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Research and Application of Deep Learning Models for Detecting Brain Abnormalities Based on CT Images

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Abstract – This paper studies a method to improve the accuracy of a deep learning model for detecting brain abnormalities based on computed tomography images. The process begins with image preprocessing using the Histogram Equation algorithm and Gabor filter. Then, features are extracted from the fully connected layer of the AlexNet model. To optimize feature extraction, we use the MIFS algorithm to identify the most important features. Finally, the SVM machine learning model is deployed to detect brain abnormalities. To confirm the effectiveness of the proposed model, we compare it with other popular deep learning models, including AlexNet. Experimental results show that our method achieves an accuracy of over 93%, higher than pure deep learning models.

Keywords – CT images, AlexNet, MIFS, SVM.

1. Introduction

Early detection of brain abnormalities is essential. This not only helps identify brain diseases but also helps plan appropriate treatment, minimizing the risk of serious complications and death. A simple and popular method to identify brain-related diseases is computed tomography. Each type of disease leaves abnormal signs on the images, and based on these signs, researchers have developed methods to apply advanced technology to detect abnormalities early, thereby reducing the burden on the healthcare system. Recently, deep learning algorithms have been widely used because of their ability to detect abnormalities in the brain quickly and accurately. Image recognition algorithms based on convolutional neural networks are capable of learning and extracting complex image features effectively. Therefore, many researchers have applied CNNs to detect brain abnormalities from medical images.

In the paper [1], the authors proposed a deep learning model with the ability to diagnose Alzheimer's syndrome and schizophrenia through patient time-series EEG data. From the synthesis of EEG time-series data, the authors converted it into a brain region connectivity matrix using three methods (Granger relation, Pearson correlation, Spearman correlation) and then used it as a dataset for the deep learning model with optimal algorithms. The model proposed by the authors achieved a maximum accuracy of 92% when diagnosing Alzheimer's syndrome and 52% when diagnosing schizophrenia with the corresponding matrix formation methods of Pearson and Granger. In the paper [2], the authors studied the feasibility of applying deep learning to diagnose fetal brain abnormalities using ultrasound images. With a hospital image dataset of 10.251 normal brain images and 2.529 abnormal brain images, through data enrichment and training, comparing the conclusions with previous diagnoses of doctors and experts, the studied model achieved an accuracy of 96.3%. In the article [3], the authors proposed a deep learning model capable of supporting

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the recognition of undetected abnormalities from MRI scans of newborns. Using the input image preprocessing method, training a 3D automatic decoding structure to analyze brain features, reapply the analyzed features, and highlight abnormalities, the research team built a model to analyze and recognize abnormalities with an AUC of 83%. The deep neural model "ASD-SAENet" for diagnosing bipolar depression disorder proposed by the authors of the article [4] uses the SAE algorithm to optimize the ability to separate features used for the classification process. Using the dataset of fMRI images "ABIDE", the model achieved an accuracy of 70.8%. The authors of the article [5] proposed a deep learning model using EEG signal data processed by a combination of CNN and LSTM models to identify EEG rhythm frequencies similar to bipolar depression disorder, achieving an accuracy of 96.43%. To solve the risk of cerebral hemorrhage, the authors of the article [6] suggested a model to assist in identifying cerebral hemorrhage using CT scans of patients. Using the MobileNetV2 architecture trained on the "RSNA Intracranial Hemorrhage" dataset, CT scans indicating potential brain hemorrhage risks are flagged and processed through the Hounsfield Unit scale and the DBSCAN method to emphasize risk areas and reduce noise. This model achieved an AUC of 99.1%. In a separate study, the authors of article [7] proposed a brain tumor diagnosis system based on MRI images, utilizing a deep convolutional neural network optimized with an ADAS method. The process involves simplifying the input images by removing unnecessary details, which are then used to train the deep neural network to identify risk factors and classify the images. This model achieved an accuracy of 94%. The paper [8] applied trained deep learning strategies such as VGG16 and ResNet50 to classify brain MRI images using multi-class classifications with groups of Normal, Stroke, Low-grade Neuroma, and High-grade Neuroma. The authors used different classifiers such as SoftMax, SVM-RBF, and SVM-Cubic to compare the results between them. The authors of the paper [9] conducted a feasibility test of abnormality detection in fetal brain ultrasound images using deep learning algorithms by training the model with 12780 real images from the hospital database. The results of the project can also accurately localize the abnormal detection area. The paper [10] proposed a ResNet-based deep learning model capable of classifying brain MRI images to support doctors in reducing the volume of images that need to be examined in depth. Data enrichment methods, learning rate optimization, and appropriate tuning were applied in the model-building process. In 613 MRI images, this model achieved 100% accuracy according to the authors, and is ready to be tested with larger data volumes. In order to build a deep learning model to detect brain tumors and classify brain tumors, the authors of the article [11] proposed a model to identify and classify brain tumors from MRI images using deep learning methods. The model applied transfer learning techniques and combined VGG16 with the "23-layer CNN" block to improve the accuracy of brain tumor classification. The proposed model successfully achieved 97.8% accuracy. The authors of the article [12] proposed three deep learning methods to analyze the impact of local features and deep features on detecting abnormalities in brain MRI images. The first method uses a deep autoencoder using directional bit planes to differentiate and learn local and directional features. The second method uses a separable scaling convolutional neural network to extract deep and shallow features in the image. The final method is a combination of DBP-DAE and DSRCN. The results are comparable to the popular deep learning algorithm. A hybrid deep learning model between a deep neural network and a Random Forest classifier is proposed by the authors of the paper [13]. The hybrid approach helps the model compete with simple DNN and DNN+SVM models, achieving training AUC of 94% and validation of 87%.

2. Motivation

In this paper, we present a novel method to improve the accuracy of detecting brain abnormalities from computed tomography images. The collected data is characterized by a large amount of random noise, which can degrade the image quality and affect the analysis process. Therefore, the first step is to perform image preprocessing to improve the input quality. We use the Histogram Equalization technique to balance the brightness and enhance the contrast of the image, helping to highlight important structures. Gabor filters are then applied to enhance edge features, helping to emphasize details and complex textures in the image. After preprocessing, we proceed to extract features using the AlexNet model. From the fully connected layer of AlexNet, we obtain 4096 features, each representing a different aspect of the image data. These features contain rich information in the data. However, not all of these features are equally valuable in distinguishing between normal and abnormal brain states. Therefore, to optimize the classification process and reduce the computational load, we apply the Mutual Information Feature Selection (MIFS) algorithm. MIFS helps to remove redundant or irrelevant features, retaining only the most important and discriminating features. With the selected optimal feature set, we use the Support Vector Machine (SVM) machine learning model to classify normal and abnormal brain states.

Experimental results show that our method achieves an accuracy of 93.68%, which is significantly higher than the pure AlexNet model and other deep learning models such as VGG-16 and DenseNet-121. Figure 1 illustrates an overview of the brain abnormality detection process that we propose.

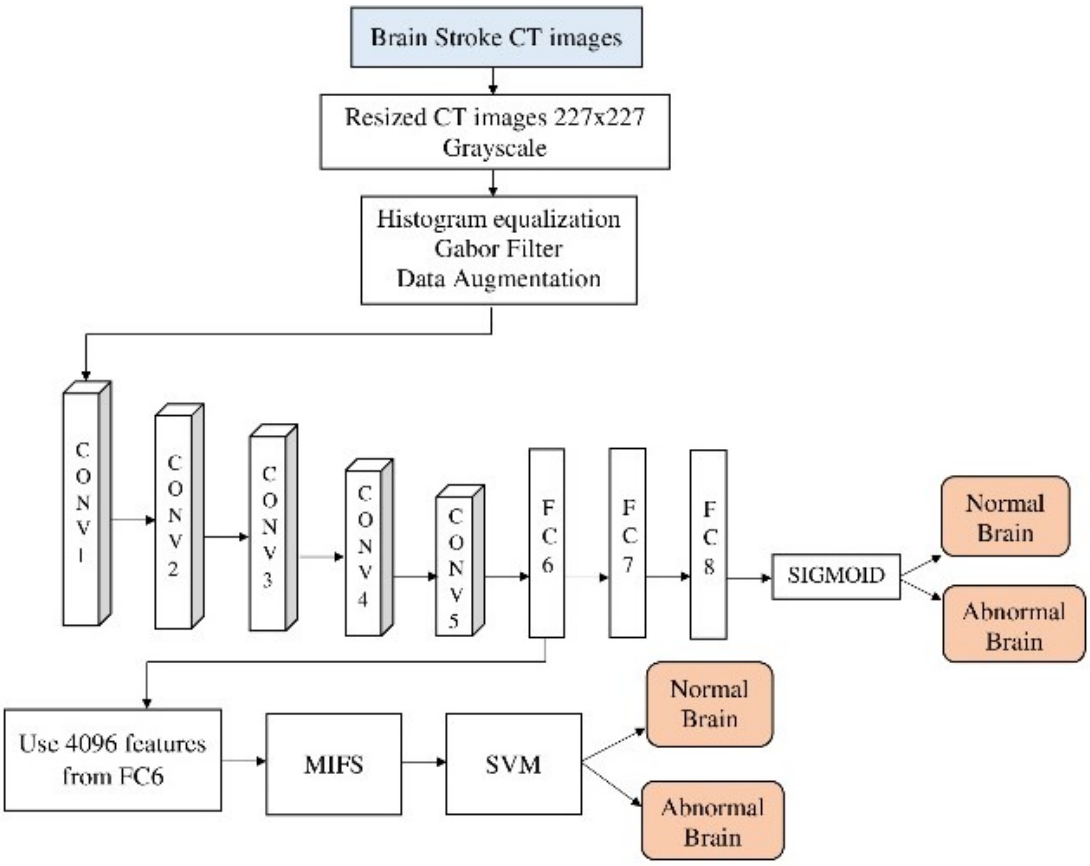


Figure 1. Overall processing workflow in the paper

3. Methodology

3.1. Histogram Equalization

Histogram Equalization is an image preprocessing method used in our paper to enhance the contrast of computed tomography images, in order to more accurately detect brain abnormalities. This technique redistributes the intensity values of the image so that the entire intensity range is used more evenly, helping to highlight the details in the image [14]. The Histogram Equalization algorithm can be described by formula (1).

$$H' : I'(x,y) = H'(I(x,y)) \quad (1)$$

where, $H'(i) = \sum_{j=0}^{i} H(j)$, is the Histogram normalized to $[0, 255]$, $H(i)$ is the Histogram of the original image, $I(x,y)$ is the original image, $I'(x,y)$ is the Histogram normalized image. This technique provides clearer and more informative input data, which helps to improve the feature extraction ability and the performance of the next classification steps in the anomaly detection process.

3.2. Gabor Filter

Gabor Filter is an image processing technique used in our study to extract spatial and frequency features from CT images, which improves the detection of brain abnormalities. Gabor filter simulates the responses of the human visual system by combining a Gaussian function with a harmonic wave function, allowing it to capture local features such as edges, corners, and textures with sensitivity to frequency and orientation [15], as shown in the formula (2).

$$g(x, y, \lambda, \theta, \varphi, \sigma, \gamma) = e\left(\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right) e(i(2\pi\frac{x}{\lambda} + \varphi)) \quad (2)$$

where, $x' = x\cos\theta + y\sin\theta$ and $y' = -x\sin\theta + y\cos\theta$, λ denotes the wavelength of the sinusoidal coefficient, θ denotes the direction of the normal of the Gabor function, ϕ is the phase shift, σ is the standard deviation of the Gaussian envelope, and γ is the phase shift of the Gabor function. In this paper, we extract Gabor features in 16 directions. By applying Gabor Filter on CT images, we can extract features related to direction and frequency, especially details

such as the structure and border of the brain. These features are used as input for the next steps in the feature selection process.

3.3. AlexNet Model

AlexNet [16] is a deep learning model used in our study to extract features from computed tomography images, and is also a model used to detect brain abnormalities. The structure of AlexNet consists of five convolutional layers and three fully connected layers. AlexNet uses techniques such as ReLU, dropout, and local normalization to improve performance. The convolutional layers consist of 96 11x11 filters in the first layer, followed by layers with 256 5x5 filters, 384 3x3 filters, and 256 3x3 filters, all interleaved with ReLU and pooling layers. The fully connected layers consist of two layers of 4096 neurons and an output layer of 2 neurons, using a sigmoid function to classify normal and abnormal brains. The output from the first fully connected layer is a feature vector of 4096 values, which is used as input for feature selection using MIFS and then classification using SVM. Therefore, AlexNet not only helps detect brain abnormalities, but also provides useful features for subsequent processing steps, contributing to improving the accuracy of the classification system.

3.4. MIFS algorithm

Mutual Information Feature Selection (MIFS) [17] is a feature selection technique used in our model to optimize the input feature set, extracted from the AlexNet model. MIFS works on the concept of mutual information, which measures the degree of dependence between variables. The goal of MIFS is to select the features with the highest discriminative power, while minimizing the information redundancy between the features, which is described by formula (3).

$$J(S,f) = I(f;c) - \beta \sum_{s \in S} I(f;s) \qquad (3)$$

where, $J(S,f)$ is the value of feature f when considering the set of selected features S. $I(f;c)$ is the mutual information between feature f and the target variable. By optimizing this objective function, MIFS helps to select a set of features with the highest representativeness and least redundancy, which helps to improve the accuracy and efficiency of the data before using the SVM model to classify brain abnormalities from CT images.

3.5. SVM machine learning model

Support Vector Machine (SVM) [18] is a machine learning algorithm used in our model to classify brain abnormalities from preprocessed and feature-extracted CT image data. SVM works by searching for a hyperplane in the feature space, with the goal of maximizing the margin between data classes, in this case between normal and abnormal brain states. Specifically, SVM determines the hyperplane through formula (4).

$$w.x + b = 0 \qquad (4)$$

where, w is the weight vector, x is the feature vector of the data sample, b is the bias correction coefficient. The objective function of the SVM to be optimized is $\frac{1}{2}||w||^2$ with the constraint $y_i(w.x_i + b) \geq 1 - \delta_i$, where y_i is the class label, x_i is the data point and δ_i is the slack variable allowing some points to violate the boundary. The combination of SVM with the features selected through the MIFS algorithm ensures that our model achieves high accuracy in detecting brain abnormalities.

4. Results

Data in the paper

In this paper, we use the Afridi Rahman dataset, which consists of 1900 CT images, including 950 normal brain images, and 950 abnormal brain images of stroke [19]. These images are taken in cross-section, each image representing a different depth of the brain. Figure 2 illustrates some of the data in the paper, with the first row depicting images of normal brains, and the second row depicting abnormal brain images of stroke on the same CT scan slice.

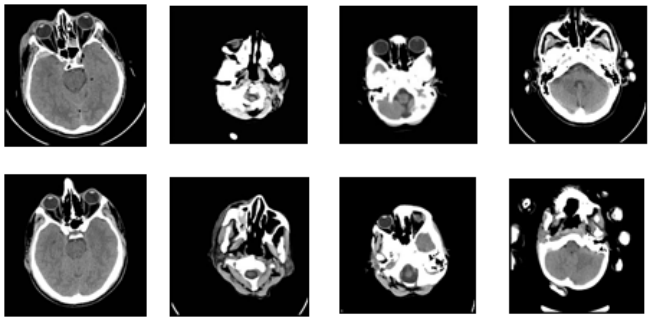


Figure 2. Some data collected in the paper

The images are preprocessed using white balance, Gabor filter and data enrichment techniques as presented in Section 2. After preprocessing, we split the data into two parts, 80% for training and 20% for testing, then put them into the AlexNet model and MIFS algorithm for feature extraction, then classified with the SVM machine learning model.

5. Discussion

Experimental results

Our proposed method was implemented and trained on a computer with a Core i7-10700 2.9GHz

configuration, 64GB RAM, Windows 10 operating system, and Python 3.6 development environment. The training parameters for the models include Learning Rate = 1e-3, batch size = 64, and number of epochs = 100. We conducted experiments with four deep learning models including the proposed model, VGG-16, AlexNet, and DenseNet. The accuracy of each model during training is shown in Figure 3. The results show that our method has outstanding performance. Specifically, in Figure 3a, the accuracy of the proposed model reaches a stable level from the 20th epoch, with the difference between the training and testing values being insignificant, and the Test values fluctuating little, demonstrating the good convergence ability of the model. The VGG-16, AlexNet, and DenseNet models, shown in Figures 3b, 3c, and 3d, respectively, show that the achieved accuracy is 92.1%, 90%, and 72.63%, respectively. The proposed model not only achieves the highest accuracy but also maintains stability and efficiency during training.

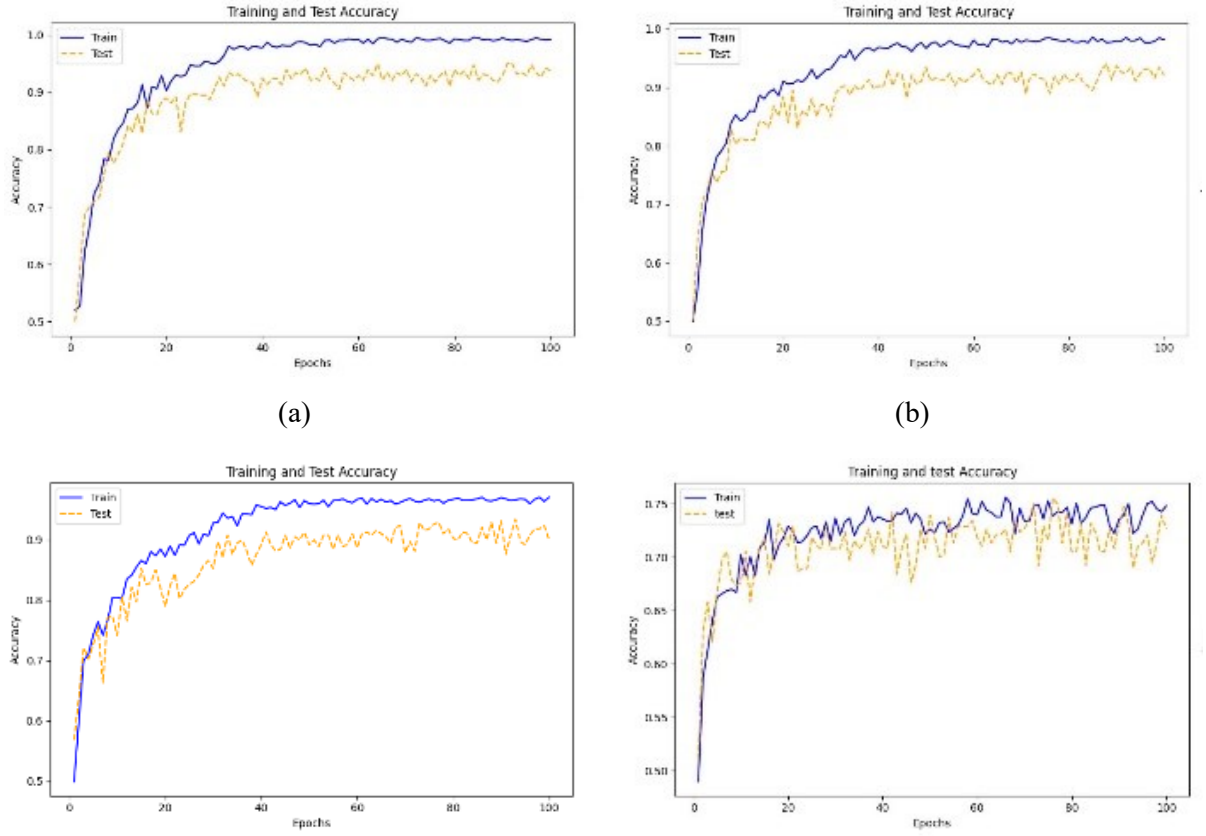


Figure 3. Training accuracy of four models

To provide a more intuitive view of the prediction accuracy on the test dataset in the proposed model, we used the Confusion matrix. In this matrix, the vertical axis represents the actual label, which includes two classes: Normal Brain and Abnormal Brain, the horizontal axis represents the model's predicted label, which also corresponds to these two classes. The Confusion matrix for the proposed model is presented in Figure 4a, showing the distribution of correct and incorrect predictions. Similarly, the Confusion matrices for the VGG-16, AlexNet, and DenseNet models are presented in Figures 4b, 4c, and 4d, respectively.

To further demonstrate the effectiveness of the proposed method, we conducted statistical and comparison analyses of six important metrics during the training of the models, including Accuracy, Precision, Sensitivity, Specificity, G-mean, and F1-Score. These metrics provide a comprehensive view of the model's classification ability and are the basis for evaluating the superiority of the proposed method over other deep learning models. Specifically, Accuracy reflects the proportion of correctly predicted cases for both normal and abnormal brain classes on the total data of the test set, calculated by formula (5).

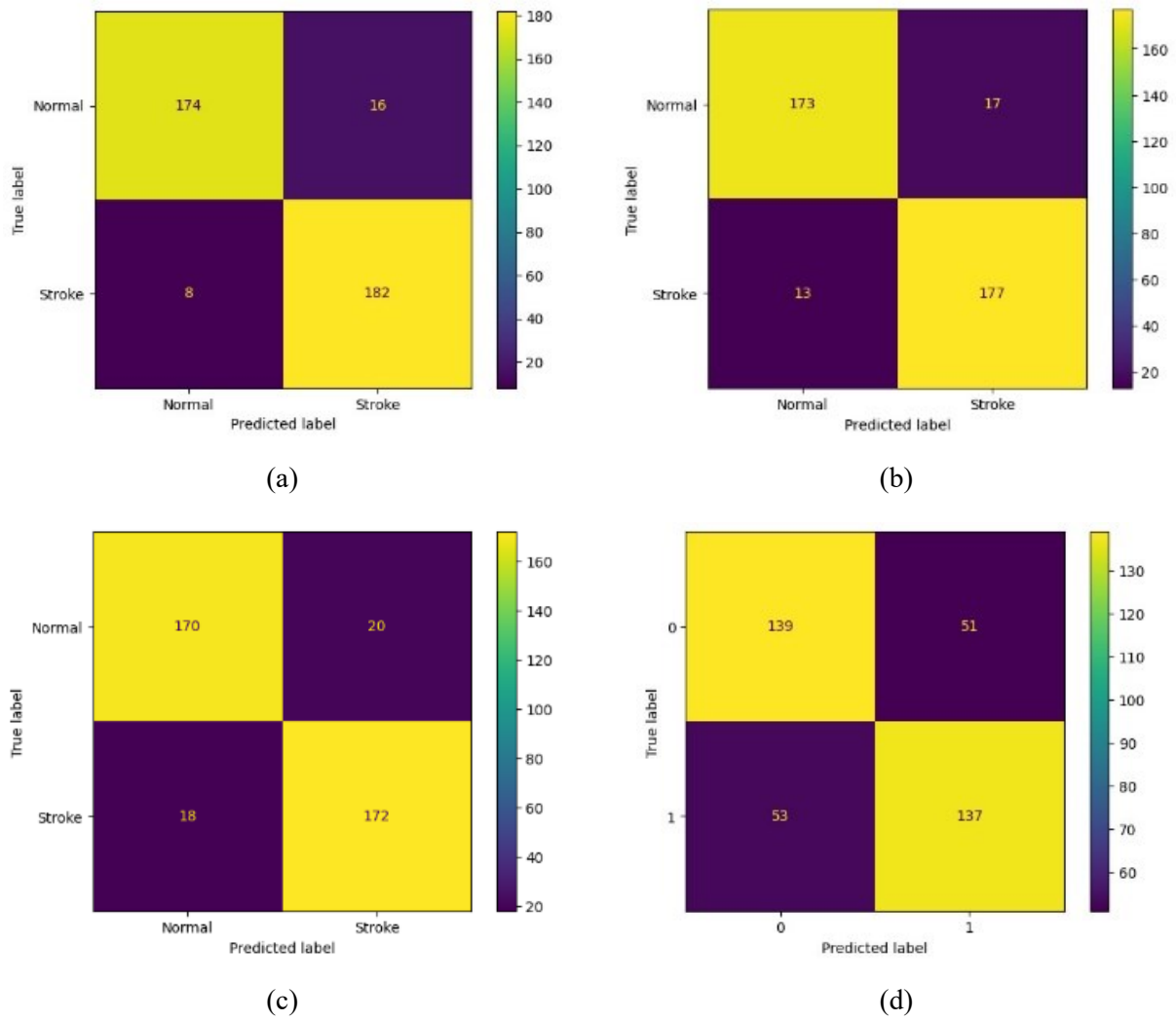


Figure 4. Confusion Matrix of Four Models

Precision measures the accuracy in predicting abnormal brain cases, calculated as the ratio of the number of correct predictions as abnormal to the total number of abnormal predictions, according to formula (6). Sensitivity (also known as Recall) evaluates the model's ability to detect brain abnormalities, calculated as the ratio of the number of correct predictions as abnormal to the total number of actual abnormal cases, according to formula (7). Specificity measures the ability to correctly identify normal brain cases, calculated as the ratio of the number of correct predictions as normal to the total number of actual normal cases, according to the formula (8). The G-mean value is a comprehensive performance measure that balances Sensitivity and Specificity, representing the model's ability to not only correctly detect brain abnormalities but also correctly classify normal brain cases. G-mean is calculated according to formula (9) as the geometric mean of Sensitivity and Specificity. Finally, F1-Score is the harmonic average of Precision and Sensitivity, which provides an overall measure of the model's accuracy considering both accuracy and sensitivity, which helps evaluate the model in handling difficult-to-classify cases, calculated by formula (10). The results of comparing these metrics between the proposed method and other deep learning models, including VGG-16, AlexNet, and DenseNet, are presented in Table 1. From this analysis, we find that the proposed method achieves the highest accuracy, while maintaining a good balance between Sensitivity and Specificity, as evidenced by the G-mean and F1-Score values. This demonstrates that our method outperforms other deep learning models in detecting and classifying brain abnormalities, while minimizing classification errors.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (7)$$

$$Specificity = \frac{TN}{TN + FP} \quad (8)$$

$$G - mean = \sqrt{Sensitivity * Specificity} \quad (9)$$

$$F - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (10)$$

Table 1. Statistical table of post-training values of four deep learning models

Model	Proposed model	VGG16	AlexNet	DenseNet
Accuracy	93.68%	92.10%	90.0%	72.63%
Precision	95.60%	93.01%	90.42%	72.39%
Sensitivity	91.57%	91.05%	89.47%	73.15%
Specificity	95.78%	93.15%	90.52%	72.10%
G-mean	93.66%	92.09%	89.99%	72.62%
F1-Score	93.54%	92.02%	89.94%	72.77%

6. Conclusion

In this paper, we present a novel architecture for brain anomaly detection based on computed tomography (CT) images. To improve the image quality and highlight the brain features, we apply preprocessing methods including Histogram Equalization and Gabor Filter. The AlexNet deep learning model is not only used to detect the anomaly with an accuracy of 90% but also plays an important role in extracting 4096 features from the dataset. These features are then filtered and optimized by the MIFS algorithm, to select the most prominent features. The final classification is performed using the SVM machine learning model. Experimental results show that the proposed model achieves an accuracy of 93.68%, which outperforms pure deep learning models. However, the current study is still unable to classify different types of brain abnormalities, and the images used are CT scans instead of MRI. While CT imaging speeds up the diagnostic process, MRI provides greater reliability. Therefore, in future studies, we plan to collect data from MRI and develop and refine the deep learning model to improve the accuracy and detection of other types of brain abnormalities. The goal is to improve diagnostic efficiency, and support earlier and more accurate detection of brain abnormalities, thereby contributing to the advancement of medicine.

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