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Research Paper

MRI görüntüleri üzerinde Derin CNN'ler ve Topluluk Algoritmalarını Kullanarak Beyin Tümörü Tespiti

Brain Tumor Detection using Deep CNNs and Ensemble Algorithms over MRI Images

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Özetçe— Beyin tümörleri insan ölümünün en yaygın nedenlerinden biridir. Beyin tümörlerinin erken ve doğru tanısı etkili tedavi için önemlidir. Bilgisayarlı tomografi, manyetik rezonans görüntüleme, röntgen ve ultrason gibi görüntüleme teknikleri, hastalıkların tanı ve tedavisi alanında uzman kişiler için bir ön referans görevi görmektedir. Sağlık alanında hastalıkların erken teşhisi ve uzman yoğunluğunun azaltılması, tümör tespitininde yapılabilecek hataların en aza indirilmesi amacıyla farklı öğrenme teknikleri kullanılmaktadır. Son yıllarda makine öğrenmesi ve derin öğrenme modellerinin gelişmesiyle birlikte beyin araştırmalarında görüntü işleme çalışmalarında başarılı sonuçlar alınmaya başlanmıştır. Bu çalışmada, MRI görüntülerinden özellik çıkarmak için önceden eğitilmiş derin evrişim sinir ağı yöntemleri, tümörü tespit etmek için topluluk öğrenme kullanıldı. Analiz sonuçları, beyin tümörlerini tespit etmek için önceden eğitilmiş derin ağlara sahip topluluk tabanlı sınıflandırıcı kullanılarak %100 doğruluk puanına ulaşıldığını göstermektedir.
Anahtar Kelimeler : *Tümör tespiti, özellik çıkartma, makine öğrenmesi.*

Abstract— Brain tumors are one of the most common causes of human death. Early and accurate diagnosis of brain tumors is essential for effective treatment. Imaging techniques such as computed tomography, magnetic resonance imaging, X-ray, and Ultrasound serve as a preliminary reference for experts in field of the diagnosis and treatment of diseases. Different learning techniques have been used in the field of health to diagnose diseases early and reduce the intensity of experts, as well as to minimize errors that may be made in diagnosis. In recent years, successful results have begun to be obtained in image processing studies in brain research, with the development of machine learning and deep learning models. In this study, pretrained deep convolution neural network methods are used to feature extraction from MRI images, and ensemble learning is used to detect the tumor. Analysis results show a 100% accuracy score was achieved using the ensemble-based classifier with the pretrained deep networks to detect brain tumors.
Keywords : *Tumor detection, feature extraction, machine learning.*

1. Introduction

Brain tumor consists of abnormally growing tissues resulting from the uncontrolled proliferation of cells inside the skull. This disease is defined as an unexpectedly elevated cluster of brain cells that can severely impair the central nervous system, which is a life-threatening fatal disease. It has general symptoms of brain tumors but the causes of brain tumors are not fully known. According to the latest data of the World Health Organization, brain tumor is one of the most common types of cancer death worldwide and can occur at any age. It causes more deaths, especially for people who are under the age of 40 (WHO, 2021). Brain tumors are described as primary and secondary brain tumors. Primary brain tumors are benign and do not spread to other parts of the brain. Secondary brain tumors are malignant, they occur when cancer cells spread to the brain from other organs such as the lung or breast.

The choice of imaging technique varies depending on the symptoms observed, the area examined, and the cost and availability of the method. Different imaging techniques are used to assist experts in identifying various medical problems and anomalies such as positron emission tomography, single photon emission computed tomography, computed tomography, magnetic resonance imaging(MRI), magnetic resonance spectroscopy, and computed tomography (CT). Among these, MRI is the most used technique to obtain high-quality images of the examined body parts (Kidwell and Hsia, 2006). MRI is a radiology method that uses radiofrequency waves and a computer with a strong magnetic field to produce images of organs, soft tissues, bones, and other body structures. Neurosurgeons use it extensively to provide them with enough information to detect the smallest abnormalities in the brain.

Early diagnosis of brain tumors is crucial for the treatment and the survival of patients. For this reason, the MRI images should be evaluated quickly and accurately. Some symptoms could be confused, such as headache, vomiting, eye abnormalities or diplopia, drowsiness, difficulty swallowing, personality or behavior changes, and hand tremors usually in this disease. Manual controls by radiologists and doctors can be both time-consuming and cause erroneous decisions. For this reason, it is very important to develop computer-aided automatic detection systems that can help radiologists and doctors to diagnose brain tumors.

2. Research Motivation and Literature Survey

The goal of tumor detection is to identify the presence or absence of a tumor using MRI image databases. Factors such as the increasing number of patients, tumors of different shapes and sizes, and the fact that they can be found in different parts of the brain and make the process of diagnosing tumors more complicated for experts. So, it takes a long time for experts to manually diagnose brain tumors. Early diagnosis of the tumor plays an important role in increasing treatment opportunities and survival rates of patients. For this reason, the use of computer-aided systems to reduce the time spent by experts in the early diagnosis of brain tumors, and making improvements in this field have become the main focus of many studies. Brain tumor detection in MRI images can be done using traditional machine learning methods or deep learning techniques. In recent years, remarkable advances have been made in numerous studies aimed at processing medical images and diagnosing brain tumors. Mohsen et al. proposed a new method to classify brain tumors using deep learning methods and the Discrete Wavelet Transform (DWT) model. In experimental studies, they achieved 93.94% accuracy with this model (Mohsen et al., 2018). Vani et al. proposed a machine learning-based, Support Vector Machine (SVM) method to classify brain tumors. They stated that they predicted brain tumors positively and negatively with an accuracy of 82% and 81.48%, respectively (Vani et al., 2017). Shahzadi et al. used the ESA-based hybrid model construct to detect brain tumors. Feature extraction and classification used the Long Short-Term Memory (LSTM) structure together with the AlexNet and VggNet ESA models. In the study, they achieved 71% accuracy with AlexNet-LSTM and 84% accuracy with VGGNet-LSTM (Shahzadi et al., 2018). Swati et al. proposed transfer learning for the multiclass classification of brain tumors. For this purpose, AlexNet used ESA models VGG16 and VGG19. In experimental studies, AlexNet achieved accuracy rates of 89.95%, 94.65%, and 94.82% in VGG16 and VGG19 models, respectively (Swati et al., 2019). Rammurthy, and Mahesh proposed a method Whale Harris Hawks optimization (WHHO) based on deep convolutional neural network (DCNN). Their method gave an 81.6% accuracy for detecting tumor (Rammurthy, and Mahesh, 2022). Nayak et al., performed an algorithm based on DWT and DCNN. In experimental studies, the brain tumors were detected with accuracy, as 97% (Nayak et al., 2022). Pendela et al., proposed an approach based Exponential Deer Hunting Optimization (ExpDHO), Shepard convolutional neural network (ShCNN), deep convolutional neural network (DCNN), Exponential weighted moving average (EWMA) and they detected the tumor with 91.7% accuracy (Pendela et al., 2023). Qin et al., proposed a hybrid algorithm based on Shared-memory parallel (SPM), Stochastic gradient descent (SGC), Histogram of Oriented Gradient (HOG), and SVM. Their algorithm achieved an accuracy rate of 97.71% for detecting of tumor (Qin et al., 2023).

The most important feature that distinguishes deep learning architectures from traditional artificial neural network models is the ability to create a feature map of the data within the layers within deep networks. With these architectures, it is possible to analyze the feature maps obtained by applying filters of different sizes and numbers in the data. In this study, deep learning and ensemble learning were combined and it was aimed to develop hybrid models that can adapt to various data types and problems. Among the deep learning algorithms, ResNet and DenseNet are used to extract features from MRI images, as pretrained deep neural networks. The concept has been developed within the ResNet structure, in which the merging process is performed by skipping a layer between the inputs of the previous network and the outputs of the next network. This process is called the residual block. The main purpose of this block is to minimize data loss and ensure the model's reliability by continuing to process with the previous values even if there are zero values in the intermediate values. Also, it prevents the loss of gradients that enable learning. In this study, different image pre-processing algorithms are performed to extract the features from MRI. Image data augmentation involves creating transformed versions of images belonging to the same class as the original image. Before feature extraction, data augmentation was performed to increase the generalization ability of the model. As a classifier, ensemble learning was used. They use different models together, balancing the different faults and strengths of each model. This diversity improves the overall performance of the community. It also reduces fluctuations in the performance of a single model. This enables more stable and reliable predictions to be obtained. Ensemble models reduce the risk of overfitting individual models, using bagging and boosting. Ensemble models can detect and correct errors in the individual models. This reduces the error rate and improves the performance of the overall model. After obtaining features from MRI, ensemble learning-based boosting methods with decision trees were performed to detect the tumors. The main structure of the proposed algorithm is given in Figure 1.

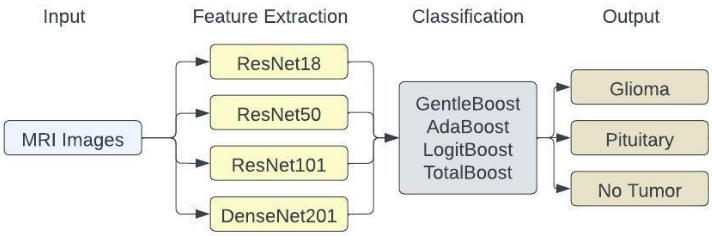

Figure 1. The main structure of the proposed algorithm

3. Material and Method

3.1. Convolutional Neural Network

The convolutional neural network (CNN) is built on a multi-layer network topology. Yann LeCun introduced this network architecture in 1998, calling it LeNet. It filters the pixel matrices of the photos and automatically extracts distinguishing characteristics. Deep neural networks are built around the convolution layer. The convolution layer produces an improved feature representation by combining the phases of convolution, activation function, and pooling to extract low-dimensional features from high-dimensional input. (Wei et al., 2018). The classification layer matches low-dimensional features and categories and is often a fully connected neural network. These layers enable the CNN to understand patterns and deal with associated issues (Bishop, 1995, 2006, 2010; Yasrab et al., 2017; Patterson and Gibson, 2017; Ozer, 2023). CNNs enable the extraction of features from high-dimensional data. Of the pretrained deep neural networks, Residual Neural Network (ResNet) and Dense Convolutional Network (DenseNet) are explained as follows:

Residual Neural Network

Residual Neural Network (ResNet) is a CNN model that achieved extremely successful results in The ImageNet Large Scale Visual Recognition Challenge in 2015. The residual post-connection layer output formula is shown in the following equation (He, et al., 2016).

$$H(x) = f(wx + b) + x \tag{1}$$

where x is layer input, f is activation function, and b is bias. The building block for residual learning is shown in Figure 2.

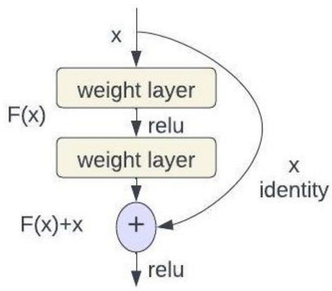

Figure 2. Residual learning: a building block

$$F(x) = H(x) - x \tag{2}$$

$$y = F(x) + x \tag{3}$$

In the above equations, $F(x)$ and y are the residual function and output, respectively. The straight line that carries the layer input (x) to the layer output is called the residual connection, which may bypass one or more layers. Inputs in residual blocks can propagate more quickly over connections between layers. Additionally, skipping layers makes it easier to learn similar mappings in the network. As the number of layers increases and the network begins to deepen, the performance of CNN models begins to decrease. To solve this situation, block-based CNN models have now been developed. ResNet's general architecture is shown in Figure 3 (He et al., 2016):

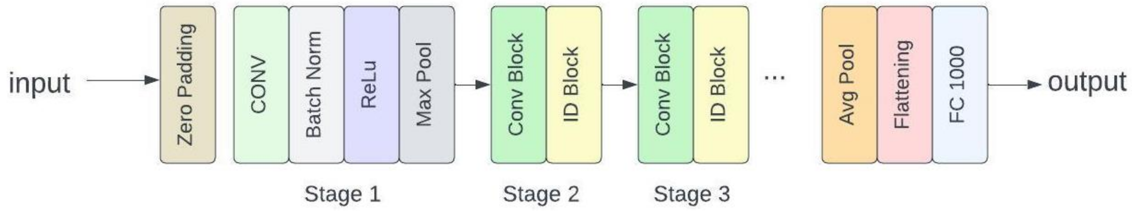

Figure 3. ResNet Structure

There are different pretrained networks, such as ResNet18, ResNet50, and ResNet101. To avoid overfitting, ResNet consists of many residual blocks, where they are placed on top of each other. All blocks consist of convolution and pooling layers and work by receiving input images of 224x224 pixels (He, et al., 2016). While the ResNet18 model has 18 layers, the ResNet50 and ResNet101 CNN models consist of 50 and 101 layers, respectively (Dong, et al., 2019).

Dense Convolutional Network

A Dense Convolutional Network (DenseNet) consists of several dense and transition blocks placed between adjacent dense blocks. The main feature of the architecture, which was developed by Gao Huang et al., in 2018 and consists of densely connected CNN layers, is that the outputs of each layer are connected to all successive layers in dense blocks (Gao et al., 2018). DenseNet accepts 224x224 pixel images as input. Its general architecture is shown in Figure 5.

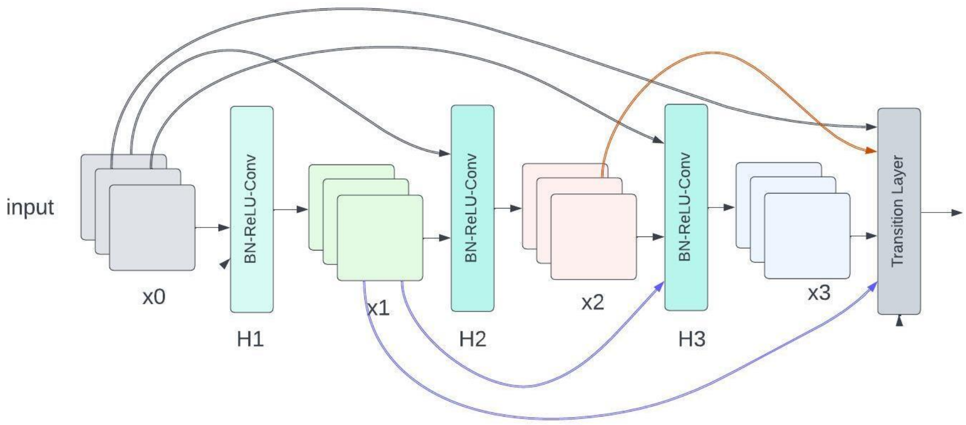

Figure 4. A 4-layer dense block with a growth rate of k=3. Each layer takes all preceding feature maps as input

As can be seen from Figure 4, the last layer, the processing layer, contains feature maps from all previous layers.

3.2. Ensemble Learning

Ensemble learning (EL) is a method for combining numerous models with the goal of improving the model's prediction performance. The ensemble learning approach combines many machine learning algorithms to provide better classification or prediction results than a single algorithm. Several methods have been developed to train ensemble classifiers. Bagging (aggregation), boosting (Adaptive Boosting, Gentle Boosting, Logit Boosting), and stacking are the most often used ensemble learning methods. Boosting, for example, uses a majority vote approach to unify a group of weak classifiers (Polikar 2012). This approach aims to generate strong classifiers from weak classifiers with low training errors. EL can handle with high-dimensional and complicated data structures, reducing variation and providing more accurate results (Bauer and Kohavi, 1998). The following algorithm gives the AdaBoost:

Input: $D = \{d_1, d_2, \dots, d_n\}$ and $d_i = (x_i, y_i)$ $x_i \epsilon X$ and $y_i \epsilon \{y_1, y_2, \dots, y_M\}$
M: maximum number of classifiers
Output: O is the classifier, $O: X \to \{y_1, y_2, \dots, y_M\}$
Algorithm:

1. Initialize the weights $w_i^1 = \frac{1}{N}$ $i\epsilon\{1, 2, \dots, N\}$
2. For $m = 1$ to M, calculate the following metrics:

- $Error_m = \sum_{i=1}^{N} w_i^m h(-y_i O_M(x_i))$ ($Error_m$ is the weighted error for O_m)
- $a_m = \frac{1}{2} log \frac{1-error_m}{error_m}$ (a_m is the weight of weak learners)
- $v_i^m = w_i^m \exp(-a_m y_i O_m(x_i))$ (Updating the weights)
- $S_m = \sum_{j=1}^{N} v_j$ and $w_i^{m+1} = v_i^m / S_m$ (Normalizing the weights)

3. $O(x) = sign \sum_{j=1}^{M} a_j O_j(x)$ (Calculating the last classifier)

The ensemble learning method's success is determined by the various mistakes and predictions made by the model's classifiers. The main advantage of this technique is its low complexity, which is excellent for both learning and categorizing material and makes it easy to grasp what is being taught. The decision tree (DT) is a classification method that involves repeatedly partitioning the information into smaller groupings. The DT's non-parametric character eliminates the need for assumptions about the dataset's distribution. It can handle group and numeric datasets, as well as missing values identified in the dataset.

3.3. Performance Metrics

Different machine learning models are created using different hyperparameters. Evaluation metrics are needed to measure which models will give better results. Evaluation metrics provide information about the success of the prediction made by the model used by comparing the predictions obtained from the model with the actual results. In this work, the following evaluation criteria were used the model's accuracy, sensitivity, specificity, precision, False Positive Rate, F1 Score, and Matthews Correlation Coefficient. All formula is given in the following table.

Table 1. The formula of Evaluation Metrics

Evaluation Metrics	Formula
Accuracy	(TP+TN)/(TP+TN+FP+FN)
Sensitivity	TP/(TP+FN)
Specificity	TN/(TN+FP)
Precision	TP/(TP+FP)
F1_score	2*(Precision*Sensitivity)/(Precision+Sensitivity)
Matthews Correlation Coefficient	(TP*TN – FP*FN) /√(TP+FP)(TP+FN)(TN+FP)(TN+FN)

True positives (TP): correctly predicted examples belonging to the positive class.
True negatives (TN): samples that are correctly predicted to belong to the negative class.
False positives (FP): samples predicted as positive that are from the negative class.
False negatives (FN): samples predicted as negative whose true class is positive.

4. Analysis

4.1. Dataset

The dataset includes three different classes patterns from MRI, which are glioma, pituitary, and no tumor. Glioma, pituitary, and no tumor files have 1621, 1757, and 2000 MRI images, respectively. Detailed information can be found at (Nickparvar, 2021). Some images are seen in Figure 5.

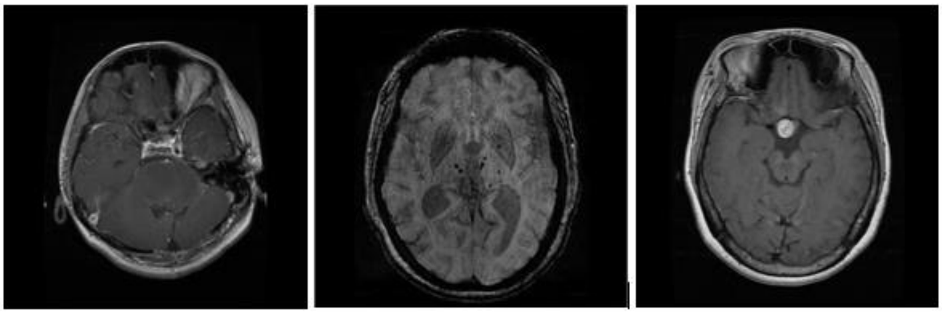

Figure 5. MRI images from the dataset, glioma, pituitary and no tumor, respectively

4.2. Analyses

All image sizes were 224 × 224 pixels in RGB format, for ResNet18, ResNet50, ResNet101, and DenseNet 201. Resnet and DenseNet are pre-trained models by obtaining images from enormous data sets. The pooling layer, which is the layer before the last classifier layer (fully connected) of these models, was used for feature extraction. Features were obtained by giving MRI images to this layer. The same process was repeated for the Glioma, Pituitary, and No Tumor classes.

All data sets have different sizes. To handle unbalanced data distribution, the size of the smallest data set was set as the common size. The data were randomly divided into training and testing datasets with 0.8 and 0.2 ratios. Ensemble learning architecture analysis necessitates extensive data, yet processing such large volumes can be time-consuming and lead to memory overload. To address this, batch size was utilized, representing the number of sub-samples fed to the network for each parameter update. Different batch sizes were performed (from 4 to 2048), but the best results were obtained when the batch size was 1024 and 512 for GentleBoost and AdaBoost, respectively. The model parameters were derived using the training dataset. Hyperparameters play a crucial role in influencing the performance of predictive models. As weak learners, decision trees and k-nearest neighbors were performed with boosting algorithms. Decision trees' performances were better than k-nearest neighbors. Different hyperparameters were performed during training procedures. But the following hyperparameters gave the best result as in the explained next section:

- Boosting: GentleBoost, Weak Learner: Decision Tree, Learning Rate: 0.9, Leaf Size:10, Max. Tree Depth:5, Number of Learners: 500
- Boosting: AdaBoost, Weak Learner: Decision Tree, Learning Rate: 0.5, Leaf Size:10, Max. Tree Depth:5, Number of Learners: 500

The proposed algorithm in this work is shown in Figure 6.

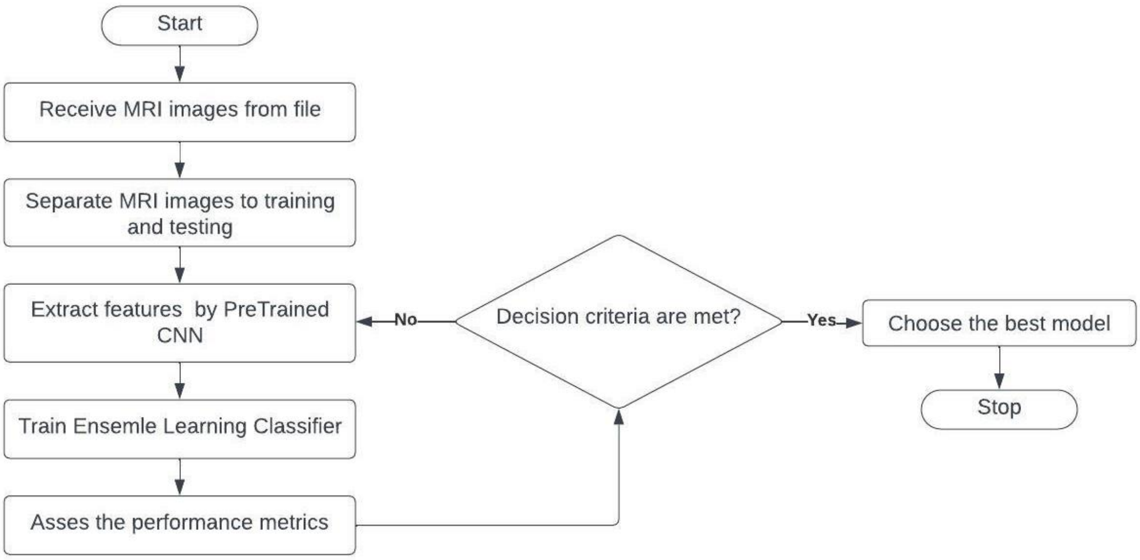

Figure 6. The proposed algorithm

4.3. Results

In this study, the features were extracted from MRI images using different deep pretrained deep CNN structures. The obtained features were trained with GentleBoost, AdaBoost, LogitBoost, and TotalBoost ensemble learning methods and decision trees. The model parameters were obtained with train data. To determine whether there was overfitting, the obtained model was processed with test data. From test data, evaluation metrics were calculated to determine the best model, among all models. This process was carried out for different parameters of the proposed ensemble learning algorithms. The model providing the highest accuracy was determined. Since GentleBoost and AdaBoost gave better results than other boosting algorithms, the comparative performances of the results are given in Table 2 for the two boosting algorithms. The successful discrimination rates of the 3 classes based on different metrics with Ensemble learning on the test data are given in the table below.

Table 2. The performance of the GentleBoost and AdaBoost algorithms with different pretrained algorithms.

Pre-trained Algorithm	Evaluation Metrics	GentleBoost			AdaBoost		
		Glioma	Pituitary	No Tumor	Glioma	Pituitary	No Tumor
ResNet18	Accuracy	98,8	99,1	99,1	98,8	99,1	99,1
	Sensitivity	98,8	99,1	99,1	98,8	99,1	99,1
	Specificity	99,7	99,1	99,7	99,7	99,1	99,7
	Precision	99,4	98,2	99,4	99,4	98,2	99,4
	F1 Score	99,1	98,6	99,2	99,1	98,6	99,2
	MCC	98,6	97,9	98,8	98,6	97,9	98,8
ResNet50	Accuracy	***100,0***	99,1	99,7	99,1	99,7	98,5
	Sensitivity	***100,0***	99,1	99,7	99,1	99,7	98,5
	Specificity	***99,4***	100,0	100,0	99,8	98,8	100,0
	Precision	***98,8***	100,0	100,0	99,7	97,6	100,0
	F1 Score	***99,4***	99,5	99,8	99,4	98,6	99,2
	MCC	***99,1***	99,3	99,8	99,1	97,9	98,8
ResNet101	Accuracy	98,8	100,0	98,5	98,5	99,4	100,0
	Sensitivity	98,8	100,0	98,5	98,5	99,4	100,0
	Specificity	99,2	99,4	100,0	99,8	99,2	99,8
	Precision	98,5	98,8	100,0	99,7	98,5	99,7
	F1 Score	98,6	99,4	99,2	99,1	98,9	99,8
	MCC	97,9	99,1	98,8	98,6	98,4	99,8
DenseNet201	Accuracy	99,4	98,8	99,4	99,1	98,1	98,8
	Sensitivity	99,4	98,8	99,4	99,1	98,1	98,8
	Specificity	99,5	99,5	99,7	99,2	99,1	99,7
	Precision	99,1	99,1	99,4	98,5	98,1	99,4
	F1 Score	99,2	98,9	99,4	98,8	98,1	99,1
	MCC	98,8	98,4	99,1	98,2	97,2	98,6

As can be seen from the tables above, to detect the brain tumor, the features, extracted by the ResNet50 (the 50-layer deep CNN) algorithm gives better results in classifier success than other pretrained algorithms. This algorithm enables feature extraction with fewer layers, so, it also provides a less complex model. Comparative results of some studies in the literature are given in the table below.

Table 3. The performances of existing approaches in the literature.

Autor's	Method	Performance
Vani et al., 2017	SVM	82%
Mohsen et al., 2018	DL, DWT	93.94%
Shahzadiet al., 2018	AlexNet, VGGNet, LSTM	84%
Swati et al., 2019	AlexNet, CNN	94.65%
Rammurthy, and Mahesh, 2022	WHHO, DCNN	81.6%
Nayak et al., 2022	DWT, DCNN	97%
Pendela ET AL., 2023	ExpDHO, ShCNN, DCNN, EWMA	91.7%
Qin et al., 2023	SMP, SGC, HOG, SVM	97.71%
This work	***ResNet, DenseNet, EL***	***100%***

DL: Deep Learning
CNN: Convolutional Neural Network
DWT: Discrete Wavelet Transform
ExpDHO:Exponential deer hunting optimization
ShCNN:Shepard convolutional neural network
Deep CNN: Deep Convolutional Neural Network
EWMA: Exponential weighted moving average
SMP:Shared-memory parallel
SGC:Stochastic gradient descent
HOG:Histogram of Oriented Gradient
SVM: Support vector machine
WHHO:Whale Harris Hawks optimization

5. Conclusions

Brain cancer is among the most common and fatal cancer types. Early diagnosis is very important in reducing death rates in brain tumors. For early diagnosis of brain cancer, in this study, the ResNet50 deep learning model and ensemble learning hybrid model are proposed. The proposed algorithm is based on the principle of working together with multiple classification algorithms. With the proposed algorithm, accuracy, sensitivity, specificity, precision, F1 Score, and Matthews Correlation Coefficient metrics are obtained as 100,0 %, 100,0%, 99,4%, 98,8%, 99,4%, and 99%, respectively. The best results were highlighted in bold and italic. When the results are evaluated, malignant (glioma) tumors with the ResNet 50 and GentleBoost, are detected with high success. In future studies, it is aimed to use ensemble models in real-time data. Therefore, as a first step, automatic model selection and optimization of hyperparameter settings for ensemble learning methods will be studied. In this way, it is planned to dynamically adjust model combinations and optimize according to the characteristics of the data or changes over time. Also, it will be evaluated that the proposed and developed methods are sufficiently reliable and can be used in other disease classifications and different imaging methods.

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Conflict of Interest

No conflict of interest to report.

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