



# DEEP LEARNING ALGORITHM BASED SCHIZOPHRENIA PREDICTION FROM FUNCTIONAL MRI

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## ABSTRACT

Schizophrenia is a neurological disorder that affects many young people. Early detection and treatment can help relieve family stress and save social expenses. For schizophrenia, there is no objective evaluation index. A method for the classification of functional magnetic resonance imaging data is proposed in conjunction with the convolutional neural network algorithm to increase the classification effect of standard classification methods on magnetic resonance data. We use functional magnetic resonance imaging (fMRI) data for schizophrenia as an example, extract effective time series from preprocessed fMRI data, perform correlation analysis on regions of interest, and classify the functional connection between schizophrenia and healthy controls using transfer learning and the VGG19 net. The classification accuracy of fMRI based on VGG19 is up to 95%, according to experimental results.

## 1. INTRODUCTION

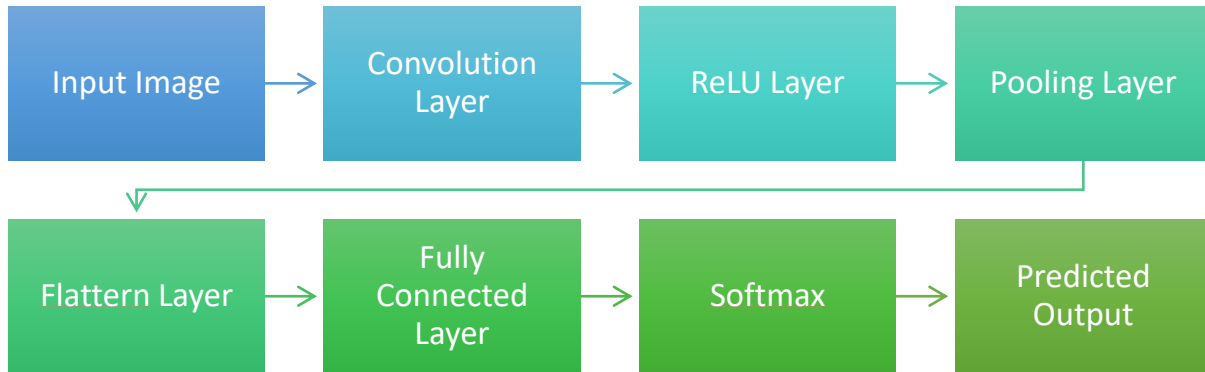
Schizophrenia is a serious and disabling mental illness. It is manifested as obstacles such as thinking, emotion, and behaviour, the condition shows a slow and progressive development, and there are various degrees of social function defects. Symptoms include false beliefs, unclear or confused thinking, hearing voices that others cannot hear, reduced social participation and emotional expression, and lack of motivation. It not only brings great pain to the patient, but also a heavy burden to the family and society. It is about 1% of the diseased population worldwide. It mostly occurs in people aged 15 to 34.

Schizophrenia is a debilitating and life-threatening mental condition. It manifests as hurdles in the areas of thinking, emotion, and behaviour, the disorder progresses slowly, and there are varying degrees of social function deficiencies. False beliefs, muddled or confused thinking, hearing voices that others don't hear, decreased social involvement and emotional expression, and a lack of motivation are some of the symptoms. It not only causes the patient a lot of agonies, but it also puts a lot of strain on the family and society. It accounts for around 1% of the world's ill population. Schizophrenia can be improved with early diagnosis, effective intervention, and therapy. The goal of the cure rate is to keep the disease from progressing too far. However, the aetiology and pathology of schizophrenia remain unknown, and objective evidence is lacking.

Clinical diagnosis is mostly based on medical history, as well as psychological symptoms, disease progression laws, and scales. Early diagnosis of schizophrenia remains a difficult challenge due to the intricacy of the disease mechanism. Schizophrenia affects human perception, thinking, emotion, and behaviour, and it most commonly affects those aged 15 to 34. Early controlled episodes, late recurrent

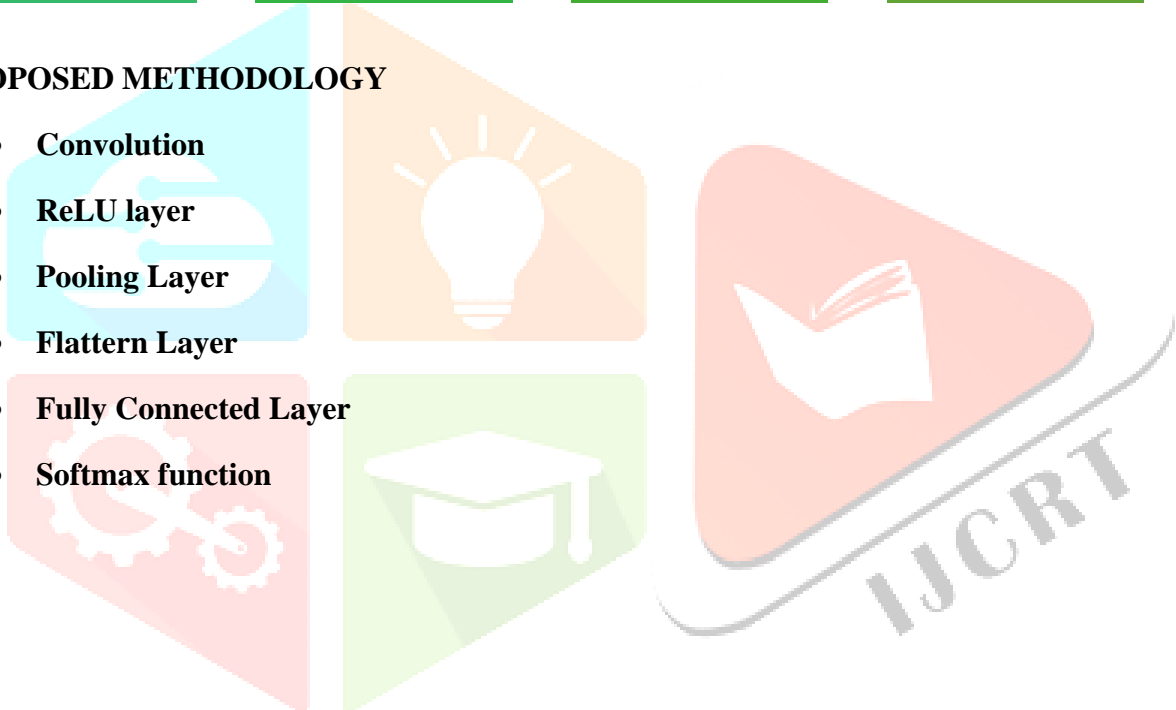
attacks, and significantly reduced cognitive function are all features of this condition. Currently, the majority of schizophrenia diagnoses are based on the patient's behaviour, such as the commonly used positive and negative symptom scales for quantitative assessment.

## ARCHITECTURE DESIGN



## PROPOSED METHODOLOGY

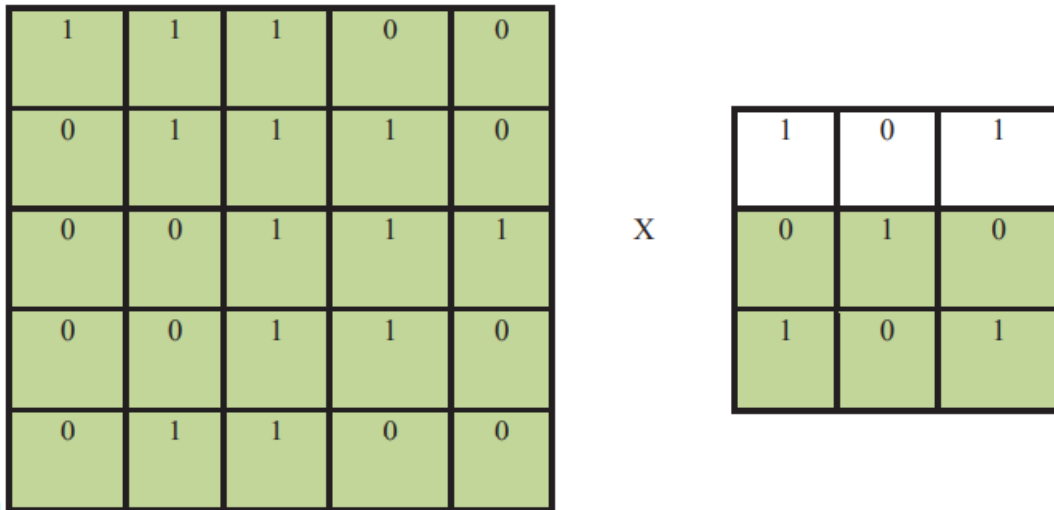
- Convolution
- ReLU layer
- Pooling Layer
- Flattern Layer
- Fully Connected Layer
- Softmax function



The module descriptions are below here

- **Convolution**

This is the initial layer which extracts features from the input image. By learning the extracted features this layer preserves the relation between pixels. This process takes two inputs such as image matrix and a filter or kernel and this operation is based on mathematics. Image matrix dimension =  $h \times w \times d$ . Here  $h$  = height,  $w$  = width,  $d$  = dimension.

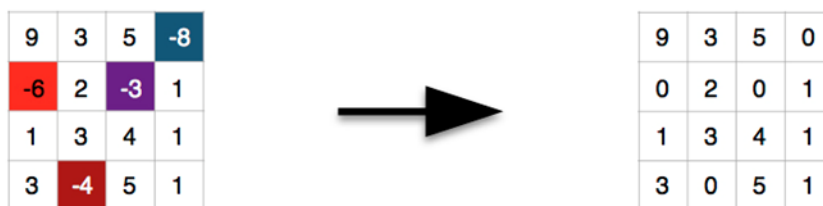


- **ReLU layer**

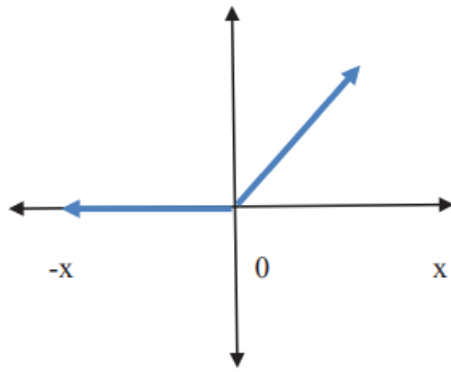
The second part of this step will involve the Rectified Linear Unit or ReLU. We will cover ReLU layers and explore how linearity functions in the context of Convolutional Neural Networks.

### ReLU Layer

#### Filter 1 Feature Map

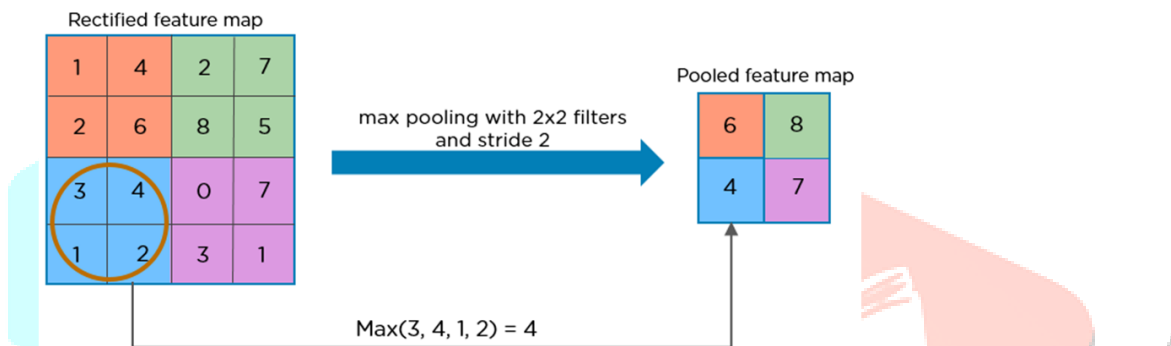


ReLU (Rectified linear unit) Layer It is a supplementary step in the convolution operation. The main purpose of the rectifier function is to increase the nonlinearity in the given input. Originally the images are naturally non-linear ReLU function. It will output the input directly if it is positive and otherwise it will output zero if it overcomes the vanishing gradient problem.



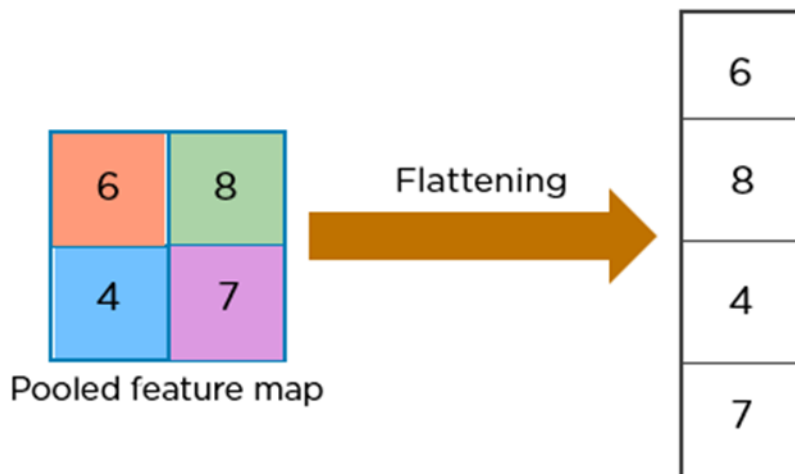
• **Pooling Layer**

In this part, we'll cover pooling and will get to understand exactly how it generally works. Our nexus here, however, will be a specific type of pooling; max pooling. We'll cover various approaches, though, including mean (or sum) pooling. This part will end with a demonstration made using a visual interactive tool that will definitely sort the whole concept out for you.



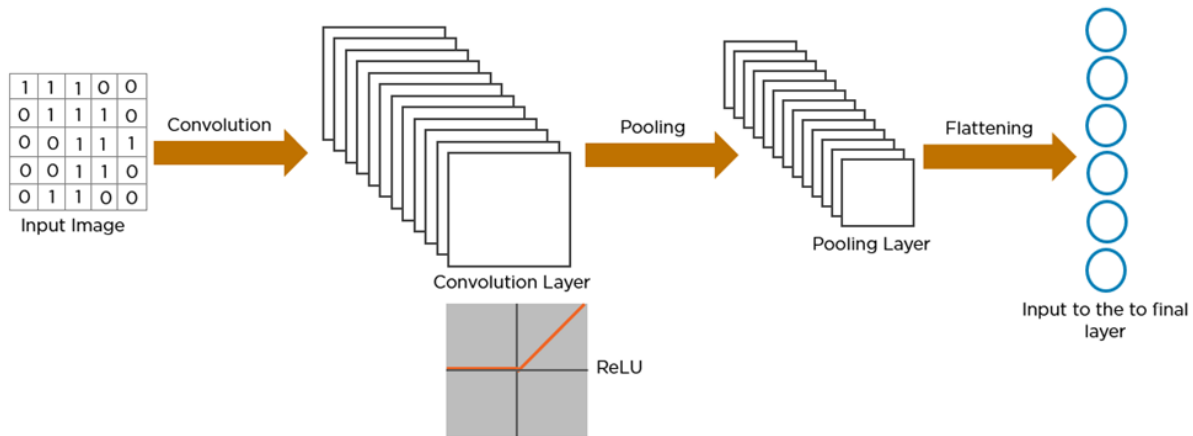
• **Flattern Layer**

- This will be a brief breakdown of the flattening process and how we move from pooled to flattened layers when working with Convolutional Neural Networks.



- **Fully Connected Layer**

In this part, everything that we covered throughout the section will be merged together. By learning this, you'll get to envision a fuller picture of how Convolutional Neural Networks operate and how the "neurons" that are finally produced learn the classification of images.



- **Softmax function**

It is a squashing function limit when the output into the range is between 0 and 1. The outputs of a soft max layer are interpreted as a probability. After applying soft max, each component will be in the interval between 0 and 1.

### VGG19.

The convolutional neural network (CNN) is shown in Figure 1, which includes a convolutional layer, a down sampling layer, and a fully connected layer. Each layer has multiple feature maps, and each feature map has multiple neurons, and the input features are extracted through the convolution filter. The parameter sharing mechanism of the convolutional layer greatly reduces the number of parameters.

The research is based on the VGG19 network to optimize and improve the network. The main structure of VGG19 consists of 5 convolution modules, 3 fully connected layers, and an input layer and output layer. Each convolution layer module is down sampled through the max pool.

The expression of the convolutional layer is as follows:

$$x_j^l = f \left( \sum_{i \in M_j} x_i^{l-1} * k_{ij}^l + b_j^l \right). \quad (1)$$

In Equation (1), assuming that  $l-1$  is the input layer or the pooling layer, and the  $l$  layer is the convolutional layer, then  $x_i^{l-1}$  is the  $i$ -th feature map of the  $l-1$  convolutional layer; the right side of Equation (1) represents the feature map of the  $l-1$  layer. Perform convolution operation with the  $i$ -th convolution kernel  $k_{ij}^l$  of the  $l$  layer and sum;  $b_j^l$  represents the bias;  $f(\cdot)$  is the activation function ReLU.

The pooling layer closely follows the convolutional layer and plays the role of scaling dimension a subj The calculation equation is as follows:

$$x_i^l = f(\beta_j^l \text{down}(x_i^{l-1}) + b_j^l). \quad (2)$$

In Equation (2),  $\text{down}(\cdot)$  is the pooling function, which seeks the maximum vfeature map region of the featuremap;  $\beta_j^l$  and  $b_j^l$ , respectively, represent the weight and bias of pooling.

The input layer size of VGG19 is  $224 \times 224 \times 3$ , and the convolution module is composed of a stack of convolution layers and pooling layers. The convolution kernel is usually  $3 \times 3$  with a step size of 1, and the pooling layer is a  $2 \times 2$  max pool. Using the convolutional layer and the pooling layer to cooperate, on the one hand, the image size is reduced and the amount of model calculation is controlled. On the other hand, the convolution data of the large receptive field is obtained indirectly, and the high-dimensional feature

map is obtained. The convolution module is followed by three fully connected layers to obtain the classification information of the feature map, and finally, the softmax layer is used to output the classification results. The structure diagram of the VGG19 network is shown in Figure 2.

The increase in the depth of the convolutional neural network in the VGG19 network and the use of small convolution kernels have a great impact on the final classification Computational and Mathematical Methods in Medicine structure.

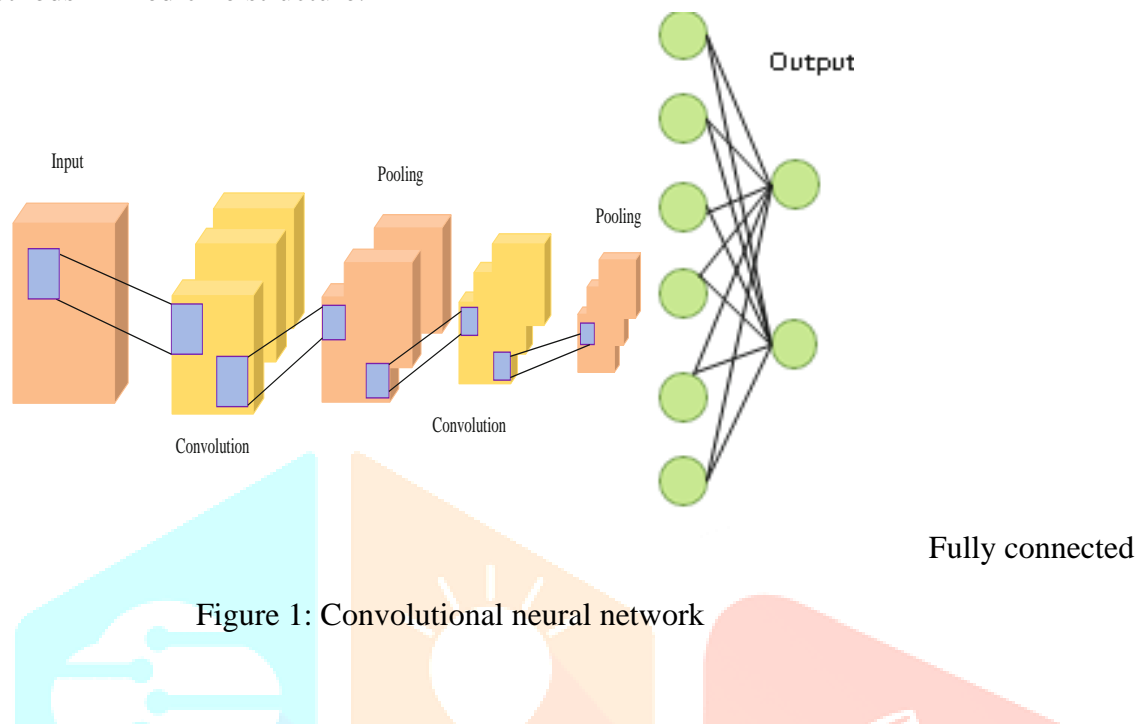


Figure 1: Convolutional neural network

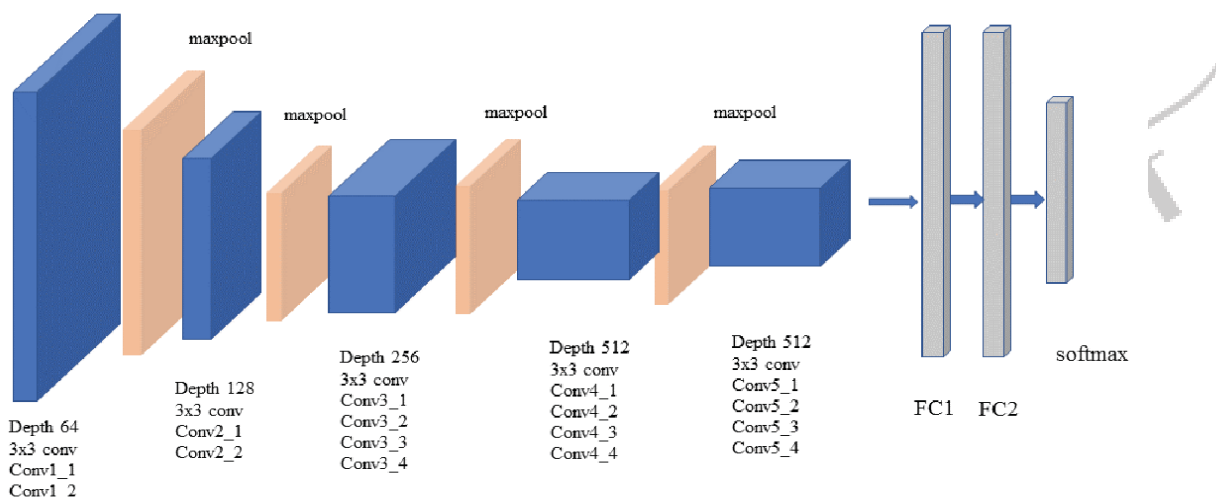


Figure 2: VGG19 structure

and recognition effect of the network. The convolutional layers all use the same 3-size convolution kernel parameters, and the pooling layers all use the same pooling kernel parameters. The combination of multiple 3×3 convolutional layers not only has a small amount of calculation but also obtains the same receptive field of the large convolution kernel at the same time. The deep network structure verifies the conjecture that network performance can be improved by continuously deepening the network structure. But for some data, a too deep network only greatly increases the training time but does not improve the accuracy. The convolution kernel of VGG19 increases from 64 to 512 sequentially and the number of image channels are first reduced to 64 and then increased to 512. However, due to a large amount of image data, this change in the number of channels will cause the data to lose a lot of information. Increasing the time cost of training and the network structure of VGG19 for this research task, while increasing the depth of the network, cannot improve the accuracy of the network.

Convolutional neural networks are mainly composed of convolutional layers, nonlinear units, pooling layers, and fully connected layers. In the classification problem, the convolutional layer, the nonlinear unit, and the pooling layer are used as the feature extraction layer to extract features, and the fully connected layer is used as the classification layer for classification. The convolutional layer is the core of the convolutional neural network, and the convolution equation is shown in Equation (3).

$$y(t) = \int_{-\infty}^{\infty} x(P)h(t - P) dP = x(t) \times h(t). \quad (3)$$

The nonlinear unit is the ReLU activation function, and its expression is shown in Equation (4).

The pooling layer is a downsampling operation to reduce the dimensionality of the extracted features while retaining important information about the features.

The VGG19 network is trained on a large data set ImageNet. The ImageNet data set is a 1000 classification problem data set, so the classification layer parameters of the VGG19 network are huge. The diagnosis of schizophrenia is a two-class classification problem and does not require a complex classification layer. Therefore, the feature extraction layer of the VGG19 network is retained, the classification layer is redesigned, and the original 3-layer fully connected layer is improved to a 2-layer fully connected layer. We take the features of 3 convolutional layers and 3 pooling layers as an example, and the process of part of the extracted features is shown in Figure 3. Use the ReLU activation function, add a dropout layer to prevent over-fitting, and change the final output classification to two categories. The data can be divided into schizophrenia and nonschizophrenia, and the amount of parameters is reduced so that the network converges faster, and the recognition speed of the data is improved. Figure 4 shows the improved VGG19 schizophrenia classification model.

**Transfer Learning.** Transfer learning solves the shortcomings of deep learning that requires a large number of sample training models. By training a pre-trained model on a large data set, it is possible to use a small number of data sets to train the model. Fine-tune is a training method that retains the model feature extraction layer and retrains the model classification layer. The pretraining model used is the VGG19 network pre-trained on the ImageNet data set, and the feature extraction layer of the pretraining model is fixed. Retrain the improved classification layer of VGG19 to complete the training of the schizophrenia classification model.

## Functional Documentation

Functional Documentation plays a vital role in describing the various functionalities of the project. Basically, it considers the various forms designed for the project and explains various functions associated with the form. As a matter of fact, each form is an integrated part of the project and has its own, intended functionality. Often, a form may be related to other forms in the project too.

In this section, we explain the functional documentation of the project. It considers various blocks of the modules and the associated forms.

## Results

### Data Set

This experimental data set comes from the public data set of the Center for Biomedical Research Excellence (COBRE). The address of the COBRE data set is [HTTP://fcon\\_1000.Projects.nitrc.org/indi/retro/cobre.html](http://fcon_1000.Projects.nitrc.org/indi/retro/cobre.html). The data set in this paper contains 200 samples between the ages of 18 and 65. The information is shown in Table 1. In this paper, the original data is preprocessed by binarization, standardization, and smoothing.



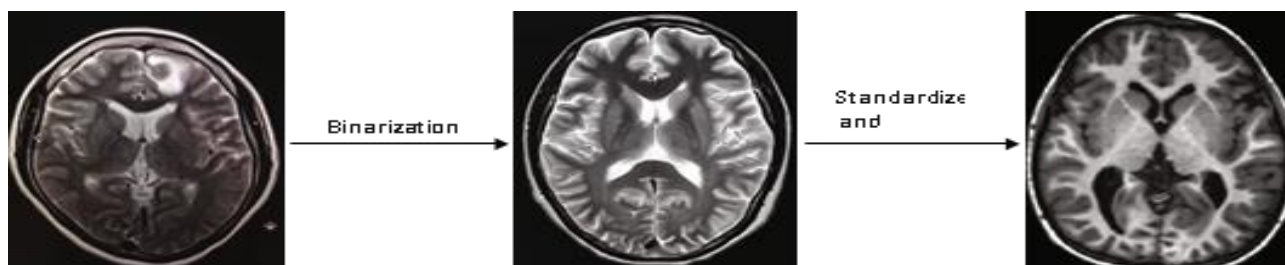


FIGURE 6: Data preprocessing process.

**Evaluation Index**

We use evaluation indicators commonly used in classification tasks: precision, recall, accuracy, and AUC. Table 2 illustrates the classification task through the confusion matrix. True positive (TP) indicates that the positive class is predicted as a positive class, and the number of sample positive classes was predicted by the model. False-negative indicates (FN) that the positive class is predicted as a negative class, and the number of negative classes in the sample was predicted by the model. False-positive (FP) indicates that the negative class is predicted as a positive class, and the number of positive classes of samples was predicted by the model. True negative (TN) indicates that the negative class is predicted as a negative class, and the number of sample negative classes was predicted by the model.

*The definition of recall rate:* it is the proportion of the true correct accounted for all actual positive. The calculation equation is as follows.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

TABLE 2: Confusion matrix.

Data type	Predicted positive class	Predictive negative class
Actual positive class	TP	FN
Actual negative class	FP	TN

TABLE 3: Comparison of effects of different models

Different models	Accuracy	Precision	Recall	AUC
AlexNet	78.36%	81.29%	75.66%	0.76
VGG19	85.27%	86.33%	87.48%	0.83



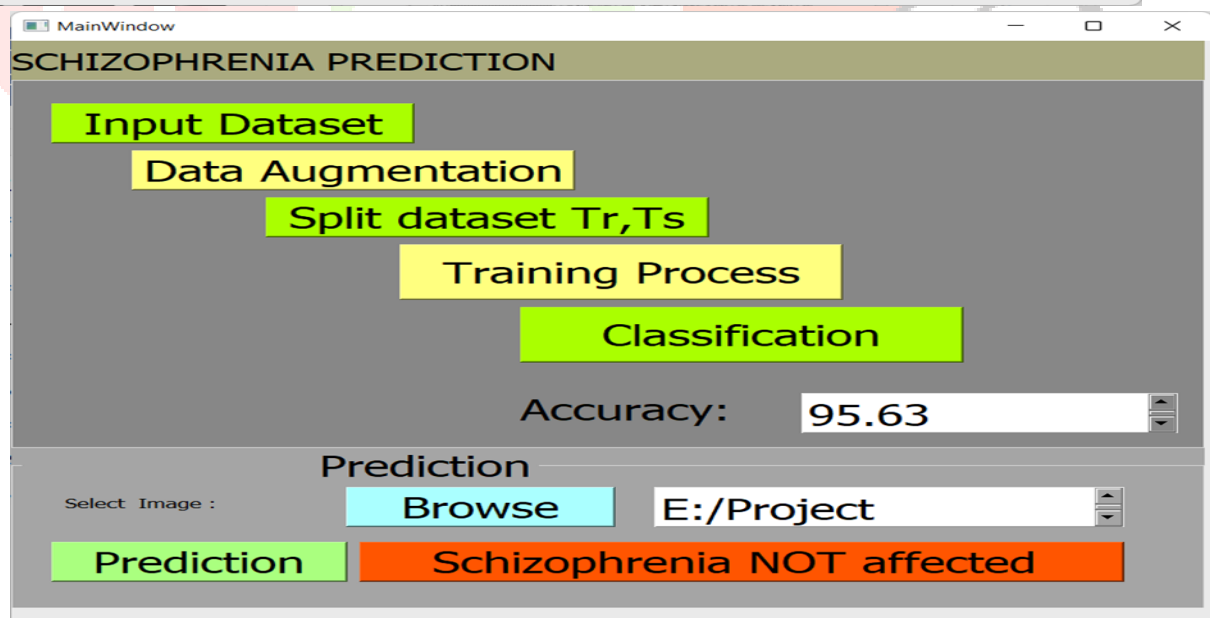
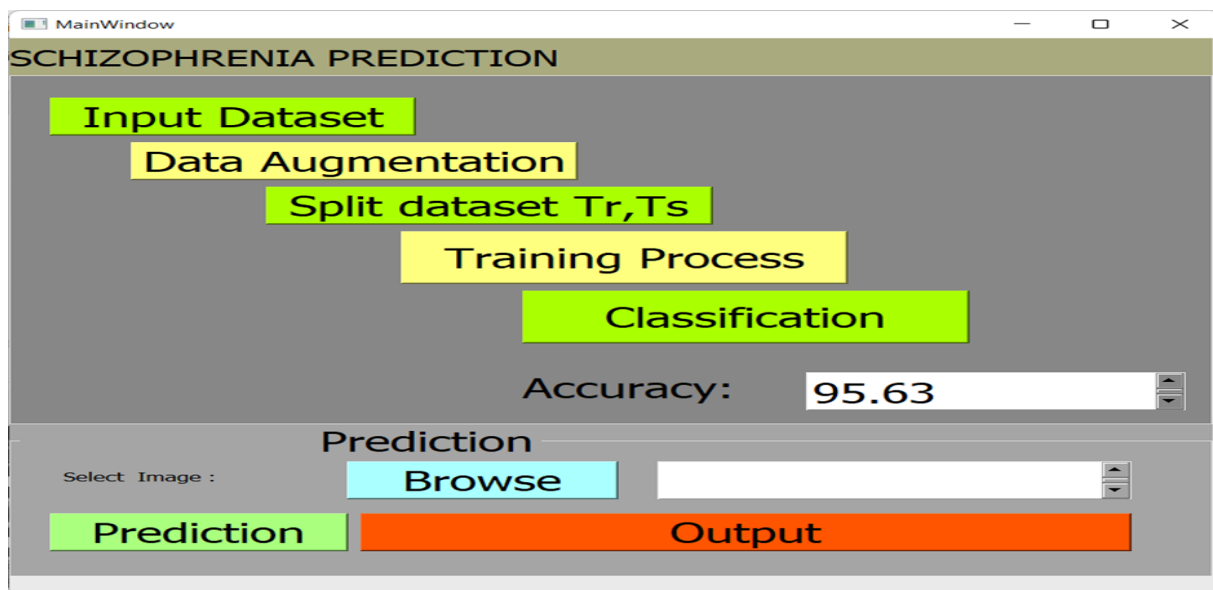
**The definition of accuracy:** it is the proportion of all truly correct predictions. The calculation equation is as follows.

$$\text{Precision} = \frac{TP}{TP+FP}$$

## EXPERIMENTAL RESULTS

Implementation of a software package refers to the installation of the package in its real environment to the full satisfaction of the users and operating system. In short, implementation constitutes all activities that are required to put an already tested and completed package into operation. The success of any information system lies in its successful implementation.

## OUTPUT



## CONCLUSION

The deep learning technique of fMRI data is used in this study to create a diagnosis model for schizophrenia patients and normal people. Schizophrenia is a severe form of schizophrenia. It is currently diagnosed clinically using a diagnostic scale and the doctor's experience, primarily based on the disease's progression. This work established a mathematical model for differential diagnosis of the disease using objective EEG data and deep learning algorithms, with promising results. It can serve as a reference for clinical diagnosis and improve physicians' abilities to diagnose schizophrenia in order to detect the condition early and provide timely treatment. A schizophrenia diagnosis model based on convolutional neural network algorithm was developed through deep learning to overcome the difficulties of low accuracy in pathological recognition and complex feature engineering development in traditional artificial recognition. The network starts with VGG19 for migration learning, then designs the convolution structure of the neural network to extract the features of fMRI, and lastly uses the fully connected layer for training and continuous optimization to get the best weight values.

The highest classification accuracy rate (87.85%) and the highest accuracy rate (87.11%) compared with the current several popular methods. And the highest recall rate is 89.63%. The diagnostic accuracy rates of AlexNet, VGG19models are 78.36% and 85.27%

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