Mesopotamian journal of Computer Science
Vol. **(2023)**, 2023, **pp**. 29-38
DOI: https://doi.org/10.58496/MJCSC/2023/005 ; ISSN: 2958-6631
https://mesopotamian.press/journals/index.php/cs

Research Article

Mobilenetv1-based deep learning model for accurate brain tumor classification

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ARTICLE INFO

Article History
Received 11 Jan 2023
Accepted 16 Feb 2023
Published 08 Mar 2023

Keywords
Deep learning,
Brain tumors
Artificial intelligence
MobileNetV1
Medical images
Machine learning

ABSTRACT

Brain tumors are among the most dangerous diseases that lead to mortality after a period of time from injury. Therefore, physicians and healthcare professionals are advised to make an early diagnosis of brain tumors and follow their instructions. Magnetic resonance imaging (MRI) is operated to provide sufficient and practical data in detecting brain tumors. Applications based on artificial intelligence contribute a very large role in disease detection, provide incredible accuracy and assist in creating the right decisions. In particular, deep learning models, which are a significant part of artificial intelligence, have the ability to diagnose and process medical image datasets. In this concern, one of the deep learning techniques (MobileNetV1model) is utilized to detect brain disease from 1265 images gathered from the Kaggle platform. The behavior of this model is studied through four main metrics. This article deduced that this model has a significant effect in diagnosing these images from the most important metric, which is accuracy, as it gained an accuracy result of more than 97%, which is an excellent effect.

1. INTRODUCTION

Brain tumors are grave medical conditions characterized by the development of abnormal masses or tumors within the brain or surrounding tissues [1-3]. There are two types of brain tumors. The first type is called primary tumors that begin in the brain, while the second type is metastatic tumors that spread to the brain from other parts of the body. Some of these tumors are benign, non-cancerous tumors, while others are malignant tumors, which are cancerous tumors [4-6]. These tumors vary according to their symptoms, size, and type. Common symptoms of brain tumors are headaches, seizures, memory impairment, vision changes, hearing problems, difficulty speaking or understanding language, as well as numbness in the extremities. Brain tumor specimen from a 16-year-old child is depicted in Figure 1. Medical specialists may operate a range of treatment options for brain tumors, including surgical procedures, radiation therapy, and chemotherapy. The treatment choice is typically based on the type and stage of the tumor. Brain tumors are among the most fatal medical conditions in the United States, as evidenced by a 2020 statistical study performed by the American Cancer Society. This report highlighted that brain tumors are particularly prevalent among adults in their thirties and forties [7,8]. In the United Kingdom, patients with brain tumors suffer financial losses estimated at £14,783 annually, which is money spent on treatment and physician visits. At the same time, the average cost for all cancers is £6,840 a year, and 16,000 people are diagnosed each year with brain tumors, and the numbers are increasing yearly [9].

Artificial intelligence techniques play a significant and influential role in the medical domain by developing complex algorithms that can automatically analyze and interpret large amounts of medical data [11-16]. This data includes various types of medical imaging such as MRI [17], CT-scan [18], X-ray [19], and ultrasound [20], as well as other types of medical data, such as genomics and electronic health records. The most famous of these techniques is deep learning, which is part of machine learning. Deep learning algorithms extract features from medical datasets, learn new patterns, help diagnose diseases, and help physicians and healthcare specialists make the right and accurate decisions [21-23]. Moreover, these algorithms are used to classify medical images, such as breast cancer, brain cancer, COVID-19, and others. These

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*Corresponding author. Email: mr.maad.alnaimiy@baghdadcollege,edu.iq algorithms are characterized by their ability to predict heart disease, diabetes, Alzheimer’s, and other diseases, as well as asset in early diagnosis and personalized treatment planning. Deep learning algorithms have been proven to be highly practical in classifying MRI brain tumor images [24,25]. These algorithms can automatically extract features from images of varying sizes, making them particularly useful for medical imaging applications. With their ability to accurately identify and classify tumor regions, these algorithms hold significant promise for enhancing the accuracy and speed of clinical diagnoses. Recently, a lot of literature has been published about applying these algorithms in classifying images of brain tumors and achieving high-accuracy effects. Convolutional neural networks (CNNs) have been particularly effective in identifying different types of tumors, such as glioma, meningioma, and pituitary adenomas, as well as in distinguishing between neoplastic and non-neoplastic images. These advances in the deep learning-based classification of brain tumor images have the potential to improve the accuracy and efficiency of diagnosis and treatment planning for patients with brain tumors [26-37].

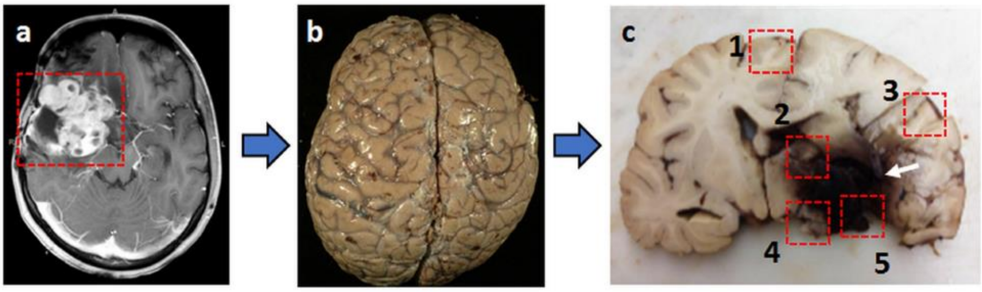

Fig. 1. Brain tumor specimen from a 16-year-old child [10].

In this article, we propose an approach for the classification of brain tumor MRI images using a MobileNetV1 model. the major contribution lies in the use of this powerful model, which has been shown to reach excellent results in image classification tasks. To evaluate our approach, we utilized a dataset of 253 brain MRI images obtained from the Kaggle platform, which are split into two classes: tumor and no tumor images. Given the limited size of this dataset, we performed five operations to increase the number of images to 1265, allowing us to study the model's ability to classify these images more thoroughly. We then assessed the performance of our approach using a variety of evaluation metrics. Finally, the results demonstrate the efficacy of our approach in accurately classifying brain tumor MRI images and suggest that this model could be valuable in enhancing the accuracy and speed of clinical diagnoses.

The rest of this article is organized as follows. In Section 2, we review recent studies published in 2022 that have explored the use of deep learning models for the classification and diagnosis of brain tumor images. In Section 3, we provide details on the dataset used in our study, as well as a description of the steps accepted to train and evaluate the MobileNetV1 model. Section 4 presents and discusses the results obtained through the experiments. Finally, in Section 5, we draw conclusions based on our study's findings and highlight avenues for future research.

2. LITERATURE SURVEY

This section will investigate the latest research that employs deep learning techniques to predict brain tumor diseases. We will organize the studies based on the specific algorithms utilized and provide a summary of the accuracy results achieved in each study.

In a study conducted by Chattopadhyay and Maitra [38], they proposed a convolutional neural network (CNN) model with activation algorithms such as softmax, RMSProp, and sigmoid to predict brain tumors from a dataset of 2892 MRI images. A study concluded that the proposed model achieved more than 99% accuracy. Younis et al. [39] analyzed 253 MRI images using the CNN, VGG-16, and Ensemble models in their study. The VGG-16 model was found to be the most effective in diagnosing the images, achieving an accuracy of 98.15%. The CNN had an accuracy of 96%, while the Ensemble model had an accuracy of 98.41%. In another study by Raza et al. [40], they applied a hybrid model named DeepTumorNet to classify brain tumor disease. The dataset of this study includes 3062 MRI images of three different types of brain tumor (glioma, meningioma, and pituitary tumor) collected from 233 patients during the period 2005-2010 at Nanfang Hospital Guangzhou China and General Hospital Tianjin Medical University in China. The hybrid model reached a high accuracy of more than 99%, which is a very high mark. Authors in [41] introduced a CNN for the classification of brain Magnetic

Resonance Imaging (MRI) scans into two categories: tumor and no-tumor. The dataset utilized in this study was comprised of 3000 images from the Kaggle platform, which included glioma, meningioma, pituitary tumor, and no tumor classes. The proposed CNN model achieved excellent results, with an accuracy of 96.89% in accurately determining and classifying these images. A study conducted by Zahid et al. [42], have employed the ResNet101 model for brain tumor classification. Their studies included the MRI images and were divided into four classes: (1) native (T1=28,446 images), (2) postcontrast T1-weighted (T1CE=28,969 images), (3) T2-weighted (T2=28,759 images), and (4) T2 fluid-attenuated inversion recovery (FLAIR= 28,413 images). The proposed model has a high classification capacity, with a rating accuracy of 94.4%.

3. MARTIALS AND MODEL

3.1 Dataset Details

In this article, MRI images are obtained from the Kaggle platform [43]. This platform is considered one of the most widespread online platforms for data science and machine learning, and it is available for everyone to download and host the dataset. It was established in 2010 and acquired by Google in 2017, and since that time, it has become an important center for artificial intelligence investigators. Also, this platform contributes to the development of skills and collaboration with others in programming and data analysis. The dataset consists of 253 images (in JPEG format and grayscale) divided into two classes: 155 images diagnosed with a tumor in the human brain and 98 images of healthy people (see Figure 2). Indeed, more than the number of images is needed to conduct MobileNetV1-model training. Therefore, the data redundancy process was carried out utilizing five rotation methods, which are among the most common data redundancy methods. Therefore, deep learning techniques are only recommended when the dataset is large [44][45]. After performing the data replication process, the total images employed in this work became 1265 images split into 775 images with a brain tumor and 490 images without a brain tumor. In addition, this image has been resized and standardized to $224 x 224$ with 3 channels RGB because all the original images have different resolutions.

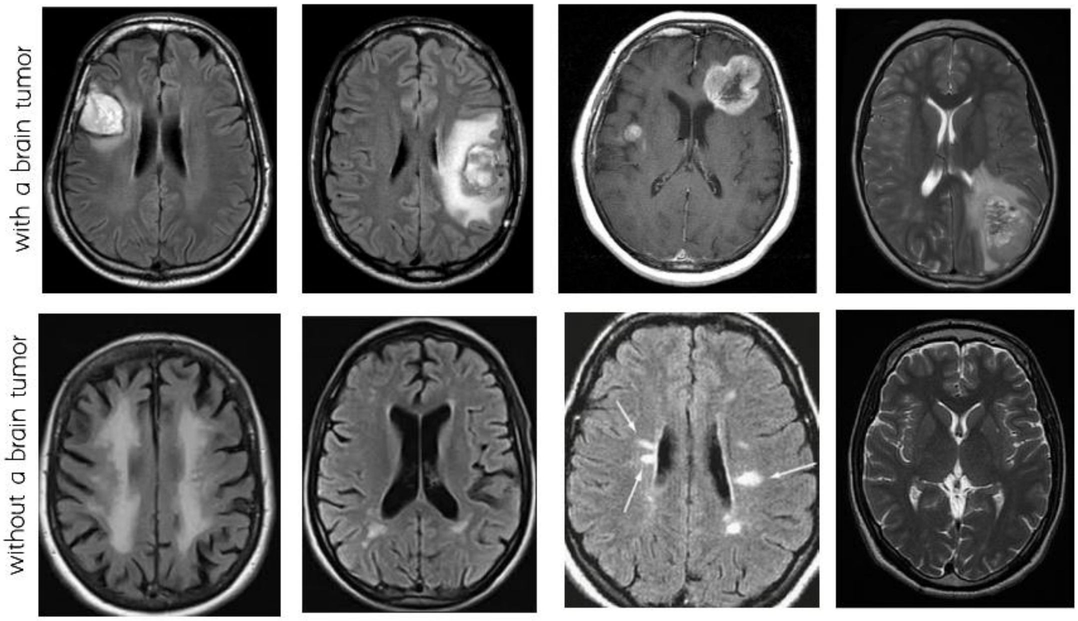

Fig. 2. Examples of images applied in this work.

3.2 MobileNetV1 Model

MobileNetV1 is a convolutional neural network architecture created for highly efficient image classification on mobile and embedded devices. It was first presented in 2017 by a group of researchers working for Google. This model is based on a simplified architecture that operates depth wise separable convolutions to reduce the number of parameters and computational costs while maintaining high image fidelity. Moreover, this model allows the network to be deployed on mobile devices with limited computational resources, making it suitable for various applications, especially in medical imaging. To clarify, this model is characterized by the fact that it contains two layers, the first is named the depth wise convolution, and it performs a lightweight filtering process by applying one convolutional filter for each input channel. The second layer, a pointwise convolution ($1 \times 1\ convolution$), is responsible for creating new features through linear computing combinations of the input channels. The MobileNetV1 architecture is composed of a series of depth wise convolutional layers, then pointwise convolutional layers and global average pooling. The depth wise convolutions operate on each input channel separately, while the pointwise convolutions combine the media and output the final classification scores. The global average pooling layer is utilized to reduce the spatial dimensions of the feature maps and produce a compact feature vector that can be used for classification. In addition, this model has been demonstrated to achieve high accuracy on various image classification tasks while using fewer parameters and less computation than other state-of-the-art models. It has since been extended to different variants, such as MobileNetV2 and MobileNetV3, which further enhance on the efficiency and accuracy of the original model. Algorithm 1 describes the steps of implementing this model with a description.

Algorithm 1: MobileNetV1's Steps

Step-1: Input image x and pre-processing,

Step-2: The 1st layer is a depthwise convolution layer, which applies a separate convolutional filter to each input channel, performing a lightweight filtering process. This can be expressed as:

$$y = DWConv(x)$$

Where: y is the output feature map, $DWConv$ is the depthwise convolution operation, and x is the input image. The depthwise convolution operation can be written as:

$$y\_i = k\_i * x\_i$$

Where: y_i is the output of the $i - th$ channel, k_i is the $i - th$ filter, and x_i is the $i - th$ input channel.

The 2nd layer is a pointwise convolution layer, which combines the filtered channels to create new features through linear computing combinations. This can be expressed as:

$$y = PWConv(y)$$

Where: y is the output feature map, $PWConv$ is the pointwise convolution operation, and y is the input feature map from the depthwise convolution layer. The pointwise convolution operation can be written as:

$$y = W * x$$

Where: y is the output feature map, W is the weight matrix, and x is the input feature map.

Step-3: Pooling is the resulting feature maps are then passed through a global average pooling layer. This layer reduces the spatial dimensions of the feature maps and produces a compact feature vector that can be used for classification. This can be expressed as:

$$y = AVGPool(y)$$

Where: y is the input feature map, and $AVGPool$ is the global average pooling operation. The global average pooling operation can be written as:

$$y\_i = (1 \div N) * sum(x\_i)$$

Where: y_i is the $i - th$ output channel, x_i is the $i - th$ input channel, and N is the total number of input channels.

Step-4: The feature vector is then passed through a series of fully connected layers. These layers use the features to predict the probability of each class. This can be expressed as:

$$y = FC(y)$$

Where: y is the input feature vector, and FC is the fully connected layer operation. The fully connected layer operation can be written as:

$$y = W * x + b$$

Where: y is the output feature vector, W is the weight matrix, x is the input feature vector, and b is the bias vector.

Step-5: A softmax activation function is applied to the output of the fully connected layers. This can be expressed as:

$$y = Softmax(y)$$

Where: y is the input feature vector, and $Softmax$ is the softmax activation function.

Step-6: Output

4. RESULTS AND DISCUSSION

This section will discuss the results obtained from this MobileNetV1 model. This model is developed and trained by Python, with a range of widespread libraries such as Keras, Numpy, PIL, Scipy, Pandas, Matplotlib, and Seaborn. All training experiments were performed using an NVIDIA 3050 RTX GPU with 16 GB of RAM for more immediate processing and Windows-10. The dataset is divided into 80% training data (n=1012) and 20% testing data (n=253). The distribution of the dataset is visualized in Figure 3. Figure 4 illustrates the workflow from data input to evaluation metric output.

To assess the performance of model, we utilized six evaluation metrics: accuracy, sensitivity, specificity, precision, F1-score, and AUC. These metrics were computed using the confusion matrix, which enables us to evaluate the model's ability to diagnose images. Mathematical equations 1-5 are used to compute the evaluation metrics. Figure 5 illustrates the confusion matrix.

$$Accuracy = \frac{TP+TN}{TN+TP+FN+FP} \quad (1)$$

$$Sensitivity = \frac{TP}{TN+TP} \quad (2)$$

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$F1-score \ = 2 * \frac{Precision * Sensitivity}{Precision + Sensitivity} \quad (5)$$

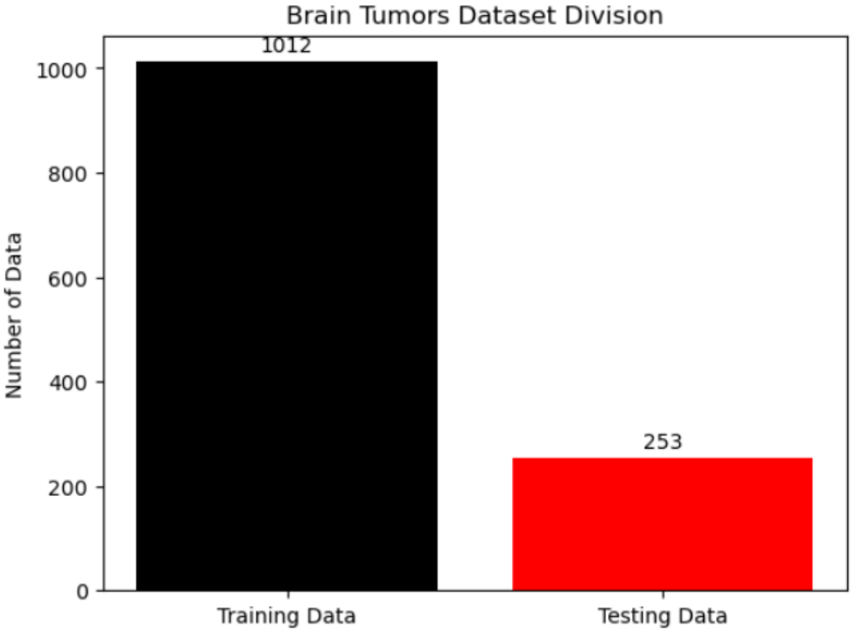

Fig. 3. Dataset distribution (80% training data & and 20% testing data)

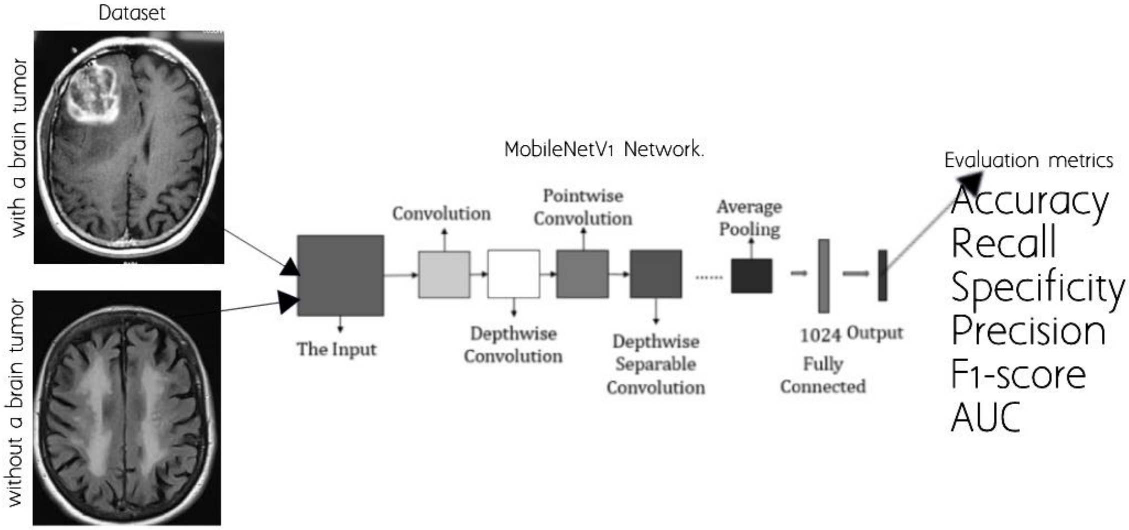

Fig. 4. Work mechanism stages.

The effects of this analysis are presented in Figure 5, which shows TP = 96, FN = 3, FP = 6, and TN = 148. Table 1 displays the evaluation metrics obtained from training the model five times using a cross-validation value ($k = 5$). The model's ability to classify disease and identify tumor and no-tumor images is reflected in its ability to make 244 correct predictions and 9 incorrect predictions. The model's performance is illustrated in Figure 6, which shows a histogram with a standard deviation. Additionally, Figure 7 displays the model's ability to distinguish between the two classes (tumor and no-tumor), as indicated by the impressive AUC score of 97%.

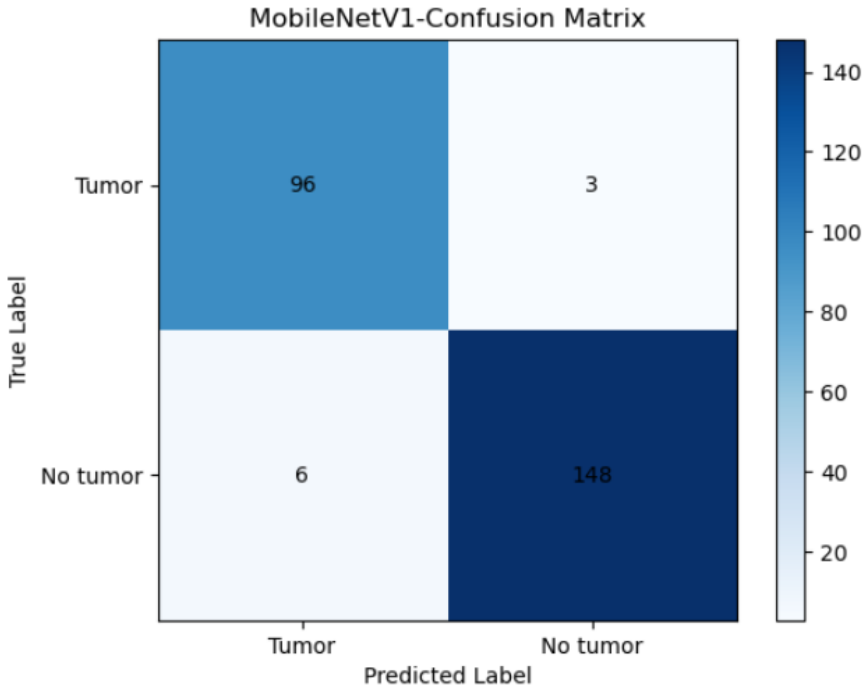

Fig. 5. Confusion matrix

TABLE I. PERFORMANCE RESULTS

Evaluation Matrix						
MobileNetV1 Model	Accuracy±std	Sensitivity ±std	Specificity±std	Precision±std	F1-score±std	AUC
	0.973 ± 0.009	0.970 ± 0.022	0.961 ± 0.014	0.941 ±0.045	0.955±0.032	97%
Training Time: 113866.89 second						

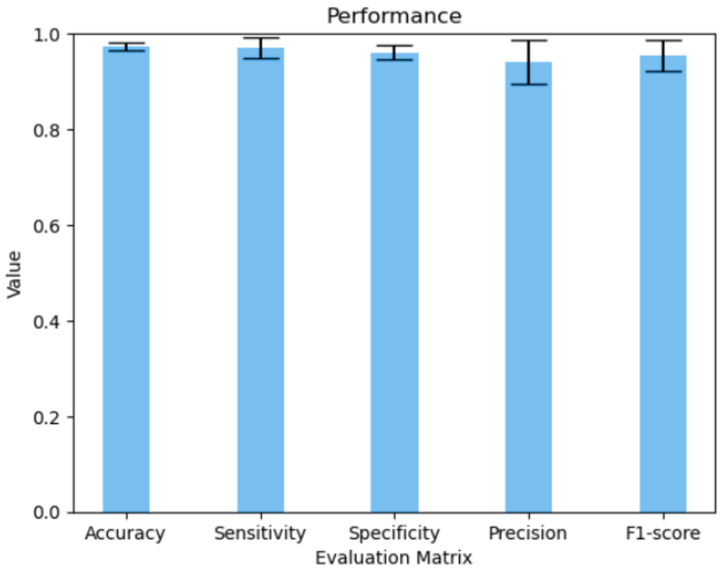

Fig. 6. Performance results with standard deviation

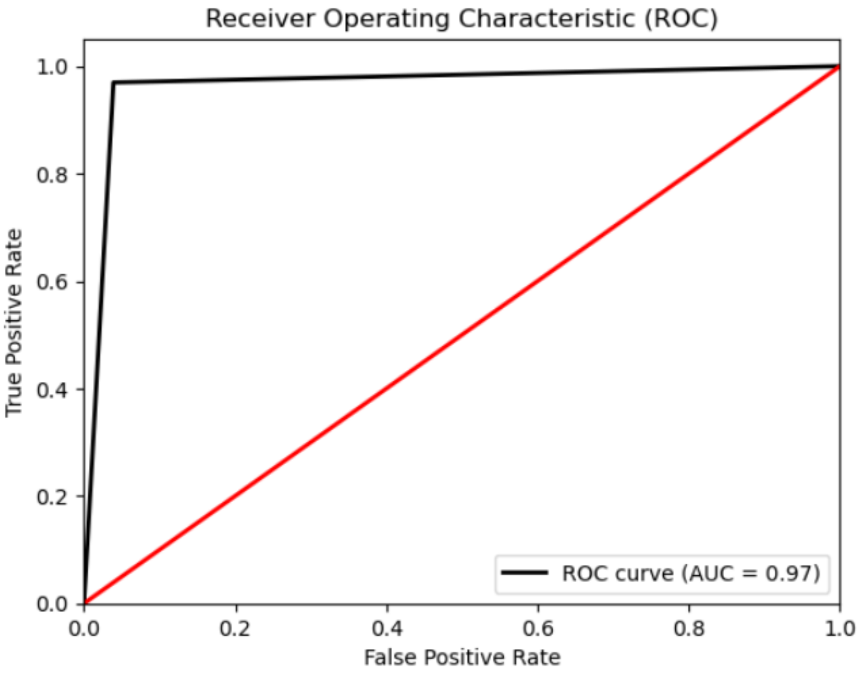

Fig. 7. AUC-ROC result

5. CONCLUSION AND FUTURE WORK

In this article, the MobileNetV1 model is utilized to predict brain tumor disease through more than 250 images taken from the Kaggle platform. This model's practice was studied through an evaluation metrics and the ability to separate between classes (tumor and no-tumor). After completing the experiments, it was found that the model's performance has a remarkable ability to make the correct diagnosis, as it reached an accuracy of more than 97%. In addition, it has excellent potential in separating between categories, as it achieved a separation result of more than 97%. The results of the other metrics, where the sensitivity reached 97%, the specificity was over 96%, Precision exceeded 94%, and the F1-score surpassed 95%. In future research, another experiment will be conducted using the MobileNetV2 and MobileNetV3 models and studying their practices in analyzing the same dataset and making comparisons.

Funding

The paper states that the author independently carried out the research without any financial support from institutions or sponsors.

Conflicts of Interest

No potential conflicts of interest with funding sources, organizations, or individuals are disclosed in the paper.

Acknowledgment

The author extends gratitude to the institution for fostering a collaborative atmosphere that enhanced the quality of this research.

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