

Research article

Improving brain tumor classification: An approach integrating pre-trained CNN models and machine learning algorithms

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ABSTRACT

Accurate detection of brain tumors is crucial for enhancing patient outcomes, yet the interpretation of Magnetic Resonance Imaging (MRI) scans poses significant challenges. This study introduces a novel approach to brain tumor classification by exploring three pre-trained convolutional neural network (CNN) models: DenseNet201, EfficientNetB5, and InceptionResNetV2, combined with softmax activation for feature extraction. These features are then subjected to Principal Component Analysis (PCA) for dimensionality reduction. Subsequently, three machine learning models—Support Vector Machine (SVM), Multi-layer Perceptron (MLP), and Gaussian Naive Bayes (GNB)—are employed for classification. The results reveal that DenseNet201, when combined with SVM and MLP, outperforms the other models in terms of accuracy, recall, and precision. Specifically, DenseNet201 achieves 100% accuracy, recall, and precision on Dataset-I and 98% accuracy, recall, and precision on Dataset-II when paired with SVM and MLP. This study provides valuable insights into the interplay between CNN models, feature extraction techniques, and machine learning algorithms for brain tumor classification, highlighting the efficacy of DenseNet201 combined with SVM and MLP.

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1. Introduction

Recently, advancements in computer vision-based medical imaging techniques have significantly improved the capabilities of medical professionals in diagnosis and treatment [1]. Various imaging modalities, including X-ray, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound, have demonstrated substantial success in healthcare applications [2]. These imaging techniques are extensively used for brain imaging analysis, diagnosis, and treatment.

Brain tumors, characterized by abnormal growth and uncontrolled cell division in the brain, pose serious health risks and can lead to fatal outcomes if not accurately detected [3]. Broadly, brain tumors are categorized into malignant (cancerous) and benign (noncancerous) types. The primary goal of tumor detection is to pinpoint the location and extent of the tumor area. This involves comparing abnormal areas in the brain with normal tissue to identify anomalies [4].

MRI is a widely adopted imaging modality for studying brain tumors, offering detailed views of the brain structure and abnormalities [5]. While both CT scans and MRI are used for brain tumor detection, MRI is often preferred due to its non-invasive nature and ability to produce high-resolution images. Brain MRI can be categorized into four modes: T1-weighted, T1-weighted contrast-enhanced, T2-weighted, and T2-weighted FLAIR, each highlighting different features of brain tumors [6].

In the existing literature, numerous automated methods have been proposed for brain tumor classification using MRI images. Over the years, support vector machine (SVM) and neural network (NN) based approaches have been widely adopted for brain tumor classification [7,8]. These methods aim to improve the accuracy and efficiency of brain tumor detection and classification, leveraging the distinctive features provided by MRI imaging modalities.

Machine learning (ML) techniques were previously at the forefront of tumor detection methods but often fell short in achieving high accuracy due to challenges with prediction models and the complex nature of medical data [9]. To address these limitations, researchers have increasingly turned to deep learning (DL), which has shown remarkable progress in predictive modeling using large datasets.

DL models, unlike traditional methods such as SVM and KNN, excel in capturing complex relationships within data without requiring an extensive number of nodes, leading to improved performance in medical imaging tasks [10,11]. Consequently, many researchers have developed computer-aided frameworks that leverage DL for medical image classification, producing impressive results.

In comparison to traditional diagnostic methods like histopathology, which involve manual examination of biopsy samples, transfer learning-based deep convolutional neural network (DCNN) frameworks offer a more efficient and less labor-intensive alternative. By leveraging transfer learning, DCNN frameworks can process brain MRI images more rapidly and accurately, facilitating quicker diagnosis procedures [12].

DCNN architectures have proven effective in detecting and classifying brain tumors due to their ability to generalize various levels of features. Furthermore, pre-processing techniques such as data augmentation and stain normalization contribute to the robustness and accuracy of DCNN models. However, the performance of DCNN architectures is highly dependent on the quality of the training data and process. To enhance accuracy and efficiency, transfer learning can be applied, either through fine-tuning the convolutional network or freezing specific network layers. By utilizing pre-trained models, the need to develop CNN models from scratch is eliminated, simplifying the classification task and improving overall performance.

This paper introduces an innovative approach for classifying brain tumors by integrating pre-trained CNN models with machine learning algorithms. The methodology encompasses several steps, including pre-processing, extracting image features, reducing the features for optimized machine learning tasks, training various models on the extracted features, and evaluating their performance on test data for classification accuracy. The primary contributions of this paper are as follows:

- Utilization of DenseNet201, EfficientNetB5, and InceptionResNetV2 CNN models to extract high-level patterns from brain tumor images.
- Implementation of techniques such as standardization and Principal Component Analysis (PCA) for dimensionality reduction to manage the high-dimensional nature of the extracted features. Two preprocessing approaches are employed: fixing dimensions and preserving a fixed percentage of data variance.
- Adoption of Support Vector Machines (SVM), Gaussian Naive Bayes (GNB), and Random Forest for analyzing the preprocessed feature datasets. Models are trained on the training dataset and evaluated using accuracy metrics, accounting for class balance.
- Presentation of accuracy results for each model on both preprocessing approaches, with GNB demonstrating the best overall performance. The extracted features from EfficientNetB5 and InceptionResNetV2 yield superior average results, suggesting the proficiency of InceptionResNetV2 in capturing essential image features.
- Emphasis on the significant correlation between the effectiveness of machine learning models and features derived from CNN models, with InceptionResNetV2 consistently showcasing superior performance. This underscores the critical role of feature extraction methods in achieving optimal model performance.
- The proposed approaches are rigorously examined using k-fold cross-validation on two distinct datasets. This validation method ensures the robustness and generalizability of the developed classification models.

The remainder of this paper is structured as follows: Section 2 provides a detailed overview of the related work in the field of brain tumor classification, highlighting the existing methodologies and their limitations. Section 3 elaborates on the proposed methodology, detailing each step from feature extraction to model evaluation. The results and discussions are presented in Section 4, followed by the conclusion and future work in Section 5.

2. Related works

Deep learning methods have gained significant recognition in the field of medical image analysis due to their capacity to deliver rapid and precise segmentation results. Among the various approaches in this field, Fully Convolutional Networks (FCNs) have emerged as a popular choice. First introduced by Long et al. [13], the FCN framework enables pixel-level semantic segmentation for inputs of any size by replacing the fully connected layer in a CNN model with a fully convolutional layer. It further employs deconvolution for feature map upsampling.

Despite its merits, FCN does have some limitations. The upsampling process can lead to a degradation of semantic content in the feature maps, and there is often underutilization of both global and local information due to challenges in exploiting image context and spatial location details. To overcome these challenges, Chen et al. [14] proposed a method that addresses the loss of fine-grained information by incorporating atrous convolution. This technique enhances the receptive field while minimizing the loss of details. Furthermore, the method utilizes Conditional Random Fields (CRF) [15] to enhance the ability to capture boundary features. It is built upon the VGGNet architecture, performing upsampling on the features and subsequently applying CRF to produce more precise segmentation results.

Deep neural networks have gained significant attention in the field of medical imaging [10]. Pei and Liu introduced a 3D ResUNet architecture for multimodal brain tumor segmentation using MRI data, achieving high Dice Similarity Coefficient (DSC) scores: 85.03% for enhancing tumor (ET), 81.96% for whole tumor (WT), and 91.95% for tumor core (TC) [4]. Another study by Sindhu et al. focused on improving brain tumor classification from MRI images. They utilized spectral angle-dependent feature extraction and Spectral Clustering Independent Component Analysis (SCICA) to categorize MRI images. Subsequently, Independent Component Analysis (ICA) and SVM were used for further analysis. The ICA-based SVM demonstrated remarkable accuracy: 98.1% for replicated lesions and 95.1% for non-replicated lesions on various MRI image types, including T1-weighted, T2-weighted, and proton-density fluid inversion recovery images [16].

Sumitra and Saxena [17] introduced an effective method for brain tumor detection in MRI images using a neural network (NN). This method comprises three main stages: feature extraction, dimensionality reduction, and classification. Feature extraction utilizes PCA to capture essential MRI features such as mean, median, variance, and intensity correlation values. A neural network classifier is then constructed and trained using back-propagation to categorize images into normal, benign, or malignant classes. The study results indicate that this NN classifier, specifically known as BPN, exhibits superior performance in terms of both processing time and accuracy. In a similar vein, Jafari and Shafaghi [18] proposed a hybrid approach for brain tumor tissue classification, integrating a genetic algorithm and a Support Vector Machine (SVM). Their approach involves four key stages: pre-processing, noise reduction, contrast enhancement, segmentation, and feature extraction for classification. Morphological methods are applied during the pre-processing stage to perform skull stripping.

Feature extraction involves utilizing a genetic algorithm to select features from various sources, including static features, Fourier and wavelet transform histograms, and their combinations. The SVM classifier is employed to process the chosen features, achieving a classification accuracy of 83.22% for distinguishing between normal and malignant images. Furthermore, Jayachandran and Dhanasekharan [19] presented a hybrid algorithm-based technique for brain tumor identification in MRI images by combining statistics and SVM classifiers. The technique commences with noise reduction in the image using an anisotropic filter, followed by feature extraction through a grey-level co-occurrence matrix. The extracted features are then subjected to dimensionality reduction using PCA. Ultimately, the reduced features are utilized as input for a Fuzzy Support Vector Machine (FSVM) classifier, which assesses whether the image is normal or abnormal. The achieved accuracy using this technique is approximately 95.80%.

T. Lakshmi Narayana and T. Sreenivasulu Reddy, [20] introduced a groundbreaking approach to automatically detect brain tumors by employing deep Convolutional Neural Networks (CNNs). Their approach involved an initial CNN-based filtering step, followed by an iterative segmentation process that employed a specialized sparse shape model. Their results indicated a sensitivity of 89% and an accuracy of 85%. In a different study, Zaw et al. [21] proposed a segmentation technique aiming to enhance the detection effectiveness of human-machine collaboration. Their method integrated morphological methods, pixel subtraction, and maximum entropy threshold segmentation. By blending morphological and intensity characteristics and employing a Naive Bayes classifier, they obtained a remarkable 94% accuracy. Narayana and Reddy proposed another efficient method for brain tumor segmentation [22]. In their research, a combination of a median filter and genetic algorithm was employed, with the Gray-Level Co-occurrence Matrix (GLCM) used as a feature. These techniques were applied to analyze the Harvard Medical Dataset using an SVM classifier, resulting in an achieved accuracy of 91.23%.

In their work, Raju and colleagues proposed a pioneering method for the detection of COVID-19, which utilized Bayesian scan fuzzy clustering segmentation, information-theoretic scatters, and wavelet features. They employed a multi-support Vector Machine (multi-SVM) classifier based on Bayesian HCS, achieving an impressive accuracy of 93%. In a different context, Minz and Mahobiya [23] proposed a technique to enhance the detection effectiveness of human-machine combinations using median filter noise reduction and threshold-based segmentation on publicly available brain tumor MRI datasets. However, this method also exhibited trade-offs in terms of the aforementioned features, yielding a precision of 74% and an accuracy of 89.90%. Furthermore, Chen et al. [24] presented a deep learning model based on CNNs for stroke classification using unenhanced brain CT imaging data. Their model surpassed the performance of VGG16 and ResNet50, achieving an impressive accuracy of 98.72%. Nevertheless, it should be noted that ResNet50 exhibited longer processing times compared to other networks, as observed during the evaluation of various hyperparameters and settings.

Hashmi and Osman [25] utilized structural multimodal MRI in their study on brain tumor segmentation, classification based on residual networks, and overall survival prediction [26]. Their approach involved employing a combination of conditional random

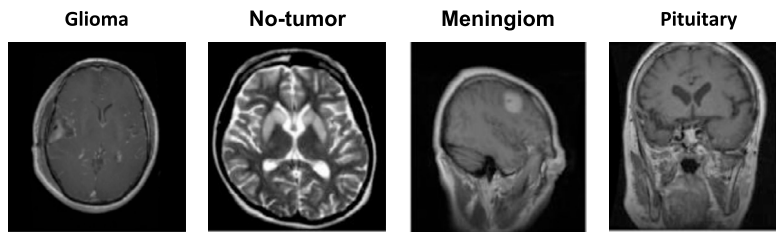


Fig. 1. Sample images for each class from Dataset-I.

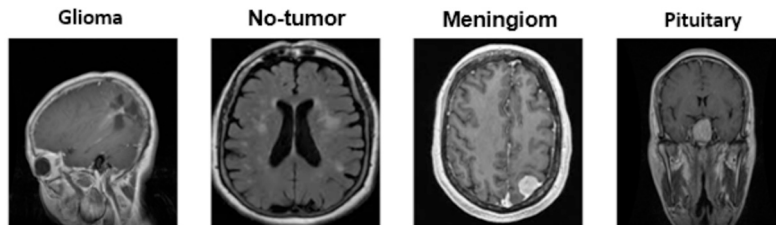


Fig. 2. Sample images for each class from Dataset-II.

field and convolution network-based segmentation to identify non-overlapping patches for efficient tumor detection. However, they encountered increased error rates when the patches overlapped. To tackle this issue, the authors proposed the integration of residual network-based feature mapping and XG-Boost-based learning. Their emphasis was on mapping features in a nonlinear space using residual features, as this approach minimizes the risk of information loss and improves the effectiveness of tumor information extraction. The authors conducted experiments on two datasets, which led to an improvement in the accuracy of both two-class and three-class classification by 3.4% and 2.3%, respectively. Furthermore, the approach was refined by incorporating a lightweight convolution network.

Despite the extensive research on brain tumor segmentation and classification using medical images, there remains a significant challenge in achieving precise and reliable tumor segmentation while maintaining computational efficiency. Existing approaches often encounter issues such as loss of semantic content in feature maps, limited utilization of contextual and spatial information, and inaccurate tumor segmentation in cases of considerable variability in size and shape. Consequently, it is imperative to develop a novel approach that effectively addresses these challenges, enhancing the accuracy and efficiency of tumor segmentation and classification in medical images.

3. Materials and methods

3.1. Datasets description

In this paper, two distinct datasets are employed to validate and examine the proposed approach for brain tumor classification. The primary dataset, referred to as Dataset-I [27], comprises 7,023 human brain MRI images sourced from a combination of three datasets: figshare, SARTAJ, and Br35H. These images are categorized into four classes: glioma, meningioma, no tumor, and pituitary. For Dataset-I, the training phase encompasses 5,812 images, while the testing dataset comprises 1,311 images. The secondary dataset, Dataset-II [28], is publicly available on Kaggle and includes 3,704 MRI images of the brain across four classes: meningioma, glioma, pituitary tumor, and no tumor. Dataset-II features images with a resolution of 256×256 pixels stored in PNG format, with a balanced distribution of samples across classes. Specifically, 3,310 images from Dataset-II are utilized for training, while 394 images are allocated for testing. Figs. 1 and 2 present sampled images from Dataset-I and Dataset-II, respectively.

3.2. Proposed method for DR detection

The proposed brain tumor detection approach comprises several key steps outlined in Fig. 3. Initially, MRI images undergo preprocessing to enhance quality and reduce noise. The dataset is then split into 80% for training and validation and 20% for testing, ensuring robust model evaluation.

To extract meaningful features, pre-trained deep learning models like DenseNet201, EfficientNetB5, and InceptionResNetv2 are fine-tuned on the training set. These models, having learned rich representations from datasets like ImageNet-1k, serve as powerful feature extractors, adapting their features to brain tumor images. Feature extraction from a CNN last layer yields high-level patterns crucial for understanding input data. During training, CNNs optimize these features for specific tasks. Typically, the last layer outputs a vector, summarizing the learned features. These vectors, often termed as bottleneck features or embeddings, represent salient data information. For instance, in image data, each vector corresponds to an image, and its elements represent recognized features. The dimensionality of these features aligns with the CNN architecture; a layer with 512 filters produces 512-dimensional vectors. Such

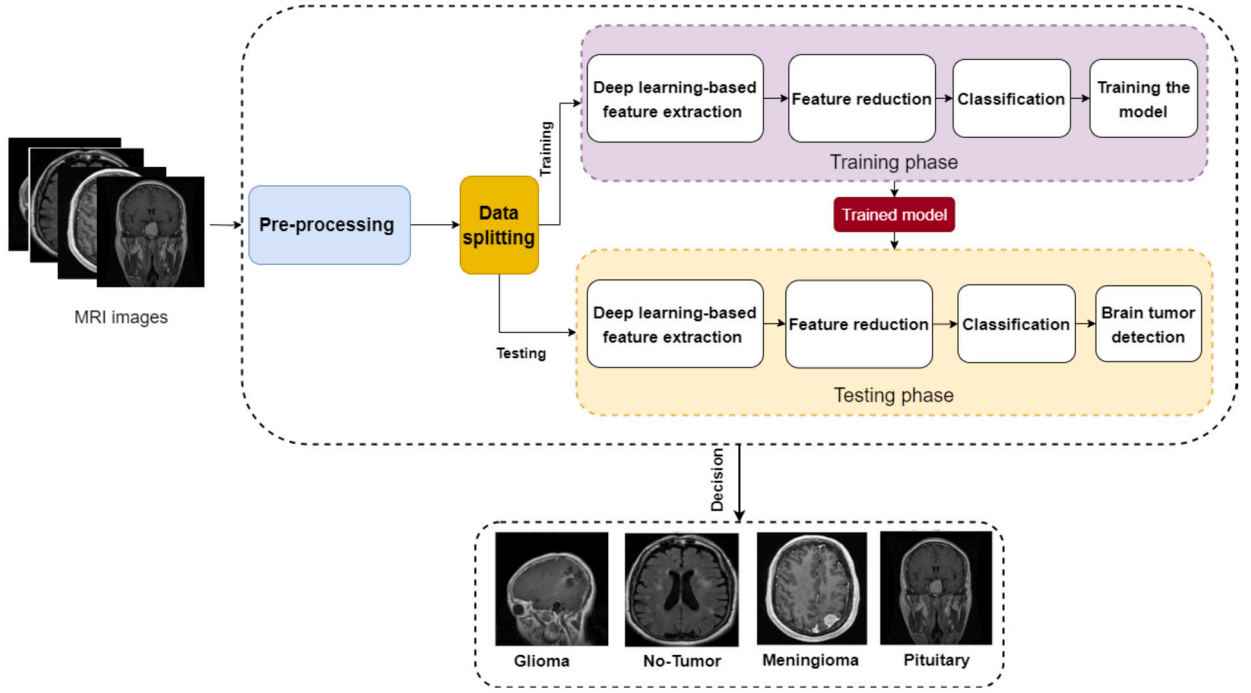


Fig. 3. Block diagram of the proposed approach.

bottleneck features prove invaluable for various machine learning tasks, such as classification. For example, using bottleneck features from a pre-trained CNN, an SVM classifier can accurately categorize new brain tumor images. In essence, CNN bottleneck features are high-dimensional vectors encapsulating key data insights, adaptable for diverse machine learning applications [29,30].

Next, feature reduction via PCA reduces high-dimensional vectors to capture essential information while minimizing loss of discriminatory power, thus reducing computational complexity and enhancing subsequent classification models performance. PCA is a prevalent method for reducing dimensionality in data, projecting high-dimensional data into a lower-dimensional space while preserving essential variance. The PCA process involves the following steps:

1. **Data Centering:** Center the data by subtracting the mean from each feature to ensure zero mean.

$$X_c = X - \bar{X} \quad (1)$$

2. **Covariance Matrix:** Compute the covariance matrix to understand feature relationships.

$$C = \frac{1}{n-1} \cdot X_c^T \cdot X_c \quad (2)$$

3. **Eigendecomposition:** Eigendecompose the covariance matrix to obtain eigenvectors and eigenvalues.

$$C = Q \cdot \Lambda \cdot Q^T \quad (3)$$

4. **Selecting Principal Components:** Choose eigenvectors with the highest eigenvalues, representing maximum variance.

5. **Dimensionality Reduction:** Select a subset of principal components based on desired dimensions or preserved variance percentage.

$$X_{\text{reduced}} = X_c \cdot Q_k \quad (4)$$

6. **Reconstruction (Optional):** Reconstruct original data from reduced-dimensional data, if necessary.

$$X_{\text{reconstructed}} = X_{\text{reduced}} \cdot Q_k^T + \bar{X} \quad (5)$$

Features from CNN models have dimensions of 1920 for DenseNet201, 1537 for EfficientNetB5, and 2049 for InceptionResNetV2. Data standardization is applied using the Standard Scaler function, adjusting the mean to 0 and standard deviation to 1 for Gaussian distribution properties. Additionally, PCA reduces data using variance preservation that, Preserve a fixed percentage of data variance, resulting in varying dimensions across CNN model features.

Following the dimensionality reduction step, the reduced feature vectors are used as inputs for various machine learning models [31]. These models include popular algorithms SVM, MLP, and GNB. The machine learning models are trained on a labeled dataset

Table 1
Tuning parameters for machine learning models.

Model	Tuning Parameters	Value
MLP	Number of Hidden Layers	2
	Number of Neurons in Each Hidden Layer	First: 256, Second: 128
	Learning Rate	0.001
	Regularization	L2 Regularization
SVM	Kernel Type	RBF
	Regularization Parameter (C)	10
	Gamma	0.0001
	Kernel Coefficient	0.01
GNB	Priors	0.5
	Var Smoothing	10^{-09}

Table 2
Training options for different pre-trained models.

Training options (random initialization weights, batch size = 64, learning rate = 0.00001 and number of epochs = 20)		
Model	Input size	No. of layers / Blocks
InceptionResNetv2 [36]	229×229	164
DenseNet201 [37]	229×229	201
EfficientNetB5 [38]	229×229	5 Blocks

Table 3
Confusion matrix parameters definition.

	Actually positive (1)	Actually negative (0)
Predicted positive	T_p	F_p
Predictive negative	F_n	T_n

that consists of samples with different class labels. Through the training process, the models learn the underlying patterns and relationships within the feature space to differentiate between different fault classes. In order to enhance the performance of the machine learning models, various tuning parameters have been customized. The specifics of these tuning parameters for the machine learning models employed in this research can be found in Table 1. Specifically, for the MLP model, two hidden layers have been fine-tuned, with 256 neurons in the first layer and 128 neurons in the second layer. Additionally, a learning rate of 0.001 has been chosen, and L2 regularization has been applied to prevent overfitting. On the other hand, for the SVM model, the radial basis function (RBF) kernel has been selected, and the regularization parameter (C) has been configured to 10. The gamma value and kernel coefficient are determined as 0.0001 and 0.01, respectively. In the case of the GNB model, the priors are set to 0.5, and the variance smoothing is set to 10^{-09} . These carefully selected parameter values play a crucial role in optimizing the performance of the respective machine-learning models, resulting in accurate brain tumor classification results [32–35]. Instead of using sigmoid function for binary classification, diverse machine learning models such as SVM, GNB, and MLP are employed for multi-class classification, well-suited for medical image analysis.

By integrating these steps, the approach forms a comprehensive pipeline, combining deep learning and traditional techniques for robust tumor detection. Utilizing pre-trained models for feature extraction, followed by PCA for dimensionality reduction, and incorporating diverse classifiers, ensures a reliable classification system.

Table 2 presents pre-trained models, their image input sizes, and training options, with methods effectively addressing deterioration while achieving convergence in minimal iterations. Stochastic gradient descent (SGD) is employed for rapid convergence and minimal computational time, with ReLU activation functions utilized in convolutional layers.

3.3. Performance metrics

Table 3 presents the expected quadrant outcomes obtained from the confusion matrix. T_p represents the count of correctly identified anomalous instances, while T_n signifies the number of accurately classified normal instances. On the other hand, F_p corresponds to the normal instances erroneously labeled as anomalies [39], and F_n pertains to anomalies incorrectly classified as normal. To assess the overall performance of each deep learning classifier, we employ various metrics, namely recall, accuracy (Acc), precision (Preci), and F1 score [39]. These metrics, commonly computed using a confusion matrix, are fundamental in evaluating binary classifier performance.

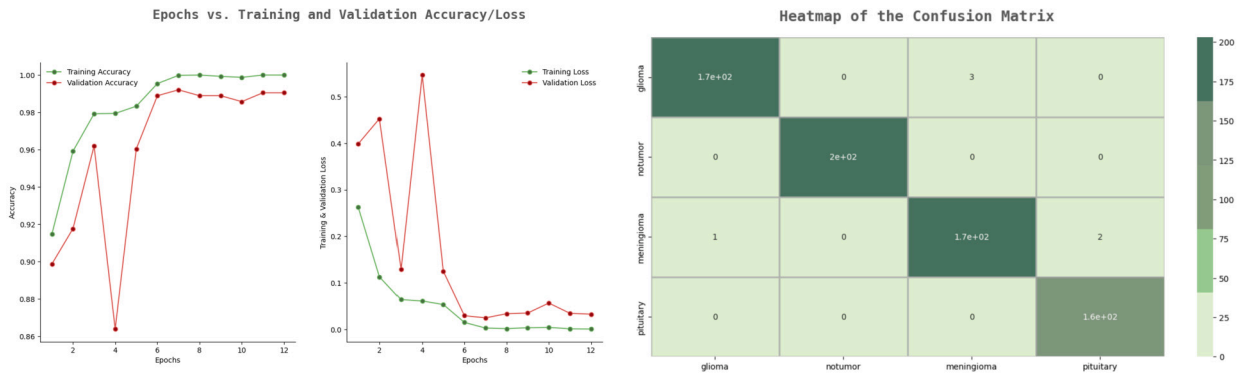


Fig. 4. Confusion matrix training/validation accuracy and loss curves for the proposed InceptionResNet-v2 pre-trained models using Dataset-I.

Recall is given by:

$$Recall = \frac{T_p}{T_p + F_n} \times 100 \quad (6)$$

Accuracy is given by:

$$Acc = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \times 100 \quad (7)$$

F1-score is given by:

$$F1score = \frac{T_p}{T_p + \frac{1}{2}(F_p + F_n)} \times 100 \quad (8)$$

The F1 score, also known as the F-measure, assesses test accuracy. It calculates the F-score by dividing true positives by the total number of positive results (including false positives). Similarly, recall computes the ratio of correctly identified positives to the total positive samples [40].

4. Results and discussion

This paper investigates brain tumor detection using diverse scenarios and methodologies. Three pre-trained models (DenseNet201, EfficientNet B5, and InceptionResNetV2) are used to classify original brain tumor data. Furthermore, hybrid models are developed by integrating PCA for feature reduction with the three pre-trained models. Traditional machine learning algorithms (GNB, SVM, and MLP) are also employed. The performance of each approach is extensively evaluated to gain insights into their effectiveness and limitations in various brain tumor detection scenarios.

4.1. Results for pre-trained models

In this subsection, the results obtained from the implementation and evaluation of three pre-trained models, namely DenseNet201, EfficientNetB5, and InceptionResNetV2 are presented for Dataset-I and Dataset-II. These models were applied to the original brain tumor dataset to assess their classification performance and overall effectiveness.

For the Dataset-I Figs. 4, 5 and 6 present confusion matrix and training/validation accuracy and loss curves for the proposed InceptionResNet-v2, EfficientNetB, and DensNet201 pre-trained models, respectively. Table 4 shows the classification reports for the proposed InceptionResNet-v2, EfficientNetB, and DensNet201 pre-trained models.

The obtained results highlight the impressive performance of the deep learning models—InceptionResNetV2, EfficientNetB, and DenseNet201 in classifying brain tumor images. Across all models, precision, recall, and F1-score metrics consistently report high scores, indicating the models' ability to make accurate predictions across different tumor classes. Specifically, InceptionResNetV2 and EfficientNetB exhibit strong performance with precision, recall, and F1-scores above 0.98, coupled with high accuracy rates of 0.99. These findings underscore the robustness and reliability of these architectures in accurately categorizing brain tumor images. Moreover, DenseNet201 stands out by achieving perfect scores across all metrics, including precision, recall, and F1-score, along with a flawless accuracy rating of 1.00. This exceptional performance highlights the superior capability of DenseNet201 in capturing intricate patterns and features within the brain tumor images, making it particularly well-suited for complex medical image classification tasks. In summary, the results across the three tables collectively demonstrate the high efficacy of these deep learning models in accurately classifying brain tumors, with each model showcasing remarkable performance. DenseNet201, in particular, demonstrates unparalleled accuracy and precision, positioning it as a promising candidate for advanced medical imaging applications requiring exceptional performance and reliability.

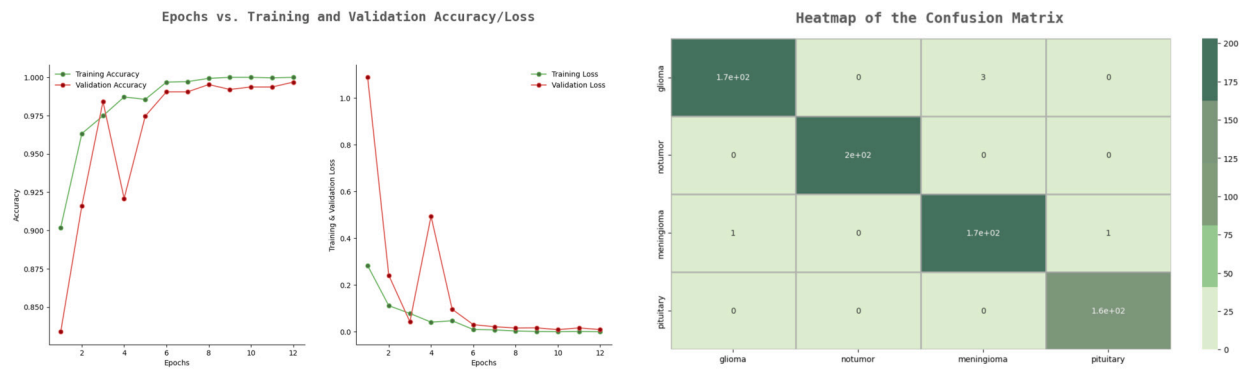


Fig. 5. Confusion matrix training/validation accuracy and loss curves for the proposed EfficientNetB pre-trained models using Dataset-I.

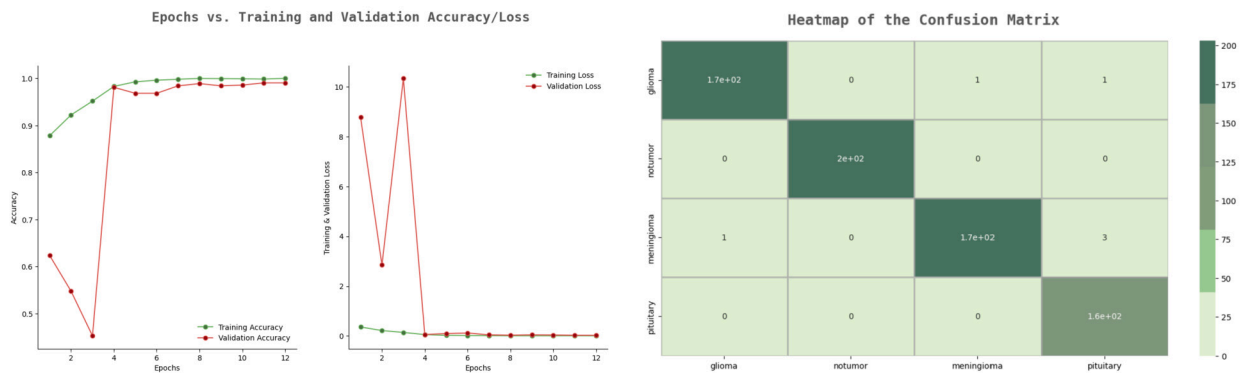


Fig. 6. Confusion matrix and training/validation accuracy and loss curves for the proposed DenseNet201 pre-trained models using Dataset-I.

Table 4

Classification reports for InceptionResNetV2, EfficientNetB, and DenseNet201 proposed models using Dataset-I.

Metric/Model	Precision	Recall	F1-Score
InceptionResNetV2			
0	0.99	0.98	0.99
1	1.00	1.00	1.00
2	0.98	0.98	0.98
3	0.99	1.00	0.99
Accuracy		0.99	
EfficientNetB			
0	0.99	0.98	0.99
1	1.00	1.00	1.00
2	0.98	0.99	0.99
3	0.99	1.00	1.00
Accuracy		0.99	
DenseNet201			
0	1.00	1.00	1.00
1	1.00	1.00	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
Accuracy		1.00	

For Dataset-II Figs. 7, 8 and 9 present confusion matrix and training/validation accuracy and loss curves for the proposed InceptionResNet-v2, EfficientNetB, and DensNet201 pre-trained models, respectively. Table 5 shows the classification reports for the proposed InceptionResNet-v2, EfficientNetB, and DensNet201 pre-trained models. The obtained classification results for InceptionResNetV2, EfficientNetB, and DenseNet201 provide valuable insights into the performance of these models for the given classification task. Firstly, InceptionResNetV2 demonstrates high precision, recall, and F1-score across all classes, with an overall accuracy of 0.98. This indicates that the model performs exceptionally well in correctly identifying each class, particularly class 1 and class 3 which

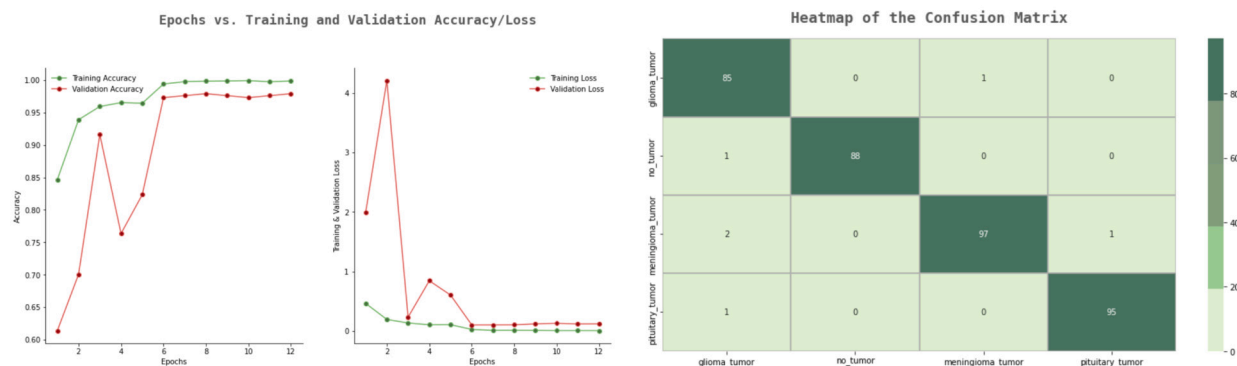


Fig. 7. Confusion matrix training/validation accuracy and loss curves for the proposed InceptionResNet-v2 pre-trained models using Dataset-II.

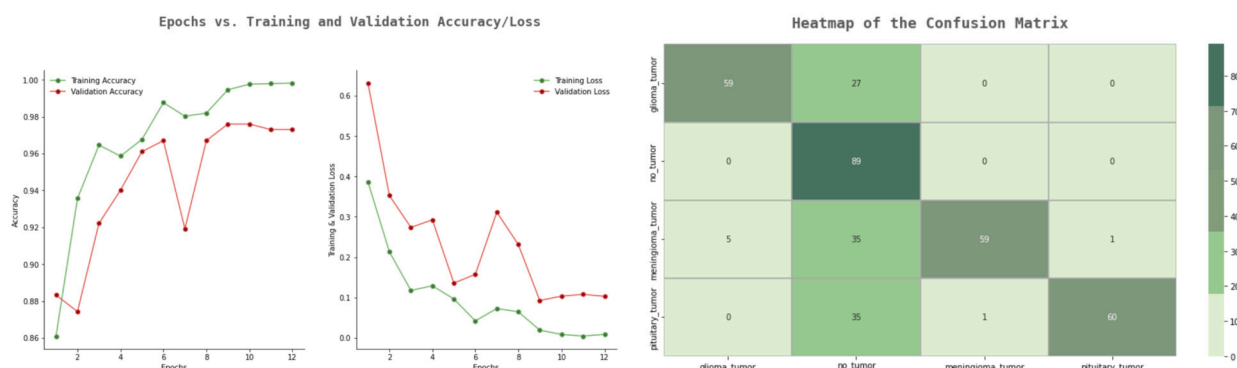


Fig. 8. Confusion matrix training/validation accuracy and loss curves for the proposed EfficientNetB pre-trained models using Dataset-II.

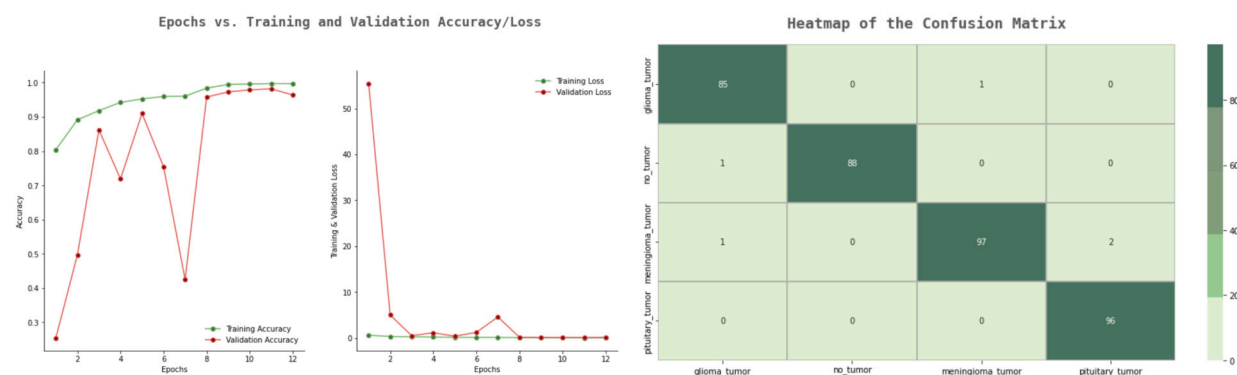


Fig. 9. Confusion matrix and training/validation accuracy and loss curves for the proposed DenseNet201 pre-trained models using Dataset-II.

have F1-scores of 0.99 and 0.99, respectively. The high performance of InceptionResNetV2 can be attributed to its complex architecture, which combines the strengths of both Inception and ResNet architectures, allowing it to capture intricate features and relationships within the data effectively. On the other hand, EfficientNetB shows a more varied performance. While it achieves perfect recall for class 1, it struggles with other classes, particularly class 0 and class 3 where the F1-scores are considerably lower at 0.48 and 0.02, respectively. This suggests that EfficientNetB may not be as effective in capturing the nuances of these classes, possibly due to its relatively simpler architecture compared to InceptionResNetV2 and DenseNet201. Lastly, DenseNet201 exhibits consistent and high performance across all classes, similar to InceptionResNetV2, with an overall accuracy of 0.99. The model demonstrates near-perfect precision and recall for all classes, indicating its robustness and capability to generalize well to the classification task. DenseNet201 dense connectivity pattern allows it to maintain feature reuse throughout the network, which can contribute to its superior performance.

Table 5
Classification reports for InceptionResNetV2, EfficientNetB, and DenseNet201 using Dataset-II.

Metric/Model	Precision	Recall	F1-Score
InceptionResNetV2			
0	0.96	0.99	0.97
1	1.00	0.99	0.99
2	0.99	0.97	0.98
3	0.99	0.99	0.99
Accuracy		0.98	
EfficientNetB			
0	1.00	0.31	0.48
1	0.38	1.00	0.55
2	0.68	0.76	0.72
3	1.00	0.01	0.02
Accuracy		0.52	
DenseNet201			
0	0.98	0.99	0.98
1	1.00	0.99	0.99
2	0.99	0.97	0.98
3	0.98	1.00	0.99
Accuracy		0.99	

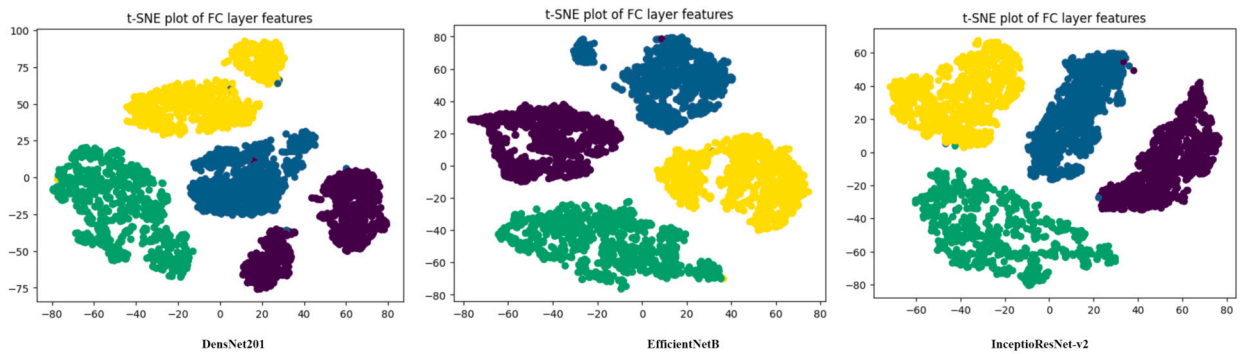


Fig. 10. t-SNE plots of FC layer features for the proposed pre-trained models using Dataset-I.

4.2. Results for hybrid models

In this subsection, the results obtained from the implementation and evaluation of hybrid models for brain tumor detection using Dataset-I and Dataset-II are presented. These hybrid models are created by integrating PCA with the three pre-trained models: DenseNet201, EfficientNetB5, and InceptionResNetV2.

For Dataset-I: Fig. 10 showcases t-SNE plots of FC layer features extracted from the proposed pre-trained models using Dataset-I. These visualizations provide a comprehensive representation of the model learned feature embeddings in a lower-dimensional space. The t-SNE plots offer insights into the models ability to discern patterns and separability of different brain tumor classes. In these plots, the x-axis and y-axis serve as two-dimensional coordinates, showcasing the reduced representations of the original high-dimensional features. Figs. 11, 12 and 13 display the confusion matrices for the proposed pre-trained models DensNet201, EfficientNetB and InceptionResNet-v2 combined with PCA and various machine learning models, respectively. These matrices provide a comprehensive visualization of the model classification performance across different brain tumor classes. By observing the distribution of predicted labels and true labels, valuable insights into the accuracy and misclassifications of the hybrid models are obtained.

Table 6 presents classification reports for DenseNet201 with PCA applied to SVM, MLP, and GNB on Dataset-I. It demonstrates outstanding performance, with all models achieving perfect or near-perfect precision, recall, and F1-scores across classes 0 to 3. This indicates robust feature representation and effective generalization capabilities, evidenced by an accuracy score of 1.00 for each model. However, such high scores raise concerns about potential overfitting, necessitating validation on independent datasets or cross-validation for comprehensive evaluation. Table 7 combined classification reports for SVM, MLP, and GNB for EfficientNetB. It showcases exceptionally high performance across all three models, with each achieving perfect precision, recall, and F1-scores for all classes. This indicates that all three classifiers are highly accurate in both identifying positive cases and capturing all instances of these cases. Additionally, the accuracy score of 1.00 for each model emphasizes their robust generalization capabilities on the given dataset.

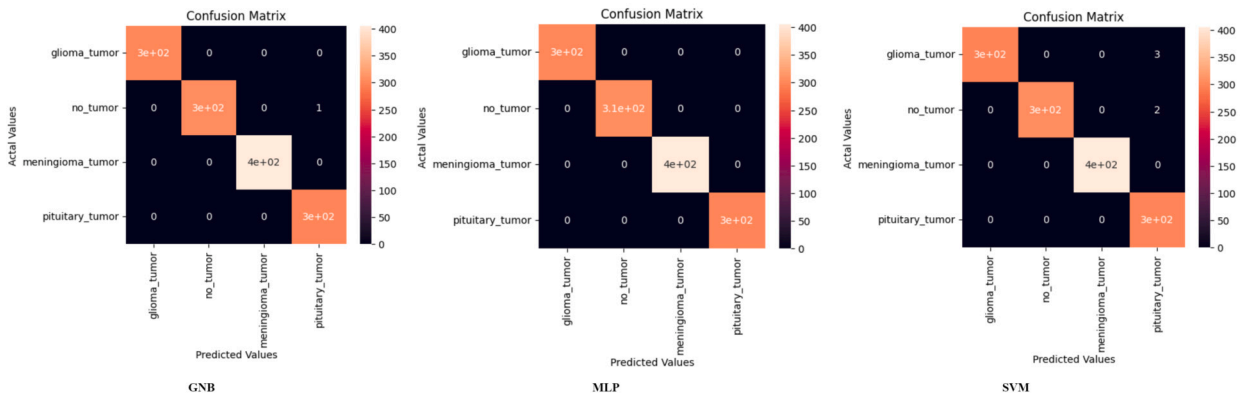


Fig. 11. Confusion matrices for the proposed DensNet201 pre-trained model combined with PCA and different machine learning models using Dataset-I.

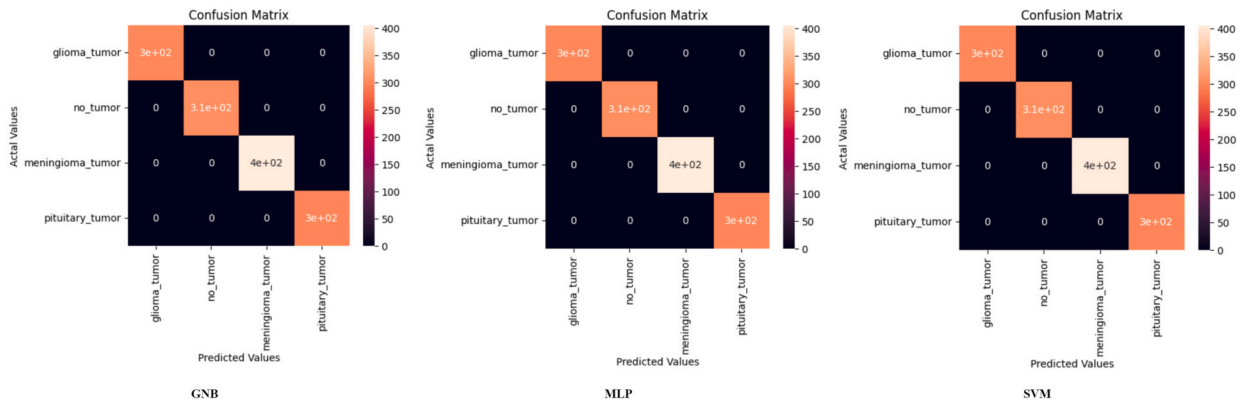


Fig. 12. Confusion matrices for the proposed EfficientNetB pre-trained model combined with PCA and different machine learning models using Dataset-I.

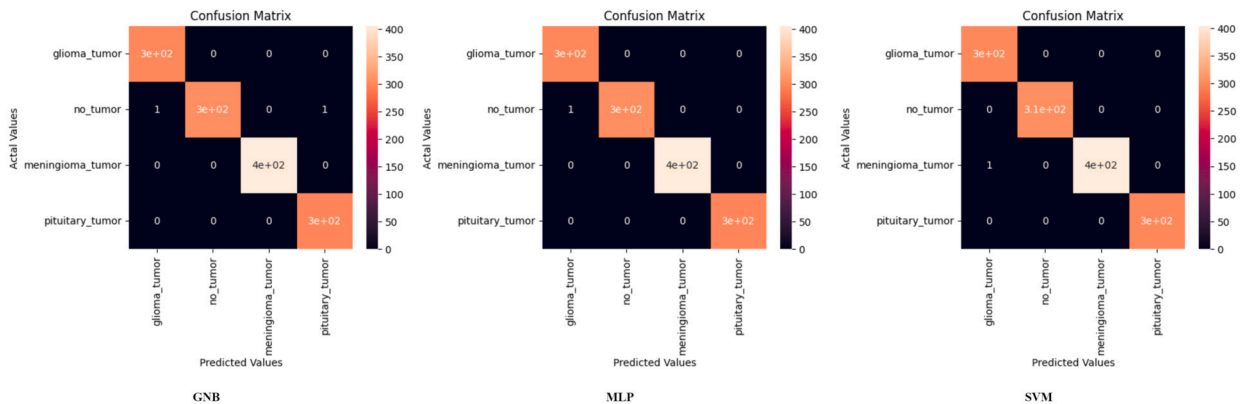


Fig. 13. Confusion matrices for the proposed InceptionResNet-v2 pre-trained model combined with PCA and different machine learning models using Dataset-I.

Like the other models, InceptionResNet-v2 achieves perfect precision, recall, and F1-scores across all classes, with an overall accuracy score of 1.00. This consistency in performance underscores the robustness and effectiveness of the InceptionResNet-v2 pretrained model in accurately classifying the given dataset. However, as with the previous models, it is crucial to verify these results with cross-validation to ensure reliable generalization to unseen data.

Table 8 presents the combined classification reports for SVM, MLP, and GNB using the InceptionResNet-v2 pretrained model with 5-fold cross-validation. It underscores the robustness and reliability of the proposed model. The use of 5-fold cross-validation enhances the credibility of these results by validating the model performance across multiple subsets of the dataset, reducing the risk of overfitting and providing a more generalized assessment of the model capabilities. Both SVM and MLP consistently achieve perfect precision, recall, and F1-scores across all classes, with an overall accuracy score of 1.00. This level of consistency across different folds

Table 6
Classification reports for DensNet201 pretrained model combined with PCA and SVM, MLP, and GNB using Dataset-I.

Metric/Model	Precision	Recall	F1-Score
SVM			
0	1.00	0.99	0.99
1	1.00	0.99	1.00
2	1.00	1.00	1.00
3	0.98	1.00	0.99
Accuracy		1.00	
MLP			
0	1.00	1.00	1.00
1	1.00	1.00	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
Accuracy		1.00	
GNB			
0	1.00	1.00	1.00
1	1.00	1.00	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
Accuracy		1.00	

Table 7
Classification reports for EfficientNetB pretrained model combined with PCA and SVM, MLP, and GNB using Dataset-I.

Metric/Model	Precision	Recall	F1-Score
SVM			
0	1.00	1.00	1.00
1	1.00	1.00	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
Accuracy		1.00	
MLP			
0	1.00	1.00	1.00
1	1.00	1.00	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
Accuracy		1.00	
GNB			
0	1.00	1.00	1.00
1	1.00	1.00	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
Accuracy		1.00	

further confirms the model ability to accurately identify and classify instances, reinforcing the robustness of the InceptionResNet-v2 pretrained model as a feature extractor. While GNB exhibits slightly lower performance compared to SVM and MLP, the use of 5-fold cross-validation highlights its stable and consistent performance across different subsets of the data. This demonstrates that, despite its assumptions of conditional independence and Gaussian distribution, GNB remains a viable and robust option for classification when coupled with the InceptionResNet-v2 pretrained model. The consistent and high-performance results across all three models, as validated through 5-fold cross-validation, emphasize the robustness and effectiveness of using the InceptionResNet-v2 pretrained model for feature extraction in classification tasks, providing a reliable and generalized approach to data classification.

For Dataset-II: Fig. 14 displays t-SNE plots depicting the feature embeddings extracted from the FC layers of the proposed pre-trained models using Dataset-II. These plots offer a clear visualization of the learned feature embeddings in a lower-dimensional space. By reducing the high-dimensional features into two dimensions, the t-SNE plots provide valuable insights into the models' ability to distinguish patterns and separability among different classes within Dataset-II. The x-axis and y-axis represent two-dimensional coordinates, illustrating the reduced representations of the original high-dimensional features. Fig. 15 presents the Confusion matrices for the proposed DensNet201 pre-trained model combined with PCA and different machine learning models using Dataset-II. Table 9 shows the classification reports for DenseNet210 combined with PCA and machine learning models with 5-fold cross-validation using Dataset-II. The numerical analysis indicates the effectiveness of the classification models employing DenseNet210 for feature

Table 8
Classification reports for InceptionResNet-v2 combined with PCA and machine learning models with 5-fold cross-validation using Dataset-I.

Metric/Model	Precision	Recall	F1-Score	Support
SVM				
0	1.00	1.00	1.00	300
1	1.00	1.00	1.00	306
2	1.00	1.00	1.00	405
3	1.00	1.00	1.00	299
Accuracy	1.00			
MLP				
0	1.00	1.00	1.00	300
1	1.00	1.00	1.00	306
2	1.00	1.00	1.00	405
3	1.00	1.00	1.00	299
Accuracy	1.00			
GNB				
0	0.99	0.99	0.99	300
1	0.99	0.97	0.98	306
2	1.00	1.00	1.00	405
3	0.97	0.98	0.98	299
Accuracy	0.99			

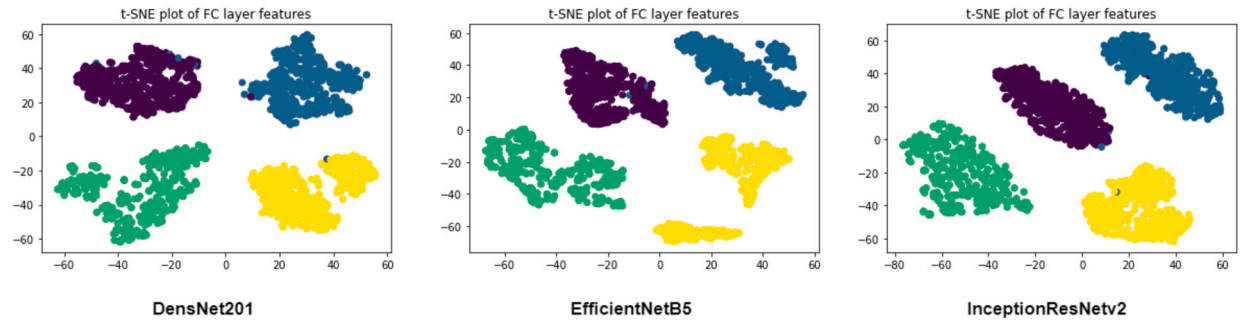


Fig. 14. t-SNE plots of FC layer features for the proposed pre-trained models using Dataset-II.

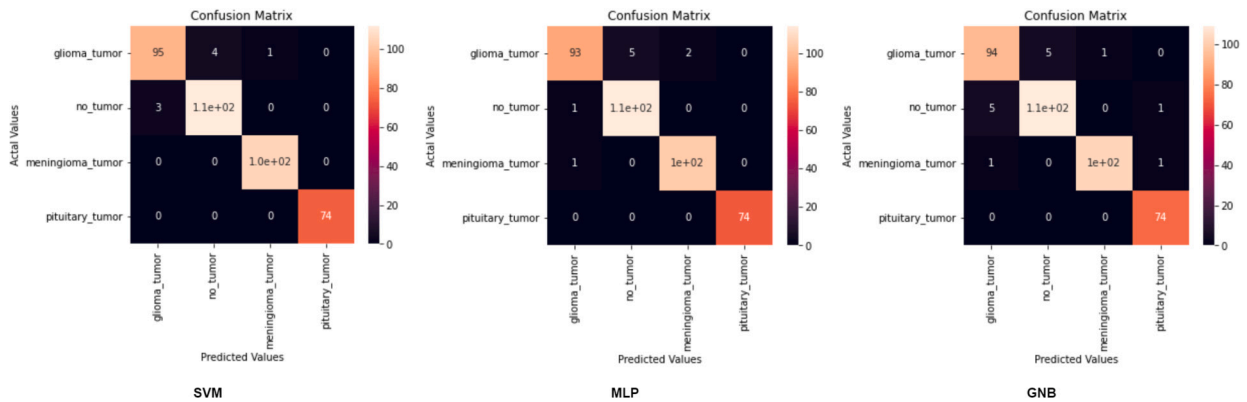


Fig. 15. Confusion matrices for the proposed DensNet201 pre-trained model combined with PCA and different machine learning models using Dataset-II.

extraction, followed by PCA dimensionality reduction, and classification with SVM, MLP, and GNB algorithms on Dataset-II using 5-fold cross-validation. DenseNet210 successfully captures intricate image features, while PCA dimensionality reduction streamlines the feature space without sacrificing discriminative power. SVM demonstrates strong performance across all metrics, with precision, recall, and F1-scores consistently exceeding 0.95 for each class, indicating its ability to capture complex decision boundaries. Similarly, MLP exhibits robust performance, achieving high precision, recall, and F1-scores for all classes, showcasing its capability to learn complex relationships between features. Despite its simplicity, GNB delivers competitive results, demonstrating its robustness in handling diverse datasets. Overall, the combination of feature extraction, dimensionality reduction, and classification algorithms,

Table 9

Classification reports for DenseNet210 combined with PCA and machine learning models with 5-fold cross-validation using Dataset-II.

Metric/Model	Precision	Recall	F1-Score	Support
SVM				
0	0.97	0.95	0.96	100
1	0.97	0.97	0.97	115
2	0.99	1.00	1.00	105
3	1.00	1.00	1.00	74
Accuracy	0.98 (394)			
MLP				
0	0.98	0.93	0.95	100
1	0.96	0.99	0.97	115
2	0.98	0.99	0.99	105
3	1.00	1.00	1.00	74
Accuracy	0.98 (394)			
GNB				
0	0.94	0.94	0.94	100
1	0.96	0.95	0.95	115
2	0.99	0.98	0.99	105
3	0.97	1.00	0.99	74
Accuracy	0.96 (394)			

Table 10

Performance comparison with the state-of-the-art models for brain tumor detection.

Paper	Methodology	Results
Saeedi et al. [41]	modified convolutional auto-encoder network	Accuracy of 95%
Mahmud et al. [42]	CNN architecture	Accuracy of 93.3%
Khan et al. [43]	DCNN+improved optimization algorithm	Accuracy of 95.94%
Hossain et al. [44]	vision transformers	Accuracy of 96.94%
Ali et al. [45]	WBM-DLNetS feature optimization	Accuracy of 94%
Rahman et al. [46]	Parallel DCNNs	Accuracies ranging from 97.33% to 98.12%.
Hammad et al. [47]	Lightweight CNN	Accuracy of 96.86%
Sharma et al. [48]	HOG Transformation + ResNet50 Model	Accuracy of 88%
Mohamed et al. [49]	Segmentation and features fusion	Accuracy: 99.8%, Recall: 99.3%, Precision: 99.4%, F1 score: 99.5%
Suraj Patil, Dnyaneshwar Kirange [50]	Ensemble of deep learning models	Accuracy of 97.77%
A. B. Abdusalomov et al. [51]	Enhanced YOLOv7 model.	Accuracy of 99.50%
Z. H. N. Al-Azzwi and A. N. Al-Azzwi [52]	Ensemble DCNNs.	Accuracy of 96.60%
Z. Rasheed et al. [53]	CLAHE with a CNN model.	Accuracy of 97.84%
Jain et al. [54]	hybrid model combining MobileNetV2 with VGG16.	Accuracy of 98%
Muath Al Hasan et al. [55]	InceptionV3	Accuracy of 97.50%.
E. Gnanamanoharan et al. [56]	Combination of DCNNs and genetic algorithms.	Accuracy of 99.56%
A. A. Asiri et al. [57]	Five pre-trained vision transformer models.	Accuracy of 98.24%
P. Neelima et al. [58]	Fine-tuned 3D-CNN.	Accuracy of 85.14%
Raza et al. [59]	Inceptionv3.	Accuracy of 99.95%
M. M. Emam et al. [60]	Improved Hunger Games Search Algorithm.	Accuracy of 99.89%.
S. Sharmin et al. [61]	ResNet50V2+Light Gradient Boosting.	Accuracy of 95%
Tabatabaei et al. [62]	Two-branch parallel model.	Accuracy of 99.30%
Pedada et al. [63]	A modified U-Net.	Accuracy of 93.40%
Proposed Approach	DensNet201+PCA+SVM using Dataset-I	Achieved 100% for accuracy, recall and precision
	DensNet201+PCA+MLP using Dataset-I	Achieved 100% for accuracy, recall and precision.
	DensNet201+PCA+SVM using Dataset-II	Achieved 98% for accuracy, recall and precision.
	DensNet201+PCA+MLP using Dataset-II	Achieved 98% for accuracy, recall and precision.

along with the rigorous validation through 5-fold cross-validation, underscores the reliability and effectiveness of the methodology in accurately classifying instances within Dataset-II.

Table 10 provides a thorough comparison of various state-of-the-art models for brain tumor detection, outlining their methodologies and achieved results in terms of accuracy. It showcases a diverse range of approaches, including modified CNN architectures, optimization algorithms, and ensemble models, all aimed at enhancing tumor detection performance. Notable achievements include accuracies ranging from 97.33% to 98.12% with parallel DCNNs, 99.8% accuracy with segmentation and feature fusion, and 99.95% accuracy with Inceptionv3. The proposed approach, utilizing DenseNet201 with PCA and different classifiers on both Dataset-I and Dataset-II, demonstrates competitive performance. Achieving 100% accuracy, recall, and precision on Dataset-I underscores the effectiveness of the proposed methodology. Although the accuracy slightly decreases to 98% on Dataset-II, the maintained high precision and recall reflect the robustness of the proposed approach across different datasets.

5. Conclusion

In this research, a diverse array of techniques was applied to categorize images of brain tumors into four distinct groups: meningioma, glioma, pituitary tumor, and the absence of tumors. This study provides valuable insights into the current state of the field. Notably, several approaches exhibit remarkable performance, achieving accuracies exceeding 98% and demonstrating commendable precision and recall rates. The proposed approach, which utilizes DenseNet201 with PCA and diverse classifiers across different datasets, showcases robust performance, particularly with its achievement of 100% accuracy, recall, and precision on Dataset-I. These findings underscore the potential of deep learning techniques in revolutionizing brain tumor detection, offering promising avenues for improving diagnostic accuracy and patient care. However, it is important to acknowledge the limitations of existing models and areas for further exploration. Future research should focus on validating model performance on larger and more diverse datasets to ensure generalizability across populations. Additionally, investigating hybrid models, integrating advanced optimization algorithms, and exploring innovative data augmentation strategies can further enhance detection accuracy and robustness. This paper contributes valuable insights into the evolving landscape of brain tumor detection, laying the groundwork for future advancements in the field. By addressing remaining challenges and pushing the boundaries of deep learning research, we can envision a future where these models play a pivotal role in improving clinical decision-making and patient outcomes.

CRediT authorship contribution statement

Mohamed R. Shoaib: Writing – review & editing, Writing – original draft, Validation, Software, Resources, Methodology, Formal analysis. **Jun Zhao:** Supervision, Resources, Funding acquisition, Formal analysis. **Heba M. Emara:** Writing – review & editing, Writing – original draft, Visualization, Validation, Formal analysis, Conceptualization. **Ahmed S. Mubarak:** Validation, Supervision, Investigation, Formal analysis. **Osama A. Omer:** Visualization, Supervision, Investigation, Data curation. **Fathi E. Abd El-Samie:** Supervision, Project administration, Investigation, Formal analysis. **Hamada Esmaiel:** Supervision, Project administration, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The datasets used in this study are publicly available:

- **Brain Tumor MRI Dataset:** Available on Kaggle, authored by Msoud Nickparvar (2021). The dataset can be accessed at <https://doi.org/10.34740/KAGGLE/DSV/2645886>. For citation purposes, please use: [27].
- **Brain Tumor MRI Classification Dataset:** Available on Kaggle, authored by Vinay Jayanti (2023). The dataset can be accessed at <https://doi.org/10.34740/KAGGLE/DSV/6758053>. For citation purposes, please use: [28].

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