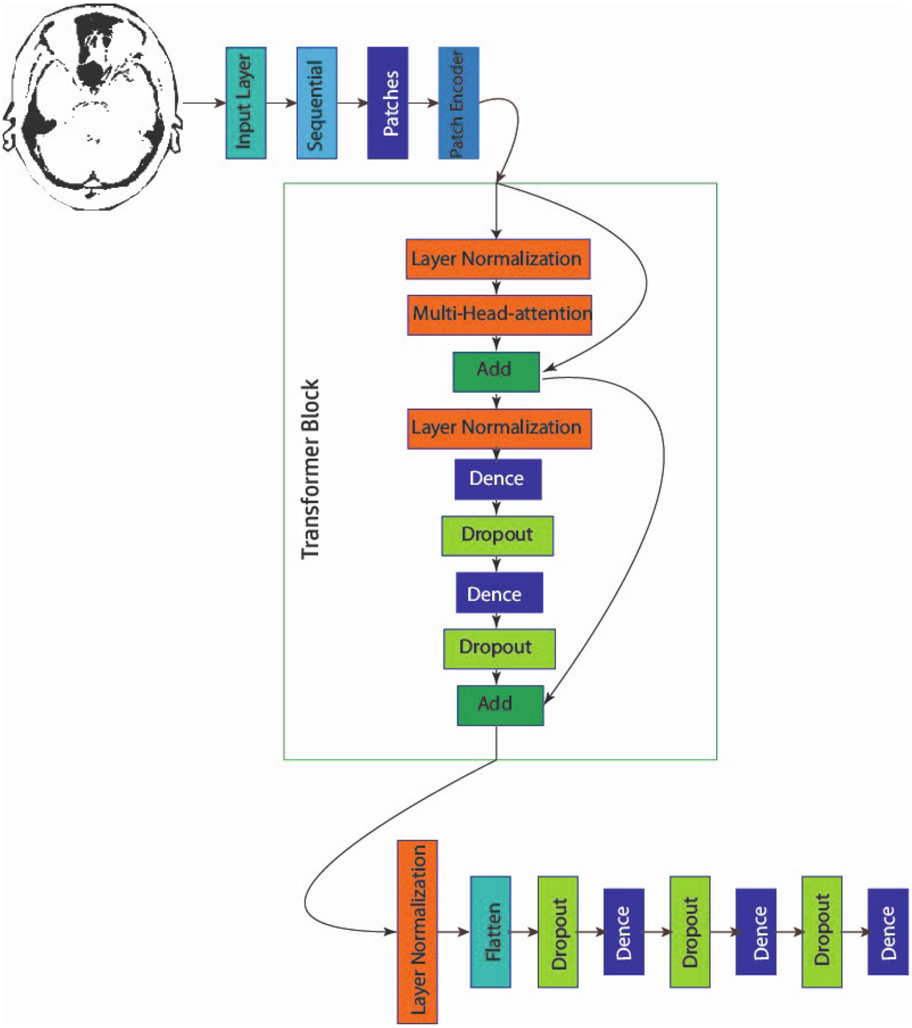

Fig. 2. General Architecture of Vision Transformer

$$K = xW^K$$

$$V = xW^V \tag{1}$$

Here $T \times d_k$ shows shape of query Q and key K and value V has a shape $T \times d_V$. Thus, output of an encoder layer rewritten as:

$$h = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

The output h has a shape of $T \times H$. The dot product of query with all keys is computed using this equation by dividing with $\sqrt{d_k}$. The softmax function is applied to obtained weights on value V. The d_k square root is normalized term. Moreover, $T \times T$ denote the inner product of Q and K^T represent feature correlation and different time steps. The correlation values are converted by SoftMax operation to probabilities along time steps indicating how much value V in a time step can be attended. The schematic diagram of the standard vision transformer is depicted in Fig. 1.

3 Results and Discussion

In our study, the results of the vision Transformer and features extracted from the vision transformer model are presented in the below table. The performance of these methods was measured using standard measures (Figs. 3 and 5).

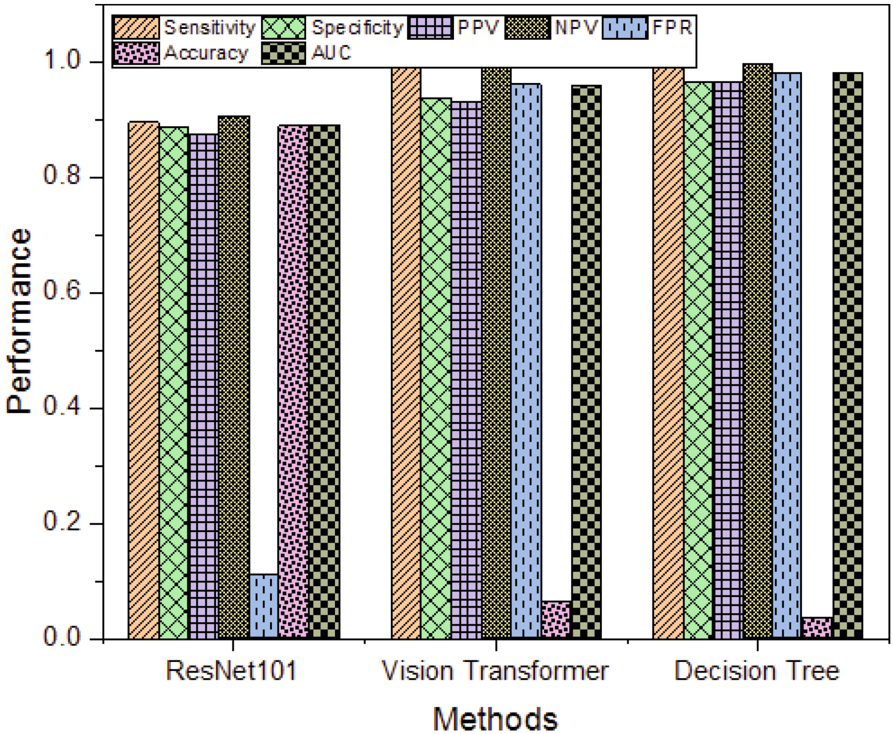

Fig. 3. Multi-class brain tumor type detection based on ResNet101-KNN

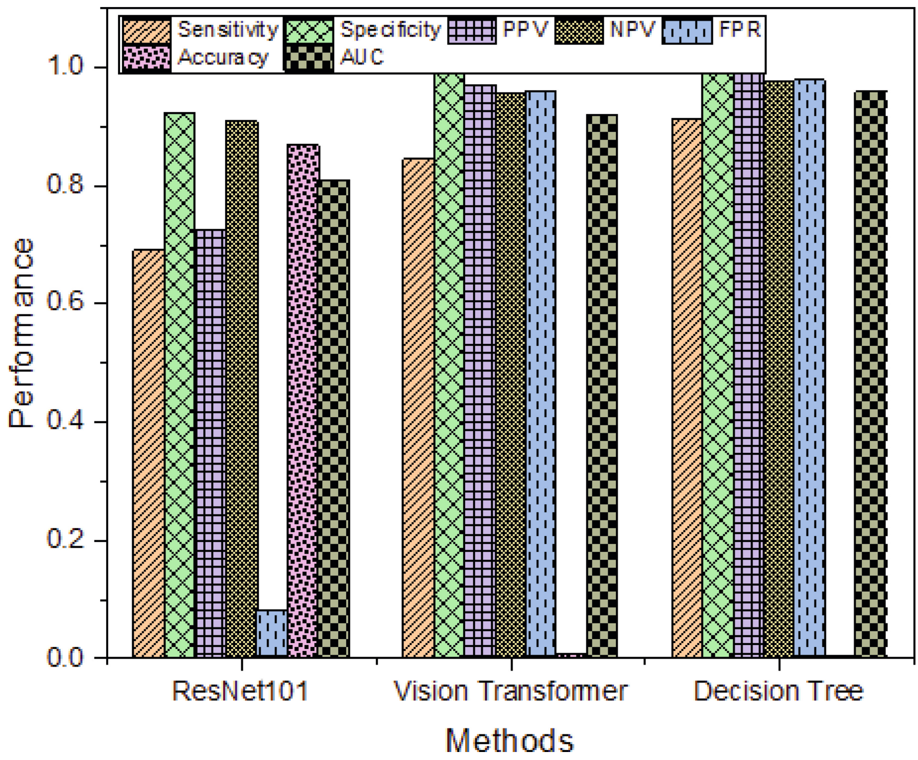

Fig. 4. Multi-class brain tumor type detection based on Vision transformer

Figures above reflects the multi-class brain tumour classification using Residual neural network 101 (ResNet101)-KNN, Vision transformer, Vision transformer-DT. The deep learning ResNet101-KNN yielded the multiclass detection performance with accuracy (98.80%), sensitivity (98.29%), specificity (99.04%), PPV (97.96%), NPV (99.20%) and FPR (0.0095). The vision transformer yielded multiclass classification with accuracy (99.89%), sensitivity (99.65%), specificity (100%), PPV (100%), NPV (99.84%) and FPR (0.0000) to predict pituitary followed by glioma with accuracy (96.19%), sensitivity (99.07%), specificity (93.66%) and meningioma with accuracy (96.08%), sensitivity (84.42%), specificity (99.30%). The vision transformer with decision tree for feature extraction yielded highest detection performance to detect pituitary with accuracy (99.89%), sensitivity (100%), specificity (99.84%), PPV (99.62%), NPV (100%), FPR (0.0015) followed by glioma with accuracy (98.04%), sensitivity (99.56%), specificity (93.66%) and meningioma with accuracy (96.08%), sensitivity (84.42%), specificity (99.30%) (Figs. 6 and 7).

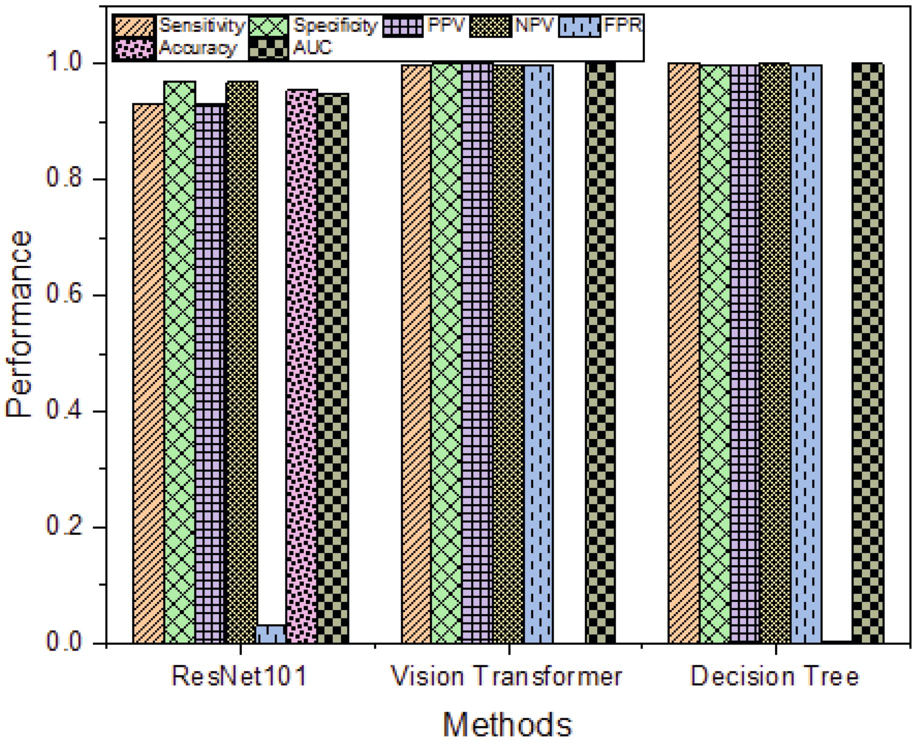

Fig. 5. Multi-class brain tumor type detection based on Vision transformer-Decision tree (DT)

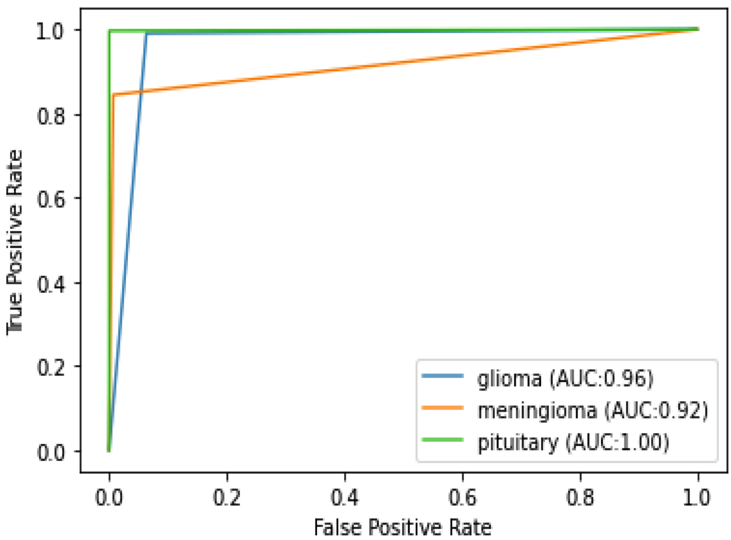

Fig. 6. Area under the receive operating curve (AUC) using Vision transformer

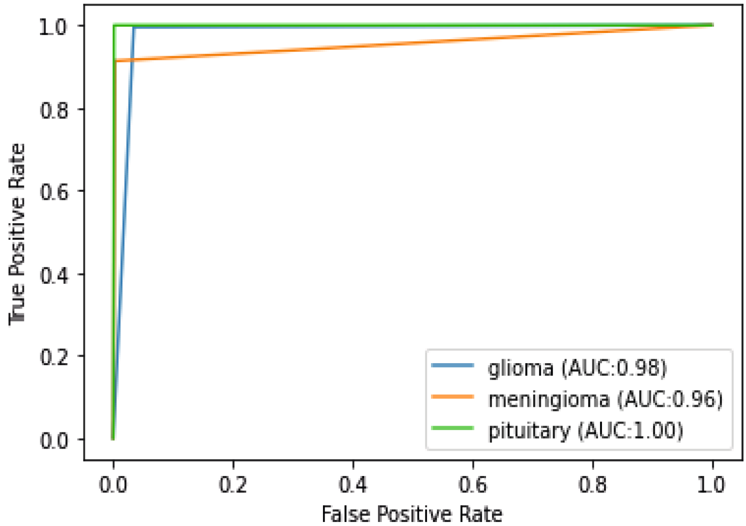

Fig. 7. Area under the receive operating curve (AUC) using Vision transformer Decision tree (DT)

The Fig. 4 reflect AUC to distinguish the multiclass classification using a) Vision transformer, b) Vision transformer-DT. Using the vision transformer the highest separation was obtained to detect pituitary with AUC of 1.00 followed by glioma with AUC of 0.96 and meningioma with AUC of 0.92. Using the vision transformer-decision tree as feature extractor, the highest AUC was yielded to detect pituitary with AUC of 1.00 followed by glioma with AUC of 0.98 and meningioma with AUC of 0.96.

Table 1. Results comparison utilizing different techniques on similar dataset

Author	Feature/Methods	Performance
Afshar et al. [39]	CapsNets	Accuracy: 90.89%
Deepak and Ameer [40]	Deep GoogleNet-SVM	Accuracy: 97.10%
Swati et al. [41]	VGG-19 - Softmax	Sensitivity:96.81% Accuracy: 94.82% Specificity:93.93%
Anjum et al. [42]	CNN ResNet101 ResNet101-KNN	Sensitivity: 98.29% Specificity: 99.04% Accuracy: 98.80% AUC: 0.99
This study	**Vision Transformer-Decision tree**	**Accuracy: 99.89% AUC: 1.00**

Multiclass brain tumor types of prediction is still a challenging task. Currently, researchers are developing different techniques to improve the multiclass classification. Table 1 summarizes the most recent methods developed to predict the multiclass brain tumor types using Fig share dataset. Recently Afser et al. [39] utilized CapsNet and obtained a highest accuracy of 90.89%. Swati et al. [41] utilized deep learning VGG-19 with accuracy of 94.82%. Deepak and Ameer [40] used deep learning GoogleNet-SVM and further improved accuracy of 97.10%. Anjum et al. [42] employed ResNet101-KNN and obtained an accuracy of 98.80% and AUC of 0.99. This study further improved the multi-class classification with accuracy of 99.89% and AUC of 1.00.

4 Conclusions

Recently the researchers utilized different deep learning convolutional neural network (CNN) algorithms with default SoftMax and replaced softmax with SVM and KNN to improve the brain tumor multiclass classification. However, the present study, utilized a vision transformer with default and Decision tree for feature extraction. The result revealed that proposed approached further improved the multiclass classification. Thus the proposed approach is more robust than the previous methods utilized for multiclass brain tumor type detection. The results reveal that proposed method can be better utilized for improved prognosis, diagnosis and treatment planning.

Abbreviations

Magnetic resonance imaging (MRI)
Scale-invariant Fourier transform (SIFT)
Elliptic Fourier descriptors (EFDs)
Machine Learning (ML)
Space Pyramid Matching (SPM)
K-nearest neighbor (KNN)
Sparse Representation Classification (SRC)
Vision Transformer (ViT)
Convolutional neural networks (CNNs)
Decision tree (DT)
Recurrent neural networks (RNNs)
Positive Predictive Value (PPV)
Negative Predictive Value (NPV)
Accuracy (ACC)
Area Under the receiver operating characteristic Curve (AUC)
Residual neural network 101 (ResNet101)
False positive rate (FPR)
Total accuracy (TA)

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