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НОВЫЙ ПОДХОД НА ОСНОВЕ ТРАНСФЕРНОГО ГЛУБОКОГО ОБУЧЕНИЯ ДЛЯ ПРОГНОЗИРОВАНИЯ ОПУХОЛЕЙ ГОЛОВНОГО МОЗГА

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РЕФЕРАТ

Опухоль головного мозга – это аномальное скопление клеток в головном мозге, которое потенциально может представлять угрозу для жизни из-за способности клеток проникать в близлежащие органы и давать метастазы. Правильно диагностировав это потенциально смертельное заболевание, можно спасти жизни. За последние несколько лет функциональность приложений глубокого обучения при автоматическом распознавании МРТ-изображений опухолей головного мозга заметно расширилась. В результате усовершенствование архитектуры модуля приводит к более точному отображению отслеживаемой конфигурации. Благодаря предоставлению надежных наборов данных, в классификации опухолей с помощью алгоритмов глубокого обучения был достигнут значительный прогресс. Цель статьи – использовать алгоритмы модуля переноса для прогнозирования опухолей головного мозга. К таким модулям относятся MobileNet, VGG19, InceptionResnetV2, Inception и DenseNet201. В предлагаемом модуле используются три основных оптимизатора: Adam, SGD и RMSProp. Результаты моделирования показывают, что предварительно обученный модуль MobileNet с оптимизатором RMSProp превзошел все другие оцененные модули. В дополнение к минимальному времени, затрачиваемому на вычисления, он обеспечил точность в 99,6 %, чувствительность в 99,4 % и специфичность в 100 %.

Ключевые слова: *медицинские изображения, опухоль головного мозга, автоматическое распознавание, машинное и глубокое обучение, компьютерное зрение, МРТ*

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Novel Approach Using Transfer Deep Learning for Brain Tumor Prediction

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ABSTRACT:

A brain tumor refers to an abnormal collection or aggregation of cells in the brain that has the potential to be life-threatening owing to the cells' capacity to penetrate and metastasize to organs that are nearby. It is possible to save lives by making a correct diagnosis of this potentially fatal condition. Within the last several years, there has been a noticeable increase in the functionality of deep learning applications. As a result, improving the module's architecture leads to better approximations in the monitored configuration. Through the provision of trustworthy datasets, the categorization of tumors via the use of deep learning algorithms has successfully achieved significant progress. The purpose of this article is to use transfer module algorithms for the prediction of brain tumors. These modules include MobileNet, VGG19, InceptionResNetV2, Inception, and DenseNet201. The suggested module uses three main optimizers: Adam, SGD, and RMSprop. The simulation findings indicate that the pre-trained MobileNet module with the RMSprop optimizer outperformed all other evaluated modules. In addition to having the shortest amount of time required for computing, it obtained an accuracy of 99.6 %, a sensitivity of 99.4 %, and a specificity of 100 %.

Keywords: *medical images, brain tumor, machine and deep learning, computer vision, MRI*

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1. Introduction

The global health organization's numbers indicate that cancer ranks as the second leading cause of death worldwide. When it comes to the many forms of cancer, the aggressive nature of the tumor, its diverse traits, and its poor relative survival rate have contributed to its reputation as one of the most lethal forms of cancer. A brain tumor can significantly alter the quality of life for patients and their families, impacting their standard of living. When it comes to treating brain cancer and boosting the percentage of patients who survive the disease, early identification and accurate classification of the disease are the most important factors. It is possible to differentiate between different types of tumors, such as meningiomas, pituitary tumors, and gliomas, by taking into consideration a number of criteria, including the shape, texture, and location of the tumor [1]. Accurately determining the type of tumor is crucial as it significantly impacts the available treatment options and can also predict the patient's survival rate. Doctors often use resonance imaging and biopsies to diagnose brain tumors. Doctors advise magnetic resonance imaging (MRI) because it does not involve any intrusive procedures. In some instances, however, magnetic resonance imaging (MRI) alone is not sufficient to determine the kind of tumor that calls for a biopsy for diagnosis. The procedure carries considerable dangers and the findings of the biopsy are not guaranteed to be correct. Those technicians who carry out these actions will have a favorable influence on the outcomes, but they will also add problems related to human error. To assist medical professionals in making the appropriate choices, we want a computerized system.

There has been a significant amount of study conducted on this topic in recent years, utilizing a variety of machine learning approaches. Prior to the development of deep learning, researchers utilized feature selection methods such as principal component analysis (PCA) and discrete wavelet transform (DWT). Later, researchers utilized classifiers such as support vector machines (SVM) and artificial neural networks (ANN). In the present moment, the primary emphasis is on the use of neural networks in order to produce better outcomes [2]. There are a number of variables that influence the prognosis of a brain tumor. These factors include the location of the tumor, the histological subtype of the tumor, and the margin of the tumor. State-of-the-art imaging methods, such as magnetic resonance imaging (MRI), can be used for various diagnostic purposes. MRI can investigate the tumor's course and identify areas used for surgical planning before the procedure. Magnetic resonance imaging also analyzes the anatomy, physiology, and metabolic activity of lesions, as well as their hemodynamics. Because of this, magnetic resonance imaging (MR) pictures continue to be the predominant diagnostic technique for brain malignancies. Cancer identification, particularly early discovery, may have a significant impact on the therapy that is administered.

Early diagnosis is crucial because it increases the likelihood of healing for lesions detected at an early stage [3]. Therefore, early intervention has the potential to be the deciding factor in whether or not a person lives or dies. Deep learning and its associated approaches can automate the process of identifying and categorizing brain lesions. In addition, limiting the focus of the radiologist's attention to malignant lesions might provide relief from the strain of having to read a large number of pictures. Consequently, this finally results in an increase in overall efficiency and a decrease in diagnostic mistakes. 6. According to the findings of recent research, deep learning techniques in the area of radiology have already attained superhuman levels of effectiveness in the diagnosis of some diseases [4], [5].

2. Related Work

Researchers have conducted a significant amount of research to automate the identification and categorization of brain tumors due to their fatal nature. Because of recent developments in machine learning, neural networks are becoming more popular for use in the process of constructing models for the diagnosis of brain cancer. The principles of transfer learning may be applied to these models, and they can also be utilized for other diagnoses that are comparable [1]. This study aims to examine established methods for categorizing brain tumors. In this respect, more study and modifications to the approach are still required in order to make it possible for the system that was created to be implemented for use by medical professionals.

The article [2] announced a novel multigrade brain tumor classification system based on a convolutional neural network (CNN). The researchers use the InputCascade CNN algorithm to segment the tumor region. The researchers determined that the pre-trained VGG19CNN architecture optimally categorizes tumor grades. The influence of the data expansion was shown by the fact that the original data achieved an accuracy of 87 %, while the extended data achieved an accuracy of 90 %.

The paper [3] put out the concept of further improving a CNN architecture for the purpose of tumor classification by making use of genetic algorithms (GA). This investigation makes use of a gadolinium-enhanced T1 image that has a resolution of 128 by 128 pixels. Increasing the size of the dataset may be accomplished by the use of simple methods like as rotation, scaling, and mirroring. The implementation of GA allows for the selection of parameters such as the number of convolution layers and maximum pooling layers, as well as the number of filters and the size of each filter. The accuracy achieved for glioma staging and tumor staging was 90.9 % and 94.2 % respectively.

In the study [4], transfer learning was employed to extract features from the classification system. First, the researchers reduced the image obtained from magnetic resonance imaging (MRI) to 224×224 pixels and then normalized it as a first therapeutic therapy. The pre-trained GoogleNet has been tweaked so that it may learn function from magnetic resonance imaging of the brain. The researchers evaluate the effectiveness of the collected features using the support vector machine (SVM) and artificial neural network (ANN) classifier models, in addition to the GoogleNetsoftmax layer. The classification accuracy of the Deep Transfer Learned (standalone) model, the Support Vector Machine, and the Artificial Neural Network is 92.3 %, 97.8 %, and 98 %, respectively.

Researchers used the capsule neural network, also known as CapsNet, in the research paper [5] to assess how pretreatment methods affect the categorization of brain tumors. Rotation and patch extraction are two pretreatment processes used in the study. CapsNet applies the original dataset, resulting in an accuracy of 87°. Applying the same architecture to the preprocessed data yields an accuracy of 92.6, demonstrating an improvement in accuracy through preprocessing.

The researchers that published the study [6] used a deep CNN model that had been pre-trained. This paper suggests a fine-tuning technique that is based on transfer learning and is implemented block-by-block. The performance is evaluated using a cross-validation that is performed in five different directions. The suggested approach achieves an accuracy of 94.82 %.

The paper [7] attempted to determine the most effective CNN architecture for classifying brain tumors. Currently, researchers are investigating five alternative CNN designs, each with a unique combination of convolutional layers and fully connected layers. The CNN architecture, which comprises of two convolutional layers with 32 filters: activation (ReLu) and Maxpool, followed by a fully connected layer with 64 neurons, has 84.19 % verification accuracy.

The study [8] found that researchers developed a statistical system to detect and classify high-grade glioma (HGG) and low-grade glioma (LGG) tumors. Binarization is often used to convert photos into binary files. After implementing the discrete wavelet transform, we subject the segmented picture to the process of feature extraction. This not only assists in the extraction of features, but it also helps to minimize noise. We tested this system with one hundred different photos, and it achieved a 99 % accuracy rate.

The research publication [9] explored a deep neural network to categorize 66 brain MRI datasets into four distinct categories. A deep neural network (DNN) with seven hidden layers, an artificial neural network (ANN) with k = 1 and k = 3, linear discriminant analysis (LDA), and support vector machines (SMOSVM) are the classifiers that are used.

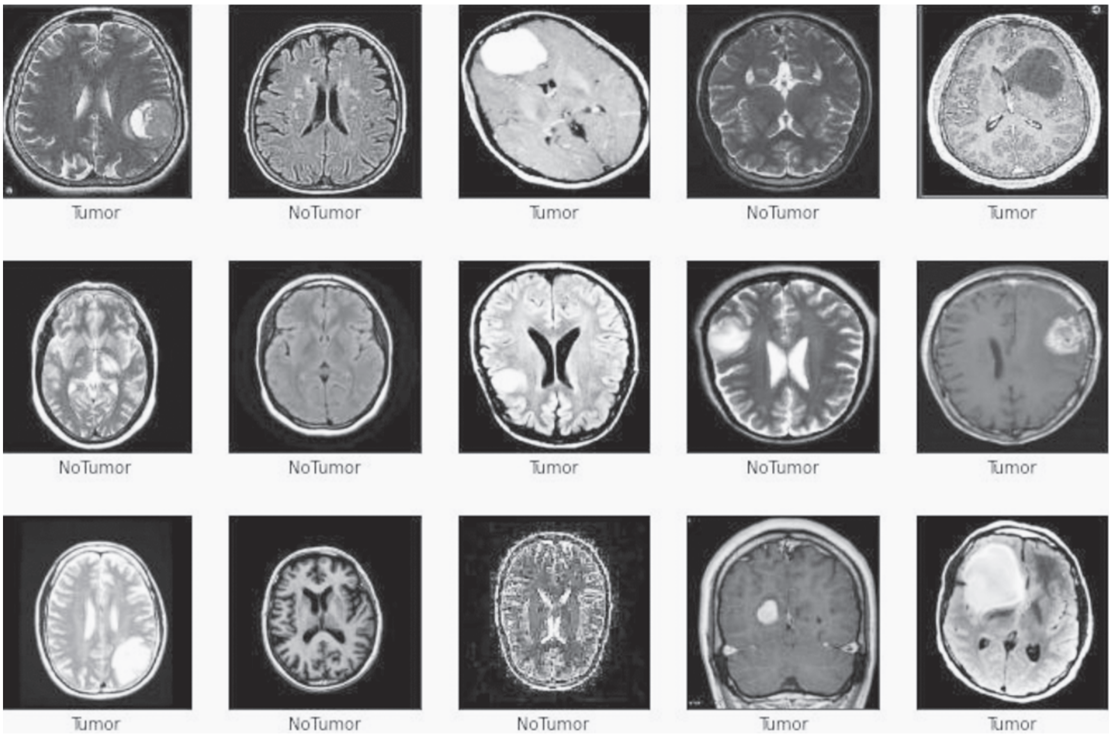

Fig. 1 The raw image of the dataset

Рис. 1. Необработанные изображения набора данных

With an accuracy rate of 98.4 %, DNN is the most accurate technology currently available.

The paper [10] presented a method for classifying brain tumors that was based on the use of a normalized histogram and segmentation via the application of a K-means clustering algorithm. When compared to Naive Bayes, support vector machines (SVMs) have been shown to be more effective, with a 91.49 % efficiency rate. The K-means technique was used in order to segment the images, which included tumors that were being identified.

Based on the findings of the study [11], it developed a CapsNet architecture for categorizing brain tumors. With a accuracy of 90.89 %, the suggested architecture is effective.

3. Proposed Approach

3.1 Image Processing

As can be seen in Fig. 1, the dataset is made up of unprocessed images, which need some kind of preprocessing.

As can be seen in Fig. 2, the images of the dataset after the application of image processing with histogram equalization. This method generally improves the overall contrast of a large number of images, especially when the image is represented by a limited range of intensity values. By making this modification, you will be able to employ the complete spectrum of intensities in an equitable manner and improve the distribution of the intensities on the histogram accordingly. It is possible for regions that have low local contrast to have high contrast as a consequence of this.

3.2. Procedures for the deep transfer learning proposed technique

By the steps that are provided for the construction of the transfer model are as follows, as illustrated in Fig. 3:

1. Loading images from directories as a class for each directory is the first step in the data loading process.
2. Apply histogram equalization by using the sci-lit images application programming interface (API) for imagine processing.
3. Split the data into sets that can be used for training, testing, and validating.
4. Utilize the tf.keras.applications file to load the required application in Keras.
5. Downloading the base model from the Keras API is the fifth step in the load transfer model.
6. Train the model and evaluate its performance by using the sci-kit-learn metrics API to assess the efficiency of the training process.

4. Empirical results and discussion

There is an application and testing of the most famous deep transfer learning modules utilized in the Br35H (Brain Tumor Detection 2020) dataset [12].The accuracy comparison of these modules that were optimized with three distinct optimizers is shown in Table 1, as can be seen in the attached table. It is clear that MobileNet, which was optimized using RMSprop, attained the highest level of accuracy, which was 99.55 %. Furthermore, Fig. 4 illustrates a comparison of accuracy.

Table 1

Comparing module accuracy with three optimizers

Сравнение модуля с тремя оптимизаторами по точности

Module/optimizer	Adam %	RMSprop %	SGD %
MobileNet	98.76	**99.55**	97.92
VGG19	97.43	96.22	80.76
InceptionResNetV2	98.23	98.29	95.55
Inception	99.12	98.76	97.12
DenseNet201	99.10	99.22	97.40

As can be seen in Table 2, it gives a comparison of the sensitivity of three distinct optimizers compared to five different modules that were optimized. According to the results,

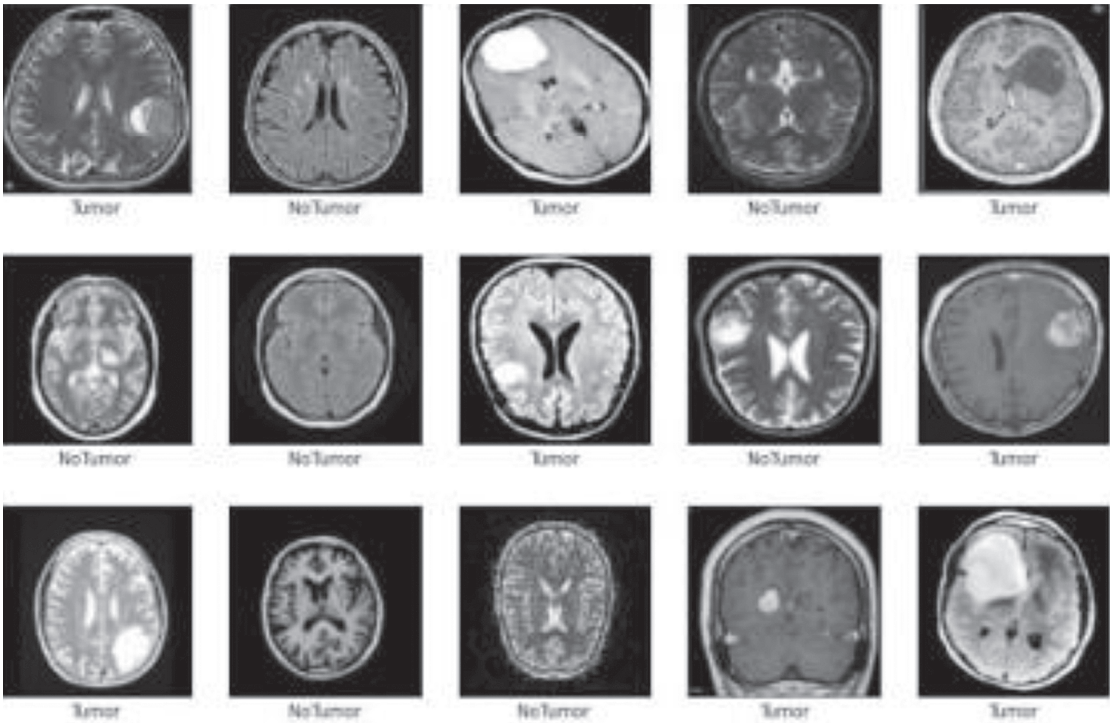

Fig. 2. Images after the use of image processing
Рис. 2. Изображения после использования программы обработки изображений

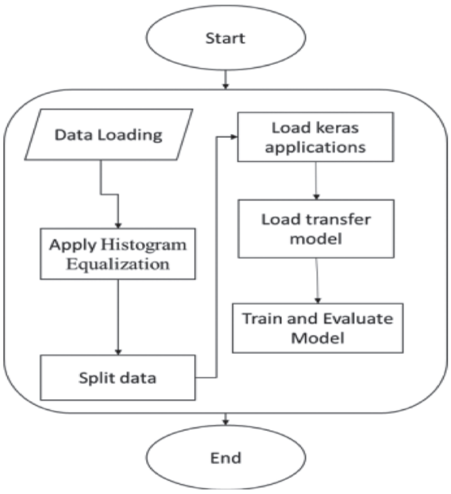

Fig. 3. The steps of deep transfer learning proposed technique
Рис. 3. Этапы предложенной методики глубокого трансферного обучения

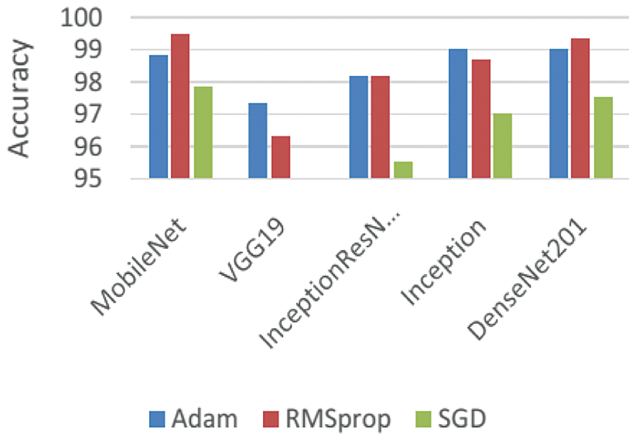

Fig. 4. Comparing module accuracy with three optimizers
Рис. 4. Сравнение точности модуля с тремя оптимизаторами

MobileNet and DenseNet201 obtained the maximum sensitivity, which was 99.4 %. Additionally, the comparison of sensitivity between the various modules is shown in Fig. 5.

Table 2

Comparing module sensitivity with three optimizers
Сравнение чувствительности модуля с тремя оптимизаторами

Module/optimizer	Adam %	RMSprop %	SGD%
MobileNet	99.12	**99.40**	97.10
VGG19	96.00	93.76	83.76
InceptionResNetV2	96.52	97.22	93.44
Inception	99.12	98.76	95.65
DenseNet201	99.10	**99.40**	97.23

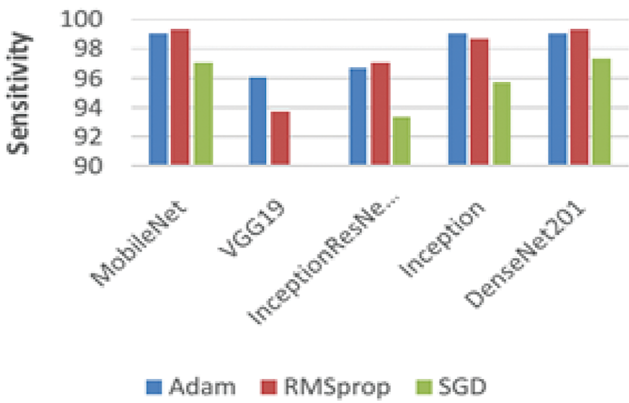

Fig. 5. Comparing module sensitivity with three optimizers
Рис. 5. Сравнение чувствительности модуля с тремя оптимизаторами

Table 3 presents a comparison of the specificity of modules optimized using three different optimizers. Fig. 6 shows a comparison of the specificity of the different modules. According to the results, MobileNet obtained the maximum specificity, which was 100 %.

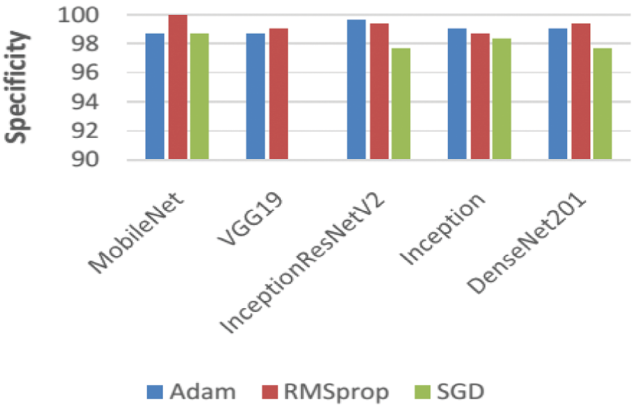

Fig.6. Comparig module specifity with three optimizers

Рис. 6. Сравнение специфичности модуля тремя оптимизаторами

Table 3

Comparing module specificity with three optimizers

Сравнение специфичности модуля с помощью трех оптимизаторов

Module/optimizer	Adam%	RMSprop%	SGD%
MobileNet	98.78	**100.00**	98.67
VGG19	98.56	99.00	77.76
InceptionResNetV2	99.56	99.21	97.74
Inception	99.00	98.66	98.33
DenseNet201	99.00	99.22	97.76

5. Conclusion

In Various deep transfer learning techniques found in this article were used to classify brain tumors. Deep learning and CNN training from scratch with a tiny data set might be challenging to implement in some medical imaging applications because of the limited amount of data available. The solution that we offer is a block-by-block fine-tuning method that is supported by transfer learning modules such as MobileNet, VGG19, InceptionResNetV2, Inception, and DenseNet201. This will allow us to tackle this problem. With a maximum effective accuracy of 99.6 %, 99.4 % sensitivity, and 100 % specificity for RMSprop-optimized MobileNet modules, the suggested module does not make use of hand-crafted features, has little pre-processing, and has the greatest effective accuracy.

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