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Brain Tumor Detection Using Transfer Learning with Dimensionality Reduction Method

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Abstract: A tumor is a mass of abnormal cells that accumulate forming a tissue. These abnormal cells feed on the normal body cells and destroy them and keep growing bigger. One of these tumors is a brain tumor. A brain tumor is imaged with MRI (Magnetic Resonance Imaging), giving a cross-section image of the brain. In this paper, we have proposed a novel brain tumor detection method, which uses a convolutional neural network with a transfer learning approach along with the dimensionality reduction method. The comparative analysis of various transfer learning models with and without dimensionality reduction methods is included to present the effectiveness of the proposed model.

Keywords: *Brain Tumor Detection, Medical Imaging, MRI Images, Transfer Learning, Dimensionality Reduction, Deep Learning.*

1. Introduction

In medical research, a brain tumor is one of the most critical diseases that can result in death. According to the American Cancer Society's brain tumor prediction to be diagnosed in the United States in 2019, there are 23820 brain or spinal cord malignant tumors (13,410 in males and 10410 in females) [1]. Benign (non-cancer) tumors are not included in this calculation. There is a risk that a total of 17760 individuals, out of which 9910 will be male and 7850 will be female) will die in 2019 from the brain and spinal cord tumors, according to their assessment. Brain tumor survival rates differ according to tumor type and the patient's age[1] [22].
In medical terms, a brain tumor is an abnormal growth of cells inside the brain [1]. It induces pressure and influences the normal functioning of the brain in the skull region. A brain tumor may be primary or secondary. A primary brain tumor creates within the brain or adjacent tissues, such as the cranial nerves, meninges, pineal organ, or pituitary organ, while a secondary brain tumor develops when cancer cells migrate to the brain from other organs such as the lung, kidney, or breast. Brain tumors can be divided into two categories: benign and malignant tumors [2]. Benign tumors are non-cancerous. Malignant tumors are cancerous tumors that split continuously in the brain and can spread to other tissues. Tumors are classified from grade I to grade IV by the World Health Organization (WHO) based on abnormalities found in brain tissue [2]. Grade I tumors are minute malignant tumors that are almost always treated with visual interpretation for long-term survival. Grade II tumors develop and look slightly abnormal. Grade III tumors are malignant and aggressively form abnormal cells. Grade IV tumors, which reproduce quickly, are the most dangerous. These tumors grow quickly and develop new blood vessels [2]. The size, shape, location, and type of tumor in the brain make brain tumor diagnosis a difficult task. The size and resolution of a brain tumor cannot be accurately determined in the early stages of tumor development, making diagnosis difficult [3]. Furthermore, identifying and classifying brain tumors into benign and malignant forms is important for patient treatment and survival. Figure 1 shows two MRI images of two brains, one healthy and the other with a tumor.

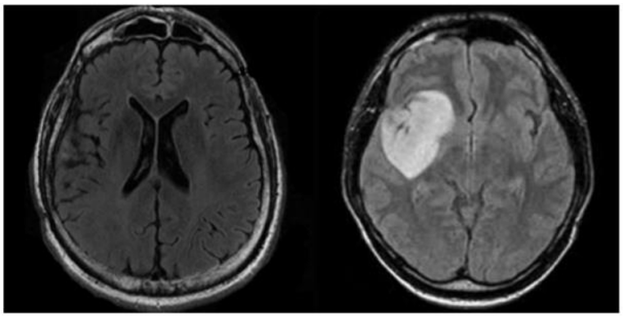

Figure 1. Healthy and Tumor Image [4]

Various medical image modalities such as Computer Tomography (CT), Poisson Emission Tomography (PET), and Magnetic Resonance Imaging (MRI) are used to detect brain tumors. MRI is a non-invasive technique that uses a magnetic field and radiofrequency pulses to reveal the internal structure of the body. Since MRI provides a variety of excitation images, Sequences, and detailed information about brain tissues. It is a useful medical image modality for enhancing diagnosis in the clinic. For brain tumor diagnosis, three types of MRI sequences are used: T1 weighted, T2 weighted, and FLAIR weighted (Fluid Attenuated Inversion Recovery). [5]. Figure 2 shows different MRI sequences. In this paper, we proposed a novel approach in which we use deep learning techniques such as the CNN model with a transfer learning approach for feature extraction. Moreover, the dimensionality reduction method is used to reduce the extracted features and accurately classify the brain tumor.

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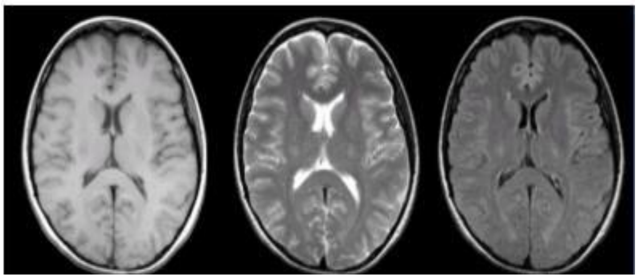

Figure 2. Different MRI Sequences [5]

The remaining sections of the paper are arranged as follows: Section II presents the related research that has been carried out in this sector. In Section III, the proposed methodology is discussed, along with theoretical justifications. In Section IV, the results are illustrated in detail with several performance measurements. Section V is where the overall conclusion is drawn.

2. Related Work

Das et al. [1] have used CNN in their study. They have been concentrating on developing a CNN model for classifying brain tumors in T1-weighted contrast-enhanced MRI images. The proposed method consists of two main stages. First, preprocess the images using different image processing techniques, and then classify the preprocessed images using CNN. The study uses a dataset of 3064 images that includes three different types of brain tumors (glioma, meningioma, pituitary). Using the CNN model, they were able to obtain a high testing accuracy of 94.39%, an average precision of 93.33%, and an average recall of 93%. Their proposed method outperformed a variety of well-known existing methods on the dataset.

The authors Narayana and Reddy [2] used a genetic algorithm that is a metaheuristic optimization technique and a support vector machine to segment and classify MRI images of the brain. The experimental results were about 91% precise in recognizing normal and abnormal tissues from brain MRI pictures.

In research work, Mohsen et al. [6] classified 66 brain MRIs into four different categories which are glioblastoma, sarcoma, mild, and metastatic bronchogenic carcinoma tumors using a deep neural network architecture. Here the Fuzzy C-means clustering technique is used to segment the image into five sections. The features of the segmented tumor are extracted using a discrete wavelet transform (DWT). The extracted features are provided to one of the dimensionality reduction methods Principal Component Analysis (PCA) to reduce the overall feature dimension. The resulting feature vector is fed into the Deep Neural Network classification phase. The classifier was integrated with the DWT, a strong feature extraction method, and PCA provides excellent results on all performance metrics. Using the Deep Neural Network (DNN) classifier proposed approach achieved 96.97% accuracy, 0.97 recall, 0.97 precision, F-Measure 0.97 and AUC(ROC) 0.984.

In another study, Kumar and Kumar [7] used ensemble methods to perform brain tumor segmentation and classification. Neural networks, Extreme learning machines (ELM), and support vector machine classifiers are combined in ensemble methods. There are several stages in the proposed system such as Preprocessing, segmentation, feature extraction, and classification. First, the Median filtering algorithm is used to perform preprocessing tasks on the input MRI image. Second, the FCM clustering algorithm is used for segmentation. In the third stage, the Gray Level Co-Occurrence Matrix (GLCM) is employed to extract features. Using ensemble classification, an automatic brain tumor stage is determined. The ensemble classifier classifies tumors and non-tumor images in brain images. The approach was found to be more stable, quicker, and accurate as a result of the experiments. The proposed approach had achieved an accuracy of 91.17 %.

A research work published by Byale et al. [8], has used Gaussian Mixture Model (GMM) and Grey Level Co-occurrence Matrix (GLCM) with a machine learning approach. The Proposed method includes an adaptive median filter pre-processing method for noise removal. The segmentation is carried out by using the GMM model to discover the region of interest and GLCM is used to extract the features of various types of tumors from segmented MRI image. The Neural network (NN) is used to classify the tumor as normal, benign, or malignant. They achieve overall 93.00% accuracy on 60 samples of the MR images which have been collected from MS Ramaiah Memorial Hospital Bangalore.

Hemanth et al. [9] used machine learning techniques to detect tumors from MRI images in the proposed work. The proposed model has a method for automatic segmentation of MRI image using CNN model consisting of a small size kernel of 3 x 3. This single technique is used for segmentation and classification. data collection, pre-processing, average filtering, segmentation, feature extraction, and classification are major stages included in the proposed model. The overall 91.00% accuracy has been achieved by this model on the UCI dataset.

Shree and Kumar [10] used DWT and probabilistic NN in research work to identify and categorize brain tumors from MRI images. The research work proposed preprocessing for noise removal, image smoothening and feature extraction from a mixture of discrete wavelet transformation (DWT), textural and GLCM (gray-level co-occurrence matrix) features. The noise that can form after segmentation is removed by using morphological operations on segmented images. To classify and detect tumors in brain MRI images, a probabilistic neural network (PNN) classifier was used. The experimental results show that the proposed technique was effective in detecting normal and abnormal tissues from brain MR images with about 100% accuracy on the diacom dataset.

Badisa et al. [17] proposed CNN model for feature extracting and brain tumor classification. The Gaussian filter is used as a preprocessing phase before feature extraction in this research work. In this research work, Patil et al. [18] presented a predictive model for brain tumor detection using deep learning approach. In this approach, a proposed CNN model is implemented and the results are compared with the pre-trained CNN model VGG16 on the brain tumor detection dataset provided by the Kaggle. The testing accuracy and F1 score received by the proposed model is 80% and 0.80 respectively. Moreover, the fine-tuned VGG16 has shown 90% accuracy and 0.85 F1 score over the same dataset.

Pashaei et al. [19] presented Kernel Extreme Learning Machines with CNN model to classify three different types of brain tumor. The results are compared with other classifiers such as multi-layer perceptron, stacking, XGBoost, support vector machine, radial basis function kernel, as well as fully connected layer on brain tumor dataset, proposed used by Cheng et al. [29] and compared accuracy with state-of-the-art results.

In another research, Sajjad et al. [20] suggested an extensive augmentation-based model which classifies the brain tumor into four different stages. In this approach, images are segmented using the CNN model, passed through an extensive data augmentation method and provided to the pre-trained CNN model VGG19 for the feature extraction and classification. The proposed approach has achieved 90.67% accuracy on radiopaedia dataset [28].

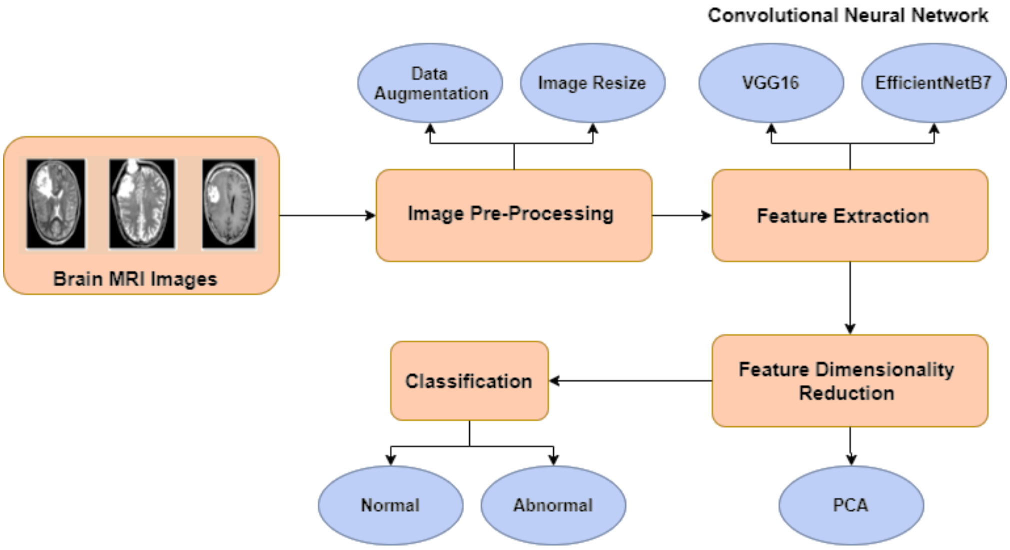

Figure 3. Proposed Approach Architecture

Ari and Hanbay [21] proposed deep learning-based extreme machine learning local receptive field (ELM-LRF) model for brain tumor detection. In this approach, the tumor image is fed to the CNN model for feature extraction. The pooled feature is provided to the ELM's hidden layer followed by the classifier. The proposed approach has 97.18% accuracy on the dataset presented in the Kwan et al. [30].

In this study, Afshar et al. [23] presented a capsule network to overcome the limitation of CNN model in brain tumor categorization. The results of the proposed model are compared with the pure CNN model to represent the effectiveness of the proposed approach. Since, in this approach, only a single layer capsule network has been used, which can be increased for better results as future work.

Deepak and Ameer [24] have suggested a transfer learning approach. The pre-trained GoogLeNet model is used for the classification, where the last layers of the GoogLeNet have been fine-tuned to receive the state-of-the-art performance on the Figshare brain tumor dataset [31].

Cinarer and Emiroglu [25] presented a comparative analysis of four different machine learning algorithms as K-nearest neighbor, Support vector machine, Linear discriminate analysis and Random forest on the Rembrandt dataset published by National Cancer Institute in the Cancer Imaging Archive (TCIA) [32]. SVM has shown 90.00% highest classification accuracy on the given dataset.

Choudhury et al. [26] presented their own 3-layered CNN model with 952278 trainable parameters.

In this research, Bhanothu et al. [27] presented a region proposal network and faster R-CNN to detect the tumor. The output of the VGG16 CNN is provided as an input to the region proposal network and classifier. It has achieved 77.60% average precision over three different categories of brain tumor dataset [29].

3. Proposed Methodology

This section explains the detailed approach for classifying brain tumor MRI images into normal and abnormal categories. The goal of this study is to use deep learning algorithms and a transfer learning (TL) strategy to extract the effective features from the MRI images and along with dimensionality reduction method to present the effectiveness of the proposed model by achieving remarkable accuracy in the detection of tumor from brain MRI images. The procedure includes the following steps: Input Dataset, preprocessing of images, Feature extraction, Dimensionality reduction, and Classification of brain tumor using a classifier, as well as system performance measures. To extract features, pre-trained CNN models is used followed by softmax layer to classify these features. The overview of the proposed methodology is depicted in figure 3.

The detailed description of each stage of the proposed system is described as follows:

3.1. Dataset description

The Kaggle Brain tumor detection dataset [11] is used in this research work. The dataset contains 3000 total samples from which 1500 positive samples and 1500 negative samples are available. The dataset has been divided into 80:20 ratio for the training and testing purpose in this research work.

3.2. Image Preprocessing

Pre-processing is the process of transforming data before giving it to the model. The images in the dataset are of a different dimension, have been resized into the size of 224*224 as a preprocessing step. Moreover, we have used image augmentation to produce different version images and get a generalized model.

3.3. Feature Extraction

Machine learning has a subfield called deep learning. The advantage of utilizing deep learning is that the system learns how to extract features on its own while being trained [12]. The CNN architectures of the deep learning network can extract visual features on their own, using kernels or convolutional filters.

The process of extracting the most important information from raw data is known as feature extraction [7]. Because it aims to extract the key information that identifies each class, feature extraction is a critical stage in the building of any classification task. By extracting essential features from images, feature vectors are formed. Extracting relevant features from images creates feature vectors. These feature vectors are used by classifiers to match the input unit to the desired output unit. Looking at these features makes it easier for the classifier to differentiate between various classes because they are relatively easy to distinguish. We have used VGG-16 and EfficientnetB7 CNN model for the experiment purpose. Moreover, transfer learning has been used to present the effectiveness of the pre-trained CNN model in brain tumor classification.

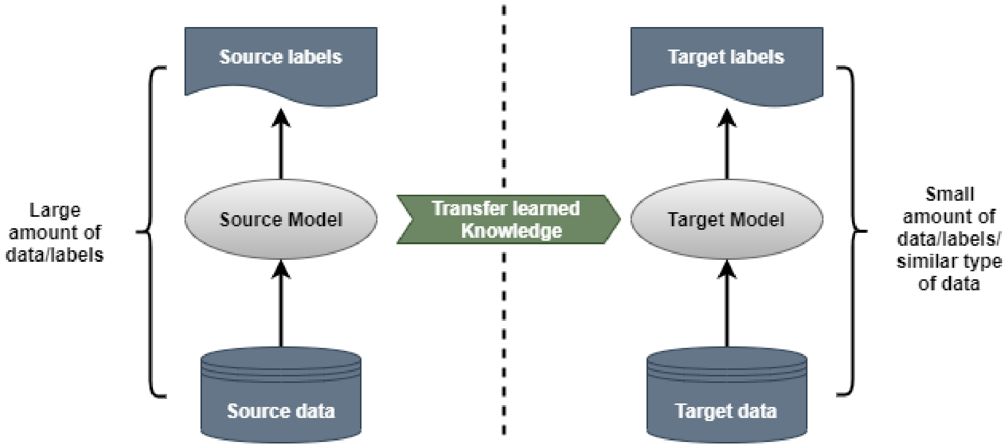

Figure 4. Transfer learning approach[12]

CNN (Convolutional Neural Network) is a multi-layered neural network [1]. It can perform both feature extraction and classification. CNN apply several filters to the raw pixel data of an image to extract and learn features, which can be used for model learning and overall classification purpose. Each input image is passed through a sequence of convolution layers with filters (Kernels), Pooling layer, fully connected layers (FC), and the Softmax function to classify an object with probabilistic values ranging from 0 to 1 in CNN models.

EfficientNet Model refers to a collection of convolutional neural network models. It is a Convolutional Neural Network architecture and scaling method that uniformly scales all the dimensions of depth/width/resolution. It provides a family of models (B0 to B7) that reflect a better balance of efficiency and accuracy than existing ConvNets by adding a heuristic scaling method that refers to variants with more parameters and higher accuracy.

Transfer learning is the process of storing knowledge gained from one problem and transferring it to a different but related problem [12]. It is the task of using the information offered by a previously trained network to learn new models on new data. The basic idea of transfer learning is shown in Figure 4. The advantage can be leverage information such as weights and features from the previously trained model in the transfer learning and even deal with difficulties such as having less data for the new task. Models and frameworks for deep learning are layered structures that learn various features at different layers. To produce the result, these layers are eventually linked to the final layer, which is known as a fully connected layer. For brain tumor detection from MRI images, we have used the pre-trained CNN models such as VGG16 as well as EfficientNetB7 as a feature extractor. We extract features from a pre-final layer of a pre-trained model and train a separate learning model for classification in the proposed method.

3.4. Dimensionality Reduction

The process of transforming data from a high-dimensional space to a low-dimensional space while preserving essential information is known as dimensionality reduction. A dataset with a large number of input features complicates model prediction, making it considerably more difficult to predict using a large number of features. In these circumstances, the dimensionality reduction technique is used. [13].

We have used PCA (Principal Component Analysis) as a feature reduction method. It is a statistical method for determining feature correlations and reducing data dimensions. With the use of orthogonal transformation, it transforms the observation of correlated features into a set of linearly uncorrelated features [14]. These new transformed features are Principal Components. The number of principal components is either equal to or less than the original features of the input feature vector. This selected feature will be fed as an input to the next phase of the model.

3.5. Classification

Classification is defined as a way of identifying and distinguishing things or patterns based on their input features [15]. The classification technique is used to classify the MRI images of the brain into two categories: normal and abnormal. The softmax classifier has been used to classify the input feature vector into desired categories.

4. Experimental Results and Discussion

In this section, we discuss the result of the proposed model. In order to classify brain MRI images into normal and abnormal, the pre-trained CNN EfficientNet-B7 model is used to extract the features. Furthermore, the PCA is applied on features extracted from the model and an effectively reduced feature set is generated for classification. In deep learning models, hyper-parameters play a critical role in achieving efficient results. We have used two different pre-trained CNN models VGG-16 and EfficientNetB7. The different hyperparameters considered such as the number of epochs, learning rate and batch size to provide an efficient trained model. The model is developed using Keras library and supported by Tensor Flow as a backend with python.

The pre-trained EfficientNetB7 CNN model followed by PCA achieved 99.00 % training accuracy and 80.00 % validation accuracy 80.00 % with the optimized hyper parameter values as the learning rate is 0.0001, the batch size is 32 and the maximum number of epochs is 100.

The confusion matrix is used to evaluate the performance of the proposed model. A confusion matrix is a tabular representation of correct and incorrect classifications [16]. A confusion matrix can be used to extract various metrics that show the classifier's performance for each tumor class. Precision, Recall (or sensitivity), and F1-score, accuracy are all important evaluation metrics. Figure 5 presents the overall classification results of the proposed model as the precision, recall, F1-score and accuracy of our model is 84%, 80%, 79% and 80% respectively. The proposed methodology's evaluation focus on the accuracy metric as an evaluation parameter. Accuracy can be defined as the ratio of the number of correctly classified samples to the total number of data samples. The mathematical expression of the accuracy can be presented as

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \qquad (1)$$

Where TP is True Positive, FP is False Positive, TN is True Negative and FN is False Negative. The overall confusion matrix of our proposed model is presented in Figure 6. It shows that 292 positive samples and 186 negative samples are correctly classified.

Classification Report

	precision	recall	f1-score	support
Yes	0.72	0.97	0.83	300
No	0.96	0.62	0.75	300
accuracy			0.80	600
macro avg	0.84	0.80	0.79	600
weighted avg	0.84	0.80	0.79	600

Figure 5. Overall classification results of proposed approach

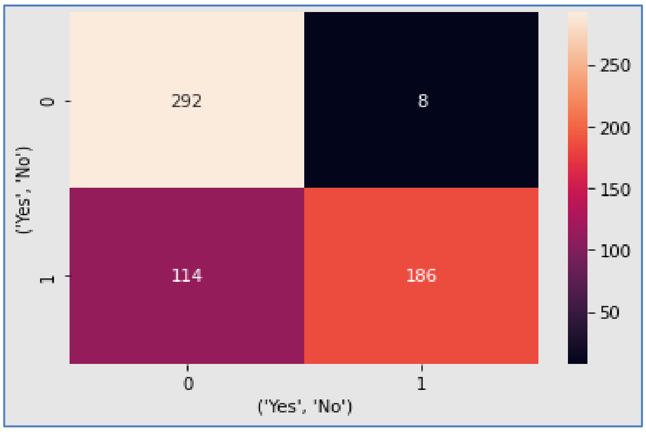

Figure 6. Confusion matrix of the proposed model

The comparative analysis of the different CNN models VGG-16 and EfficientNet-B7 with and without dimensionality reduction method is presented in the figure 7. The EfficientNet-B7 with PCA provides better accuracy results of the 80.00% compared to other configurations of the proposed approach.

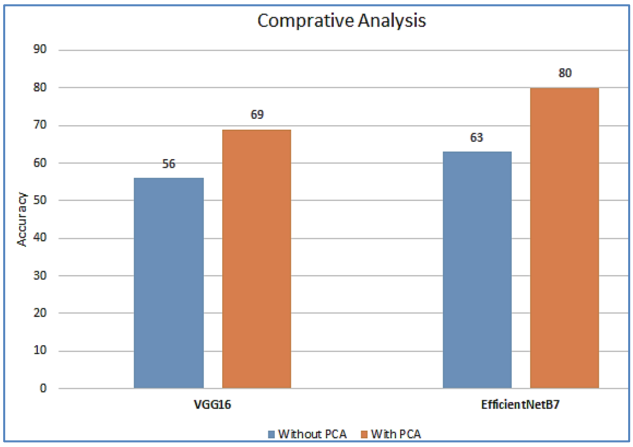

Figure 7. Comparison of result of CNN and CNN+PCA

5. Conclusion

To classify brain MRI images into normal or abnormal images, we employed the EfficientNetB7 deep learning pre-trained models with the PCA approach for feature extraction followed by feature reduction in this proposed methodology. The Kaggle brain tumor detection dataset, which contains 3000 MRI normal and abnormal images, was used to test this model. The fusion of features extracted from the CNN EfficientNet model and PCA (Principal Component Analysis) can provide the most relevant feature for detecting tumors with better accuracy. Our results show that EfficientNetB7 model with PCA obtained the training accuracy comparatively good performance over VGG16 model with PCA. Moreover, it is observed that CNN model with dimensionality reduction method as PCA provides better results over without PCA. In future work, we can use different dimensionality reduction methods of the traditional approach as well as the deep learning approach on brain tumor classification overall all performance.

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