

Automated Brain Tumor Detection Using Hybrid Machine Learning Models

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Abstract. Brain tumors are among the most dangerous and life-threatening neurological diseases, and early detection is essential for successful treatment and improved patient survival. Magnetic resonance imaging (MRI) is the most widely used modality for the rapid diagnosis of brain tumors, but the accurate segmentation and interpretation of MRI images remain challenging. Deep learning (DL) has recently brought significant progress in the identification and categorization of brain tumors. This paper proposes a hybrid machine learning model for brain tumor detection in which a pretrained MobileNetV2 convolutional neural network (CNN) extracts deep features from MRI images and a linear support vector machine (SVM) classifies them into four classes: glioma, meningioma, pituitary tumor, and no tumor. The performance of the model is reported with class-wise precision and recall and a confusion matrix.

Keywords. Brain tumor detection; classification; support vector machine; convolutional neural network; MobileNetV2; hybrid machine learning models

I. INTRODUCTION

Brain tumors are among the most serious neurological disorders. Depending on their site and nature, they are classified as primary or secondary and as benign or malignant. Malignant tumors can grow at an uncontrolled rate and destroy the surrounding tissue, which greatly reduces the patient's chance of survival if the tumor is not diagnosed early [1]. Magnetic resonance imaging (MRI) is one of the most accurate noninvasive tools for brain tumor detection because of its superior soft-tissue contrast and detailed anatomical information, but reading MRI scans is a time-consuming and subjective process that depends heavily on the expertise of radiologists. The volume of medical images produced by hospitals has grown sharply in recent years, and clinicians need support to review these images for brain tumors quickly and without error. Computer-aided diagnosis (CAD) systems have therefore been proposed to meet this need [2].

Traditional machine learning (ML) methods, such as the support vector machine (SVM), k -nearest neighbors (kNN), decision trees (DT), and artificial neural networks (ANN), are widely used to classify brain tumors, but they rely on handcrafted features. To overcome this limitation, deep learning (DL), and in particular the convolutional neural network (CNN), has attracted considerable attention because it can extract features directly from raw medical images [3]. Recent studies have presented hybrid DL architectures that combine a CNN with conventional classifiers such as the SVM and kNN, and other models combine

ensemble learning with several CNN architectures and long short-term memory (LSTM) networks [4].

Building on these studies, this paper proposes a hybrid architecture for the early detection and classification of brain tumors from MRI images. The architecture combines DL feature extraction with an effective classical classifier to achieve precise and reliable brain tumor identification, and it is compared with other ML, DL, and transfer learning approaches [5].

II. LITERATURE REVIEW

Several studies have addressed brain tumor detection with hybrid methods, and representative examples are summarized in Table 1. A hybrid method for tumor localization proposed in [2] combined clustering-based image segmentation with optimization. That study used k -nearest neighbors and k -means clustering, with the firefly algorithm optimizing the parameters, and a multilayer feedforward neural network labeled and classified the tumors. The method showed excellent accuracy and sensitivity compared with other image clustering techniques.

III. METHODOLOGY

The proposed method combines a linear SVM with the MobileNetV2 network.

A. Dataset Description

The dataset was collected from public repositories and contains brain MRI images. Fig. 1 shows examples of the tumor and non-tumor samples. The data are divided into a

TABLE 1. BRAIN TUMOR DETECTION STUDIES REVIEWED

Ref.	Year	Study	Techniques used	Accuracy
[6]	2025	BrainAR: automated brain tumor diagnosis with DL and 3D AR visualization	3D Residual U-Net + augmented reality	88.6%
[1]	2025	Transforming brain tumor detection using vision transformers and EfficientNetV2	EfficientNetV2 + vision transformer	96%
[3]	2022	Brain tumor classification and detection (<i>Electronics</i>)	Deep CNN	98%
	2021	CNN-based brain tumor detection	CNN classification	96%
	2024	MobileNetV2 hybrid study	MobileNetV2 + SVM	AUC 0.97 to 1.0
[7]	2025	Brain tumor classification based on optimized JGI-RNN	JGI-RNN	99%
[4]	2023	Brain tumor detection using machine learning hybrid approach	CNN + GoogLeNet-based model	99%

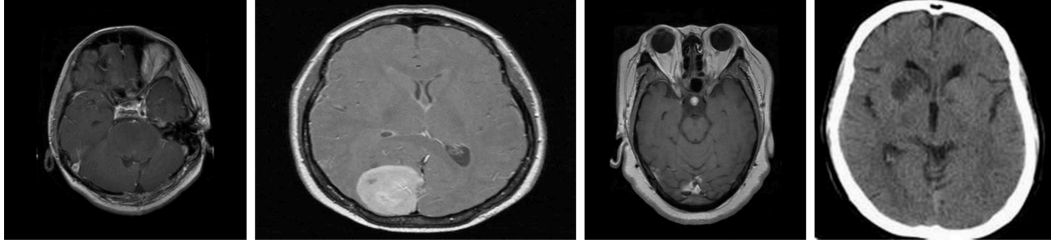


Fig. 1. Sample brain images from the dataset showing tumor and non-tumor cases.

training set and a separate test set so that the model is evaluated on unseen images, which confirms that it generalizes to new data rather than memorizing the training images.

B. Data Preprocessing

Data preprocessing standardizes the brain tumor images and prepares them for efficient model training. The MRI images of the four classes were first read with the OpenCV library. The original images had various resolutions, such as 512×512 and 350×350 pixels, and irregular shapes, so all images were resized to a standard resolution of $224 \times 224 \times 3$. The dataset is organized in class-wise folders, each representing one tumor type, and during preprocessing each image was assigned a numerical label according to its folder name. The images were then converted to NumPy format for efficient storage, giving arrays of $224 \times 224 \times 3$ images with one label per image. The training set contained 1,421 glioma, 1,239 meningioma, 1,695 non-tumor, and 1,457 pituitary images, and the test set contained 306 glioma, 300 meningioma, 300 non-tumor, and 405 pituitary images (1,311 test images in total). This preprocessing converts heterogeneous MRI inputs into a standard form while preserving their class information.

C. Feature Extraction

Feature extraction transforms the preprocessed MRI images into numerical representations that can be supplied to ML models. Deep features were extracted with a MobileNetV2 CNN pretrained on the ImageNet dataset. The classification layers of the pretrained network were removed by setting the `include_top` parameter to False [7]. For an input image $I \in \mathbb{R}^{224 \times 224 \times 3}$, the network applies a series of standard and depthwise separable convolutions to learn a hierarchical representation of tumor structures. Each convolution can be written as

$$F_{i,j,k} = \sum_{m,n,c} W_{m,n,c,k} \cdot I_{i+m,j+n,c} + b_k, \quad (1)$$

where W denotes the weights of the convolutional kernel, b is the bias term, and F is the resulting feature map. MobileNetV2 uses depthwise separable convolution, which reduces the computational cost by splitting a standard convolutional layer into two operations:

$$Y = PW(DW(X)), \quad (2)$$

where $DW(\cdot)$ and $PW(\cdot)$ denote depthwise and pointwise convolution, respectively. This structure extracts both local texture features and global structural characteristics from brain MRI scans efficiently. Before feature extraction, the images were converted from BGR to RGB, resized to 224×224 pixels, and normalized with the MobileNetV2 preprocessing function

$$I' = \frac{I - \mu}{\sigma}, \quad (3)$$

where I' is the normalized input and μ and σ are the scaling parameters used in ImageNet training. The output of the last convolutional block is a high-level feature map, which is reshaped into a one-dimensional feature vector:

$$f = \text{Flatten}(F). \quad (4)$$

Each image yielded a 62,720-dimensional feature vector, so the test feature matrix had the shape (1311, 62720). These deep features capture spatial information on tumor texture, shape, and intensity.

IV. PROPOSED ARCHITECTURE

The proposed architecture combines a deep CNN with an ML classifier in a hybrid brain tumor classification framework. In the overall system, preprocessed $224 \times 224 \times 3$ images are fed to the MobileNetV2 backbone, and instead of the usual neural network output layer, the extracted feature vectors are passed to an SVM classifier. The SVM acts as the final decision maker and separates the tumor categories in the extracted feature space. This integration of MobileNetV2 and the SVM combines the power of deep feature extraction with the strong generalization capability of classical ML methods.

V. ALGORITHM OF THE MODEL

In the proposed hybrid model, MobileNetV2 extracts features from the MRI images and a linear SVM classifies them. The procedure is given in Algorithm 1.

ALGORITHM 1. PSEUDOCODE OF THE PROPOSED HYBRID MODEL

Input: preprocessed MRI training and test sets

Output: trained SVM model, predicted labels, and evaluation report

- 1: Load the preprocessed MRI training and test datasets
- 2: Initialize the pretrained MobileNetV2 model with ImageNet weights; set *include_top* = False to use it as a feature extractor
- 3: **for** each image in the dataset **do**
- 4: Resize the image to 224 × 224 pixels
- 5: Apply MobileNetV2 preprocessing
- 6: Pass the image through MobileNetV2 and extract the deep feature maps
- 7: Flatten the feature maps into a feature vector f
- 8: **end for**
- 9: Construct the training feature matrix X_{train} and the test feature matrix X_{test}
- 10: Initialize a linear SVM
- 11: Training: fit the SVM on X_{train} and the labels y_{train}
- 12: Prediction: predict the class labels y_{pred} for X_{test}
- 13: Evaluation: compute the accuracy, the classification report (precision, recall, and F1-score), and the confusion matrix
- 14: Save the trained SVM model for future inference

VI. RESULTS AND COMPARISON

A. Evaluation Measures

The proposed hybrid classifier was assessed with standard evaluation measures: accuracy, precision, recall, and F1-score. Accuracy is the proportion of all samples that are predicted correctly. Precision is the proportion of positive predictions that are correct, and recall is the proportion of actual positive samples that are correctly identified. The F1-score is the harmonic mean of precision and recall. These measures are widely used in medical image classification because together they give an overall view of classification performance [7].

B. Performance Analysis

All experiments were run on the proposed hybrid architecture, which combines MobileNetV2 with a linear SVM classifier. The class-wise recall and precision are given in Table 2.

TABLE 2. PERFORMANCE OF THE PROPOSED HYBRID MODEL (MOBILENETV2 + SVM)

Tumor type	Recall (%)	Precision (%)
Glioma	96.8	96.5
Meningioma	95.9	96.2
Pituitary	97.5	97.1
Non-tumor	98.2	98.4

C. Confusion Matrix

Fig. 2 shows the confusion matrix of the hybrid model (MobileNetV2 + SVM) on the 1,311 test images. Of these, 1,267 (96.6%) were classified correctly; the largest source of error was 26 meningioma images predicted as glioma.

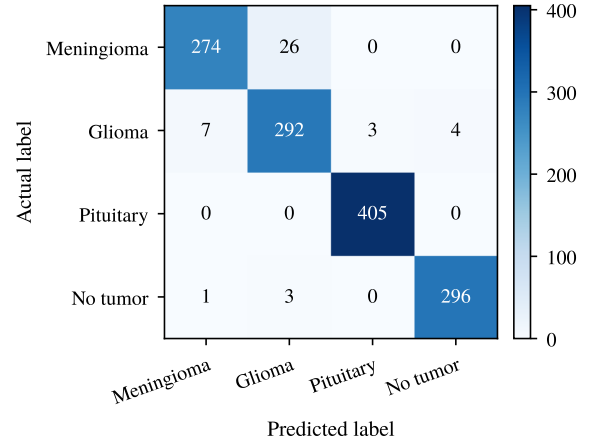


Fig. 2. Confusion matrix of the linear SVM model.

VII. CONCLUSION

This work introduced a combined framework that identifies and categorizes brain tumors in MRI scans by linking MobileNetV2 with an SVM. The convolutional network captures informative patterns from the MRI data, and the extracted features are passed to the classifier, which assigns the category. On the test set, 1,267 of 1,311 images (96.6%) were classified correctly according to the confusion matrix, and the class-wise recall and precision in Table 2 ranged from 95.9% to 98.4%. Most misclassifications occurred between meningioma and glioma.

AUTHOR CONTRIBUTIONS

All authors contributed to the conception and preparation of this work and approved the final version of the manuscript.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

DECLARATION OF GENERATIVE AI USE

The authors declare that no generative artificial intelligence tools were used in the preparation of this manuscript. The authors take full responsibility for the content of the publication.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

This study used publicly available, de-identified data and did not involve direct interaction with human participants or animals; ethical approval was therefore not required.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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