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Original Research

Accuracy Improvement of Detecting the Effect of Alcohol Consumption on Brain Structure in MRI Images using Deep Learning Methods

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Abstract

This paper proposes a deep convolution neural network model for detecting the effects of alcohol consumption in brain MRI images. The main objective of the research is to simulate and identify the structural and functional changes of the brain caused by alcohol consumption. In this research, MRI images were first pre-processed using SPM software to prepare for model training. Then, a CNN model was designed and trained to detect the effects of alcohol consumption. Experiments showed that by increasing the number of IPAKs, setting the learning rate to 0.001, and using a convolution window size of 3×3 , the best performance was achieved. The experimental results indicate a precision of 95.85%, a recall rate of 95%, and an F1 criterion of 96%, which indicates the excellent performance of the model. This research can be used as an effective tool for automatically detecting the effects of alcohol consumption in MRI images in medical and clinical research and can help increase the accuracy and speed of diagnosis in clinical processes. The results could also be useful in studies related to brain disorders caused by drug and alcohol use.

KEYWORDS: Brain Activity, Magnetic Resonance Imaging, Deep Learning, Alcohol Use

Introduction

Alcohol consumption has led to widespread health and well-being problems worldwide. These problems, which often seem insignificant during adolescence, become more serious over time and with continued consumption, requiring long-term medical and psychological management. Alcohol-related disorders can cause severe physical and psychological harm to individuals and are particularly associated with increased morbidity and mortality. For this reason, much research has been conducted worldwide to identify risk factors, prevalence, and prognosis for these disorders [1]. However, patients with alcohol dependence are often reluctant to seek medical attention due to a lack of insight and an underestimation of the urgency of treatment. This leads to social stigma and fear of treatment, and many patients seek medical help only when they are faced with serious complications such as alcoholic hepatitis, cardiovascular disease, or brain problems. In the United States, only a small percentage of alcohol-dependent patients receive specialized treatment. One of the serious harms of alcohol consumption is its effects on the



brain[2]. The brain is a vital part of the central nervous system that acts as the body's command centre and is composed of three main components: white matter, gray matter, and cerebrospinal fluid. These components contribute to the structure and function of the brain with their different properties [3]. Changes in brain structure, such as those seen in disorders such as schizophrenia, dementia, and alcohol-related damage, can be measured using imaging techniques. Neuro imaging allows researchers to identify brain damage caused by alcohol use and gain a better understanding of mental disorders and their effects. These advances in imaging have contributed to faster diagnosis, more accurate prognosis, and better monitoring of brain health [4]. Magnetic resonance imaging (MRI) is an advanced method for producing detailed images of the internal organs of the body, especially the brain. This technique uses strong magnetic fields and radio waves to produce images of areas of the body that cannot be seen with other methods such as X-rays or ultrasound. In the diagnosis of alcohol use disorders, MRI images are processed by experts, but human error can cause serious problems [5]. For this reason, the use of expert systems and techniques based on machine learning and deep learning is essential to reduce human error in this process. Neurodegenerative diseases caused by alcohol use can lead to damage to neurons and severe disabilities [6]. These disorders are not curable, and treatments are mainly focused on reducing symptoms. Recent advances in artificial intelligence and machine learning can help in early diagnosis, monitoring the disease and determining its progression, and in some cases even lead to significant improvements in the treatment of these disorders [7]. Machine learning-based methods in artificial intelligence are effective tools for identifying and diagnosing various diseases and classifying them [8]. These methods, with the help of advanced algorithms, can discover hidden patterns in data, thereby increasing the accuracy of diagnosis, reducing costs, and reducing the need for human resources [9]. However, these methods also have challenges such as over fitting and low accuracy in some cases. Research has shown that brain images, such as MRI images, are directly related to symptoms caused by alcohol consumption [10]. The use of MRI image processing techniques and deep learning in diagnosing the effects of alcohol consumption on the brain has become increasingly common. Alcohol consumption causes structural changes in the brain, and some areas related to neural networks are damaged, especially in chronic alcoholism. Deep learning has been widely used in identifying hidden patterns in brain data and can be useful in discovering the relationship between vital signs of individuals and specific diseases. These techniques have been successful in automatically detecting alcohol consumption from MRI images and have been extensively studied [11, 12]. In addition, changes in cortical thickness have been identified as a result of alcohol consumption, especially in adolescents, although previous results in this area have been inconsistent. Deep learning, as a subset of artificial intelligence, allows computer systems to improve without explicit programming and simply by increasing data, and to perform better in various tasks such as automatic face recognition or learning how robots move [13]. This research seeks to develop a deep learning-based system that can accurately identify changes and damage caused by alcohol consumption in the structure and function of the brain through MRI images. Detecting these damages, especially in the early stages, can help doctors make appropriate treatment decisions and interventions. Traditional diagnostic methods usually require complex clinical examinations and are unable to identify early changes in the brain. In contrast, MRI images are considered an effective tool for detecting these changes due to their high resolution and the lack of need for surgery to view the internal structures of the brain. Using deep learning methods and complex neural networks, this research seeks to design a system that can automatically and accurately identify brain changes caused by alcohol consumption. Several studies have been conducted on the segmentation, detection, classification, and detection of brain activity in MRI images to detect heavy alcohol consumption on the brain, but there is still a long way to go before reaching the desired point and providing an efficient and comprehensive method. In [14], three machine learning models SVM, random forest, and logistic regression were used to detect Internet gaming disorder (IGD) and alcohol use disorder (AUD) in healthy individuals. Three sets of features were used to train the models: EEG features, neuropsychological features (NF) such as gender and age, and a combination of the two. The results showed that the logistic regression model with combined features had the best performance with an accuracy of 0.712. The important features included electroencephalographic (EEG) activities in the right hemisphere and NF



features such as gender and age. The main challenge of using these models is the problem of over fitting, which can reduce the performance of the models. In [15], this study used MRI imaging and unsupervised non-negative matrix factorization (NMF) machine learning to examine cortical thickness changes in 657 adolescents (12–22 years). Results showed that cortical thickness decreases were similar in adolescents with low and no alcohol consumption, but in adolescents with moderate alcohol consumption, the decrease was faster in the younger group. In the heavy alcohol consumption group, cortical thinning was faster in younger adolescents and less in older adolescents. These findings suggest that alcohol consumption and age influence cortical thickness changes. In [16], this study identified AUD using resting-state functional network connectivity (rsFNC) analysis and machine learning. 51 alcohol-dependent individuals and 51 controls were used. The best classification performance was obtained with the neural network (AUC=0.79). The results showed that functional connectivity between visual, sensor motor, executive control, and reward networks were the most important features for identifying AUD. In [17], this research proposes a framework that uses raw EEG data as input to deep learning algorithms such as convolution neural network (CNN), short-term memory (LSTM), and CNN+LSTM combination for alcohol addiction diagnosis. The proposed models are implemented on the UCI alcohol EEG dataset and the results are compared with conventional methods. The results show that the classification accuracy of the models was 99.60%, 98.12%, and 95.95% in the training dataset and 92.77%, 89%, and 91% in the test dataset, respectively, with error rates of 7.5%, 11.90%, and 8.7% for CNN, LSTM, and CNN+LSTM. In [18], this research used data from the South Korean National Health Survey (K-NHANES) to predict alcohol addiction using deep learning and conventional algorithms. Deep learning performed better than other algorithms, predicting risky consumers with an AUC of 0.870. The most important predictor variables were energy intake and carbohydrates. Also, participants were classified into four regions based on the severity of alcohol problems, which had different AUCs. In [19], this study proposed a custom-made 8-layer deep convolution neural network for detecting brain damage caused by alcohol consumption. The network consists of five convolution layers, five convolution layers, and three fully connected layers, which are designed using deep learning to improve the accuracy of detection. Experimental results showed that the proposed model performs very well in detecting alcoholic brain damage based on MRI images. The sensitivity, accuracy, and other indices in this model were 96.14, 96.20, and 95.98%, respectively, indicating the high efficiency of the proposed method compared to other state-of-the-art approaches. In [20], this study proposed a new approach to detect alcohol consumption that can help radiologists make more accurate diagnoses. In this method, the AlexNet architecture is used as the base transfer learning model. Using a small global learning rate (10⁻⁴) and a number of iterations of 10, various experiments were conducted with different transfer learning configurations. The best performance was obtained by replacing the final fully connected layer. The results showed that the proposed method has a sensitivity of 97.44%, specificity of 97.41%, accuracy of 97.34%, precision of 97.42% and F1 score of 97.7%. This model can be useful in alcoholism screening through brain MRI images. However, the computational complexity of deep learning models remains a challenge. In [21], this study presented a 10-layer convolution neural network for detecting brain damage caused by alcohol consumption using MRI images. The results showed that the model achieved 97.73% sensitivity, 97.69% specificity, and 97.71% accuracy using PReLU, batch normalization, and over fitting rejection techniques. The performance of this model was better than seven other advanced approaches. In [22], this study used a convolution neural network (CNN) with different layers and three fusion methods (max, mean, and random) to analyze the effect of alcohol consumption on the brain. The proposed model performed best with 96.88% sensitivity, 97.18% specificity, and 97.04% accuracy. Random fusion outperformed other methods, and GPU performed faster than CPU. In [5], this study used fuzzy C-regression (FCR) and GLM to investigate the reduction of gray matter volume (GMV) in the left thalamus and right posterior insula for the diagnosis of alcohol use disorder (AUD). The results showed that the FCRAD model outperformed the GLM with an accuracy of 86.06%. However, to better model nonlinear changes in the brain, more advanced methods such as deep learning are proposed. Various methods for diagnosing alcohol use disorder (AUD) include deep learning models such as convolution neural networks (CNN) and combining CNN with LSTM, as well as classical



methods such as linear regression and machine learning (SVM, random forest). Deep neural networks perform particularly well in processing complex data such as MRI images and show high accuracy (over 97%) in detecting brain patterns caused by alcohol consumption. These models are able to simulate complex and nonlinear features, but require high computational resources and a large amount of data. In contrast, classical methods such as linear regression or SVM are simpler and faster, but cannot model nonlinear changes well and have lower accuracy. In this study, we present a novel and practical deep learning framework specifically designed for the diagnosis of alcohol use disorder (AUD) based on brain MRI data. While existing deep learning models for AUD detection often rely on complex architectures with high computational costs, our proposed model emphasizes a lightweight convolutional neural network that balances accuracy with efficiency, making it more suitable for real-world clinical environments. The key novelties of this research can be summarized as follows:

- **Development of a lightweight and optimized CNN architecture** that delivers high accuracy in detecting alcohol-induced brain changes, while reducing the computational overhead compared to conventional deep models.
- **Integration of a structured pipeline** combining MRI pre-processing, dimensionality reduction, and deep feature extraction, enabling a more efficient and end-to-end diagnostic system.
- **Precise localization of affected brain regions**, offering not only classification but also insights into the spatial distribution of alcohol-related brain damage, which can assist clinicians in understanding the neurological impact.

This approach aims to bridge the gap between theoretical research and practical deployment in healthcare settings, offering a scalable solution for early and accurate AUD detection.

The rest of this article is divided into the following sections. In the second section, deep learning is discussed. In the third, the proposed method is discussed and it is analyzed with evaluation criteria. Finally, in the last section, the general conclusion of the article is given.

1.1. Mathematical model of different layers of the proposed CNN

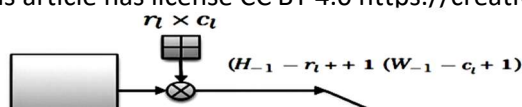
A convolution neural network (CNN) consists of 3 different types of layers:

- Convolution layers
- Sub-sampling layer
- Output layer

The network layers are arranged in a feed forward structure. Each convolution layer is followed by a partial sampling layer, and after the last convolution layer, the output layer is placed. The convolution and partial sampling layers are two-dimensional layers, while the output layer is considered one-dimensional. In CNN, each two-dimensional layer consists of several planes, each plane being a two-dimensional array of neurons. The output of each plane is called a feature map. In a convolution layer, each layer is connected to one or more feature maps from the previous layer. Each connection is assigned a convolution mask. The convolution mask is actually a two-dimensional matrix of adjustable weights, sometimes called a trainable kernel. The task of the weights in the form of trainable kernels is to learn a kind of two-dimensional neural filter for each kernel to extract local features of each input image to the convolution layers. Each plane first computes the convolution between its two-dimensional inputs with its corresponding convolution masks. The convolution outputs are then summed together and added to a configurable scalar value called the bias term. Finally, an activation function is applied to the result to obtain the output plane. In the last convolution layer, each page is connected to exactly one previous feature map. This layer uses convolution masks of the same size as its input feature map. Therefore, each page in the last convolution layer produces a scalar output. The outputs of all pages in this layer are then connected to the output layer. The following is an examination of this network.

1.2.1. Convolution Layer

Suppose l is network layer index. If L is the total number of layers in the network, the values of l vary from 1 to L . we assume $L=2(a+1)$ in a way that a is a positive integer. N_1 is number of the first layer feature maps and $f_l(0)$ is the activation function of the first layer. Y_n^l is also the n th feature map in the first



layer. In this CNN architecture, the convolution layer has an odd index. Suppose that for the l^{th} convolution layer, the mask size is defined as $C_l \times r_l$. In figure 1, the block diagram of the first convolution layer is shown.

Fig.1. Block Diagram of the First Convolution Layer.

Where, $W_{m,n}^l$ is as a convolution mask related to the feature map connection m^{th} in the layer $\{l-1\}$, to the n^{th} feature map in the layer $\{l\}$, b_n^l the bias term for the n^{th} feature map and v_n^l a collection of planes in a layer $\{l-1\}$ which corresponds to the n^{th} feature map in the layer $\{l\}$. According to the above definitions, the feature map n of the convolution layer l is calculated as follows:

$$y_n^l = f_l \left(\sum_{m \in v_n^l} y_{m,n}^{l-1} \otimes w_{m,n}^l + b_n^l \right) \quad (1)$$

The symbol \otimes , is the two-dimensional convolution operator without zero Padding with the mask operator. So if the size of the feature map y_m^{l-1} input is as $H_{l-1} \times W_{l-1}$ and on the other hand the size of convolution mask assume as $r_l \times c_l$ then the size of the output feature map that is y_n^l will be as $(H_{l-1} - r_l + 1) \times (W_{l-1} - c_l + 1)$.

1.2.2. Partial Sampling

The first sampling layer is supposed. In this structure of CNN networks, the indices corresponding to these partial sampling layers are even. we define W_n^l as the weight corresponding to the n^{th} feature map in the l^{th} sampling layer and also b_n^l as Bias sentence. Figure 2, shows the block diagram of the first partial sampling layer.

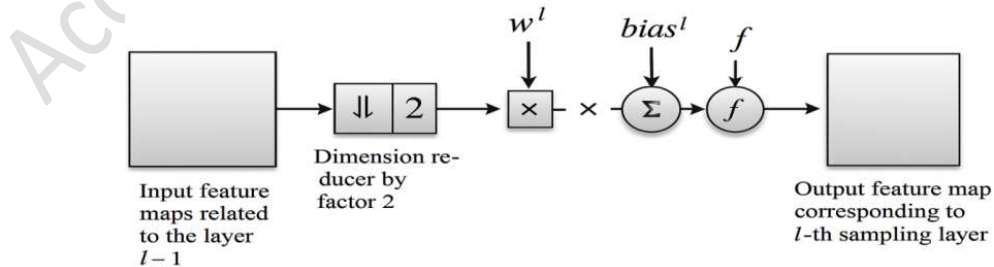


Fig.2. Block Diagram of the first layer of partial sampling.

The operator $2\downarrow$, shows the dimensionality reduction operator by factor 2. In this layer, the n^{th} feature map from the convolution layer $\{l-1\}$, is divided into non-overlapping 2×2 pixel blocks. Z_n^{l-1} , is the matrix obtained by averaging the four pixels in each 2×2 block.

$$z_n^l = \left\{ \frac{1}{4} z_n^{l-1}(i,j) \right\} \quad (2)$$

$$(2i-1, 2j-1) + y_n^{l-1}(2i-1, 2j) + y_n^{l-1}(2i, 2i-1) + y_n^{l-1}(2i, 2j) \quad (3) \quad z_n^l(i,j) = y_n^{l-1}$$

The feature map of the first sampling layer is calculated as follows:

$$y_n^l = f_l(Z_n^{l-1} \times W_n^l + b_n^l) \quad (4)$$

1.2.3. Output Activator Layer

The output activation layer L has sigmoid neurons. N_l specifies the number of output sigmoid neurons. $W_{m,n}^l$ is the weight between the m^{th} feature map of the last convolution layer and the n^{th} neuron of the output layer. b_n^l is the bias term corresponding to the n^{th} neuron of layer L. The output of the n^{th} sigmoid neuron in the output layer is calculated as follows:

$$\left(\sum_{m=1}^{N_{l-1}} y_m^{l-1} \cdot W_{m,n}^l + b_n^l \right) = f_l \quad (5)$$

The structure of the output activation layer with two neurons is shown in Figure 2, In fact, the output layer is a simple MLP that is responsible for classifying data based on the scalar features produced in the last convolution layer. Figure 3, shows the block diagram of the output layer of the Convolution Neural Network.

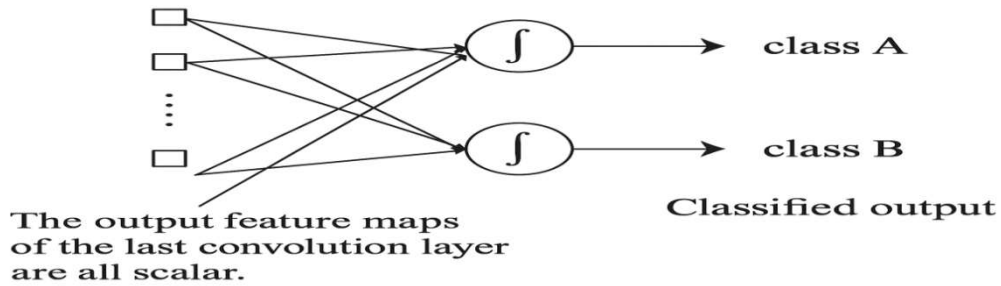


Fig.3. Block Diagram of the Output Layer of the CNN Network.

2. PROPOSED METHOD

Given the challenges associated with deploying deep learning models in clinical settings, the primary objective of this study is to develop an optimized and practical method based on convolutional neural networks (CNN) for detecting alcohol-induced brain effects in MRI images. To this end, we propose an integrated approach that combines structured preprocessing of MRI data, dimensionality reduction of high-volume medical images, and a lightweight CNN architecture. This approach not only improves detection accuracy but also reduces computational complexity and resource consumption, making it feasible for real-world applications such as clinical diagnostics. The following sections describe the components of the proposed method in detail. This method automatically identifies the affected areas and classifies the images. The research investigates the CNN (Convolutional Neural Network) algorithm, which increases the accuracy of detection by using existing data and previous results. This algorithm is specifically designed to simulate and accurately analyze MRI images to detect alcohol-related activities in the brain. The proposed method is shown in figure 4.

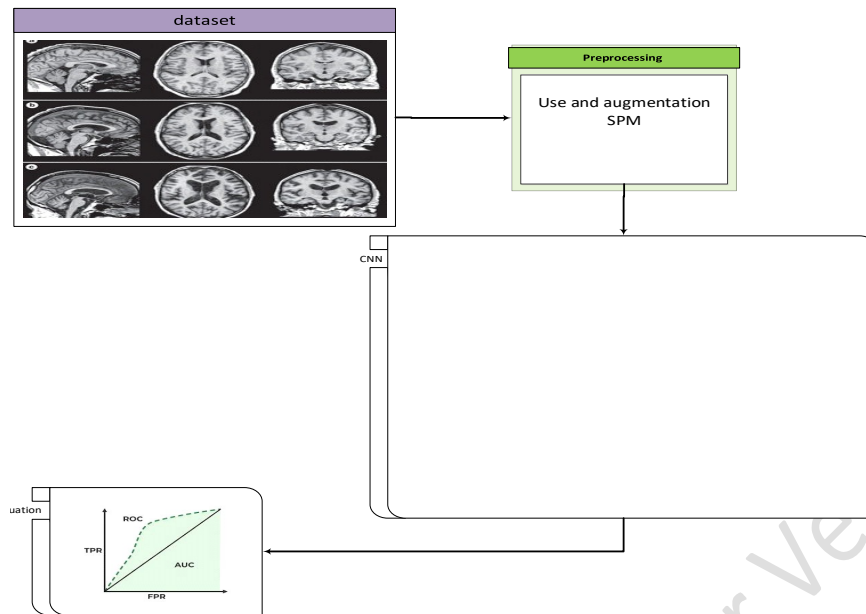


Fig.4. Block Diagram of Proposed Method.

This process involves careful model design and evaluation to ensure that the proposed model works properly and can be used in real-world situations with high accuracy and reliability. Table 1, shows these steps:

Table 1. Steps of Proposed Method.

Step	Description
Data segmentation	The database is divided into two parts: training data (80%) and testing data (20%) so that the model can use new data for evaluation.
Remove excess data	Some redundant and noisy data is optionally removed to increase processing speed and accuracy.
Selecting input and output features	Key features are selected as input and output of the model that are relevant to diabetes diagnosis.
Neural network training	The model is trained with training data, adjusting the learning rate (α) and the tuning parameter (λ) to improve learning.
Model evaluation with test data	Test data is used to check the accuracy and generalizability of the model after training.
Experiment and iterate with different configurations	The model is tested with different network configurations and different tuning parameters to find the most optimal combination.
Repeating experiments and calculating average performance	Each experiment is repeated an average of five times to calculate average performance and variability and achieve better results.

2.1. MRI Preprocessing

The pre processing step of MRI images is essential to improve the quality and prepare the data for more accurate analysis. This process includes removing initial layers for magnetic equilibrium, correcting the acquisition time of slices, correcting for head motion, and matching structural and functional images. The images are also normalized to the standard MNI space and smoothed to reduce noise. Finally, the data are numerically normalized to prepare them for machine learning models. These steps increase the accuracy of data analysis and identify brain features with high accuracy.

2.2. Reducing Dimensions

In this study, MRI data, which are in 3D format, were down sampled to reduce size and facilitate processing without losing important spatial and temporal information. 3D MRI data consist of three spatial dimensions (x, y, z) that represent different slices of the brain in these three axes. To reduce the



dimensions, the first 2D spatial slices in each axis are extracted, thus converting the data into three 2D images. This dimensionality reduction reduces the size of the data and eliminates the complexity of 3D processing, while still preserving key spatial and temporal information. The result of this process is three 2D images for each time point, which allows for faster and more efficient data processing and helps in medical analysis.

2.3. Convolution Neural Network

Figure 5, shows the structure of the proposed CNN. The U-Net architecture is a convolution neural network specifically designed for image segmentation and is widely used in medical image processing. The network consists of two main parts: the bottom-up part (Encoding) that extracts image features using convolution and down sampling layers and reduces the image dimensions, and the top-up part (Decoding) that reconstructs the image dimensions using up sampling layers. The unique feature of U-Net is the use of skip connections between the bottom-up and top-down layers, which transfers spatial details to higher layers and increases the segmentation accuracy. Finally, the output of the network is reconstructed to the size of the input image and is used for applications such as pixel-precise segmentation, especially in medical images such as MRI and CT scans.

2.4. Proposed Transfer Learning

In this study, 32×32 packets of FLAIR images are fed into a 15-layer convolutional neural network. The network consists of 12 convolution layers with 3×3 filters, 3 dense layers (256, 128, and 2) and two Soft max layers. Pooling layers are used to preserve spatially invariant features, and the weights are adjusted by the reference method [14] and the cross-entropy cost function. The ReLU activity function is used with initial Gaussian distribution weights and an initial learning rate of 0.0001, which is increased to 0.3 to prevent overtraining. The number of epochs is maximum 1000, and the model with the lowest error is selected. For the final segmentation, the dense layers are converted to the convolution equivalent in FCN, and the learning weights are used to optimize the transfer model on the new data. The structure of the convolution neural network used in this study is shown in figure 6.

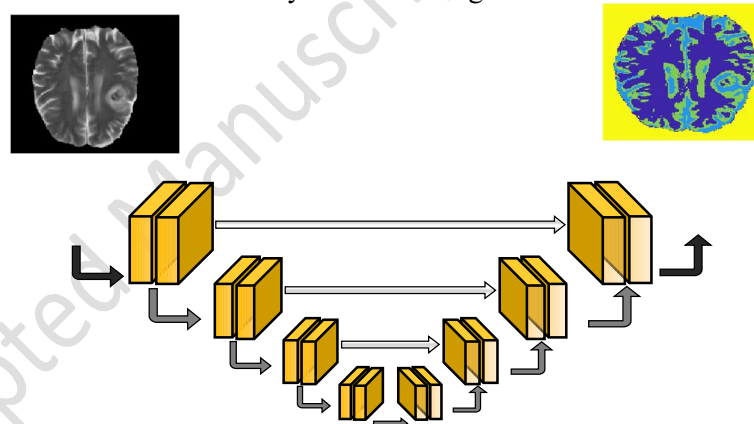


Fig.5. Proposed CNN Architecture.

3. EVALUATION

This study aims to detect the effects of alcohol consumption on the brain through the analysis of MRI images. Given the computational complexity of deep learning models, one of the primary goals of this study was to design a network architecture that balances high accuracy with low computational demand, making it feasible for deployment in clinical environments or systems with limited hardware resources. The use of a lightweight neural network structure, dimensionality reduction of MRI data, and optimized layers in the model design were all aimed at reducing processing time and resource consumption. These considerations enhance the practical applicability of the proposed method in real-world scenarios. For this purpose, a convolutional neural network (CNN) was used, which is capable of extracting and classifying brain features related to changes caused by alcohol consumption. To increase the accuracy and reliability of the model, a 10-fold cross-validation method was used. In this method, the data is divided into 10 parts,

and each time one of the parts is used as test data and the rest as training data. This process is repeated 10 times, reducing the possibility of over fitting and improving the accuracy of the model.

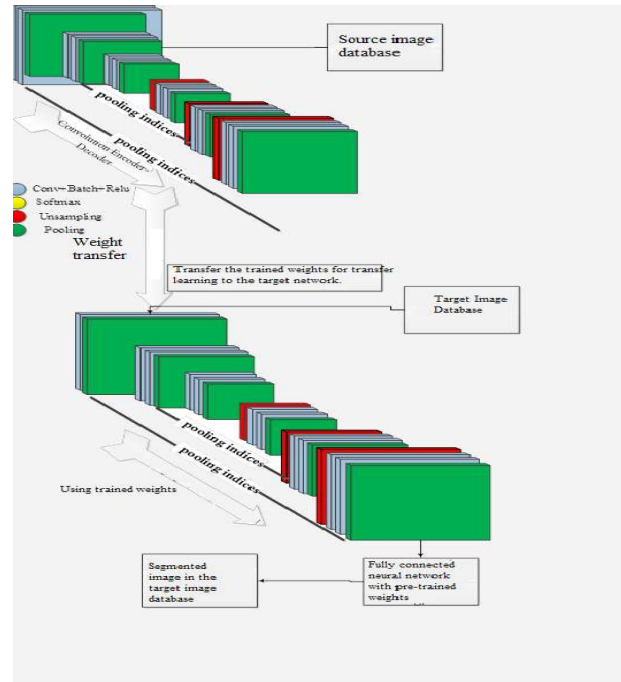


Fig.6. Proposed transfer learning structure.

The system used for simulation in this study is an Intel processor system - number of cores 7 (Core™)i7 CPU) - Q 720 @ 2.60GHz 2.60 GHz with Windows 10 operating system and 8 GB of RAM. To evaluate the proposed method, other criteria such as accuracy, sensitivity, specificity and F-Measure are considered. The following relations show the calculation of these criteria.

$$ACC = \frac{TN + TP}{TN + TP + FN + FP} \quad (6)$$

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

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

$$F_Measure = \frac{2 \times TP}{2 \times TP + FP + FN} \quad (9)$$

In the equations 6,7,8,9 ,TN, is true negatives, FN, is false negatives, TP, is true positives and FP, is false positives. In this paper, a dataset approved by the ethics committee of Henan Polytechnic University will be used. There are three hundred and seventy-nine slices in this database, in which there are 188 alcoholic brain images and 191 non-alcoholic brain images. This dataset will be divided into three parts: a training set including 80 alcoholic brain images and 80 non-alcoholic brain images. A validation set including 30 alcoholic brain images and 30 non-alcoholic brain images. A test set including 78 alcoholic brain images and 81 non-alcoholic brain images. The segmentation is shown in Table 2 [16].

Table 2. Research database specifications.

Set	Total Samples	Alcoholic Subjects	Non-Alcoholic Subjects	Percentage (%)
Training	160	80	80	42%
Validation	60	30	30	16%
Test	159	78	81	42%



Total	379	188	191	100%
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3.1. Parameter Setting in the Proposed CNN Network

In this paper, a method for detecting the effects of alcohol consumption on the brain using MRI images and a convolution neural network (CNN) architecture is presented. The network architecture is designed to have a simple and lightweight structure in addition to high accuracy and efficiency. This design helps to effectively use the model in environments with limited processing and memory resources such as medical devices or end-user applications and ensures the ability to be implemented in practical systems. Details about the parameters of the proposed deep architecture are given in Table 3.

Table 3. Parameters of the proposed deep Neural Network.

Layer	Output Feature Map Size	Kernel Size	Number of Learnable Parameters
Conv Layer 1	180×50×8	3×3	224
Max Pool Layer 1	90×25×8	2×2	0
Conv Layer 2	90×25×16	3×3	1168
Batch Norm Layer 1	90×25×16	-	64
Max Pool Layer 2	45×12×16	2×2	0
Conv Layer 3	45×12×32	3×3	4640
Max Pool Layer 3	22×6×32	2×2	0
Conv Layer 4	22×6×64	3×3	18.496
Batch Norm Layer 2	22×6×64	-	256
Max Pool Layer 4	11×3×64	2×2	0
Conv Layer 5	11×3×128	3×3	73.856
Max Pool Layer 5	5×1×128	2×2	0
Conv Layer 6	5×1×256	3×3	295.168
Batch Norm Layer 3	5×1×256	-	1024
Flattening Layer	1280	-	0
Output Layer	221	-	283.101
Total Number of Learnable Parameters			677.997

In this study, the ADAM algorithm was used to optimize the model, which combines the advantages of AdaGrad and RMSProp and helps manage sparse slopes and noise. ADAM was chosen due to its reduced training time and high computational efficiency. Learning rates of 0.01 and 0.001 were tested, and the results showed that the model quickly reached stable convergence with an accuracy of close to 99.2%. Examination of the accuracy and error plots shows that the model generalized well without overfitting and that the training and validation errors have a stable and similar trend. These results indicate the appropriate performance and stability of the model in learning and generalization to new data.

3.2. Intuitive evaluation

In order to evaluate the results obtained in detecting activity in the proposed method, SPM12 software has been used. This simulation software has been implemented in MATLAB202Rb software and the results will be in the MATLAB system. Figures 7 to 10, show the areas affected by alcohol on the brain in magnetic resonance images obtained in the database and in the SPM output. As can be seen in these figures, the areas under activity are shown in orange. The central cortex of the brain has the most changes



among individuals. These figures are also called activity maps. Figures 6 to 9 show a view of the brain that was most likely obtained using 3D MRI imaging techniques. This image shows the brain surface in 3D as a result of alcohol consumption and especially highlights the areas that are marked in different colours (blue to yellow). These colours indicate the intensity of activity or structural changes in different parts of the brain. In these types of images:

- Blue usually indicates areas with less activity or changes.
- Yellow and green can be considered as indicators of areas with more activity or changes in the brain.

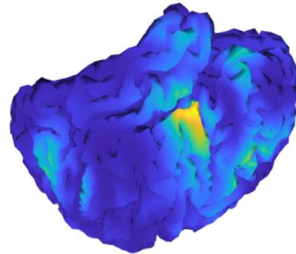


Fig.7.The cortex under the influence of alcohol in the first sample 1 in the proposed method.

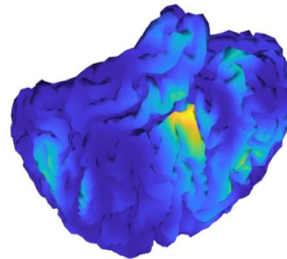


Fig.8.The cortex under the influence of alcohol in the first sample 2 in the proposed method.

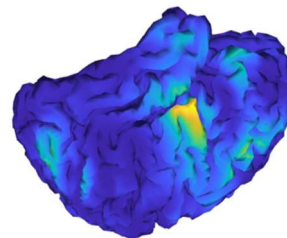


Fig.9.The cortex under the influence of alcohol in the first sample 3 in the proposed method.

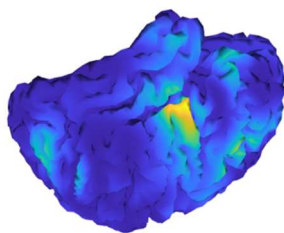


Fig.10.The cortex under the influence of alcohol in sample 4 in the proposed method.

Figures 11 to 13, depict brain maps from the side for both the right and left hemispheres of the brain in alcoholics. These maps show that alcohol consumption leads to changes in various brain regions. As can be seen in these images, not only the main brain regions but also the posterior (back) regions are affected by alcohol consumption. These changes can include a decrease or change in the volume of brain tissue, as well as structural changes in areas responsible for various cognitive and behavioural functions. Examining these brain maps allows specialists to better understand the effects of alcohol consumption on brain structure and use this information to improve diagnostic and therapeutic processes.

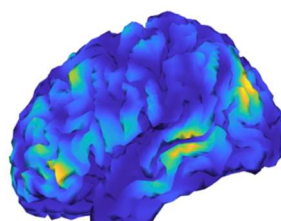


Fig.11.The cortex under the influence of alcohol in sample 1 in the proposed method.

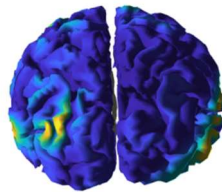


Fig.12.The cortex under the influence of alcohol in sample 1 from a top view in the proposed method.

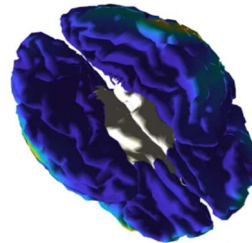


Fig.13.The cortex under the influence of alcohol in sample 1 from the bottom of the brain in the reconstructed image in the proposed method.

3.3. Quantitative Assessment

The following are experiments conducted to determine the appropriate learning rate in machine learning models. In these experiments, a kernel size of 3×3 was used for all convolution layers:

- Determining the appropriate learning rate (η).
The learning rate (η) is an important parameter in the process of training machine learning models. This rate determines how often the model should update the parameters of the neural network weights at each step of its training. The goal is to choose the learning rate so that the model achieves the best performance, not too high to lead to oscillation or divergence, and not too low to make the learning process too slow.
- Test results.
According to the results obtained, the best result was observed when the learning rate was $\eta = 0.001$ and the number of IPAKs (the number of times the model is trained on the data) was 1000 times. These results are shown in figure 14, which shows that with these settings, the model had the best accuracy in detecting the effect of alcohol consumption in magnetic resonance images (MRI) of the brain. Effect of the number of IPAKs and learning rate on accuracy:

This section explains that by increasing the number of IPAKs (i.e., the model is trained more), the accuracy of the model in detecting the effect of alcohol consumption improved. This shows that more training leads to improved model performance. However, another important point that is noted is that if the learning rate is higher, the detection accuracy also improves. This means that by increasing the learning rate, the weight update process is faster.



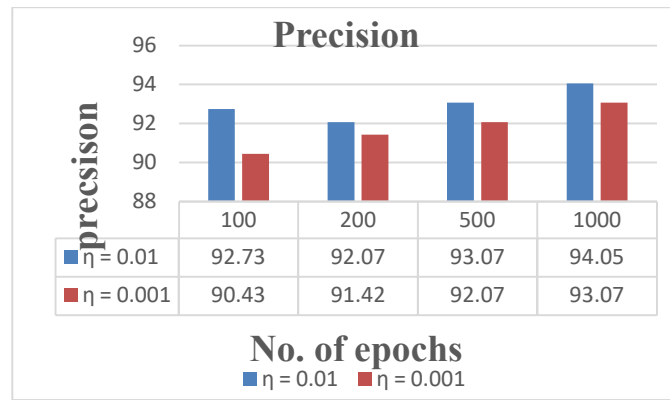


Fig.14.The Average accuracy of detecting the effect of alcohol consumption in magnetic resonance images of the brain at different learning rates and numbers of IPAKs.

Similarly, in the accuracy evaluation, in the recall rate evaluation, classification settings have been made. The learning rate η has been set in two modes: 0.001 and 0.01. The recall rate in these settings and based on the settings presented in figure 15, in the proposed deep neural network at a learning rate of 0.001 and 1000 IPAKs has reached 95%. This value indicates the effectiveness of the proposed method in detecting alcohol consumption in magnetic resonance images of the brain without over fitting. With increasing the number of IPAKs, the oversleep rate has improved.

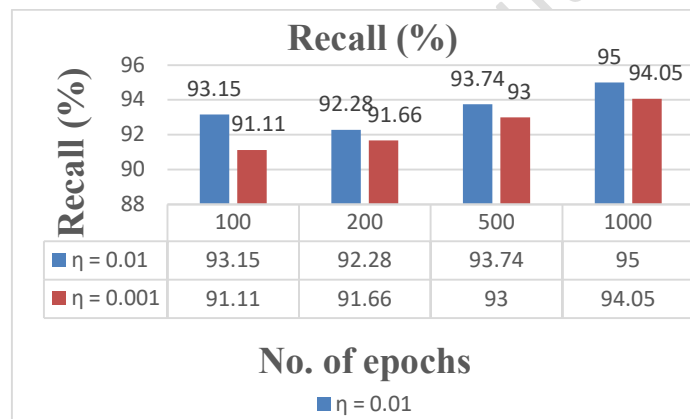


Fig.15.Average recall rate of the effect of alcohol consumption in magnetic resonance images of the brain at different learning rates and number of IPAKs.

In figure 16, the desired evaluations have been made in the F1 score criterion and with the desired settings. Like the recall rate and precision, the F1 score criterion has also improved with increasing the number of IPAKs and also with increasing the learning rate. In such a way that it has reached 85.95 at a learning rate of 0.001 and a number of IPAKs of 1000.

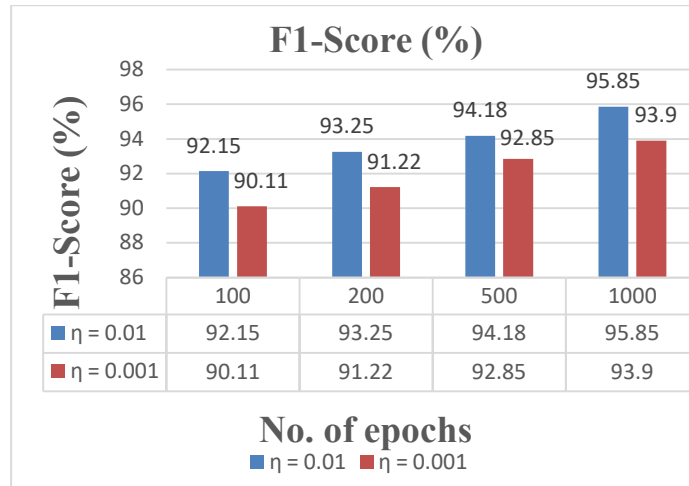


Fig.16. Average F1 score of the effect of alcohol consumption on magnetic resonance images of the brain at different learning rates and number of IPAKs.

3.4. Evaluation of Window Dimensions

The learning rate $\eta = 0.01$ is proven to be the best learning rate. For further testing, to determine the best kernel size for deep CNN, experiments are conducted using different kernel sizes. Kernel sizes of 5×5 and 3×3 were selected as part of the experiment to maintain the aspect ratio of the image. The results of the experiment for different kernel sizes in the accuracy benchmark are given in figure 17. The detection accuracy decreased with increasing the window size. Although the accuracy of the effect of alcohol consumption on brain magnetic resonance images improved with increasing the number of IPACs. However, increasing the window size for convolution caused the detection accuracy to decrease.

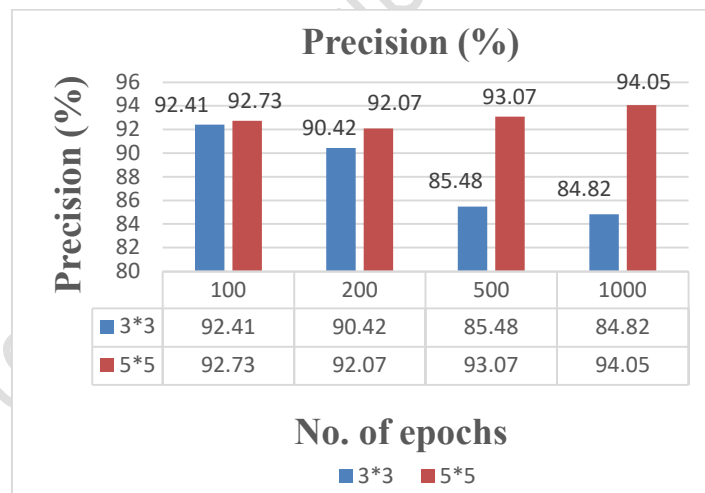


Fig.17. Average accuracy of detecting the effect of alcohol consumption in magnetic resonance images of the brain in different window sizes and numbers of IPAKs.

The comparison of the call rate in different kernel sizes of 3×3 and 5×5 is shown in figure 18. The call rate decreased with increasing kernel size. While the call rate improved with increasing number of IPAKs. The reason for the superiority in smaller window sizes is better engineering and feature learning.

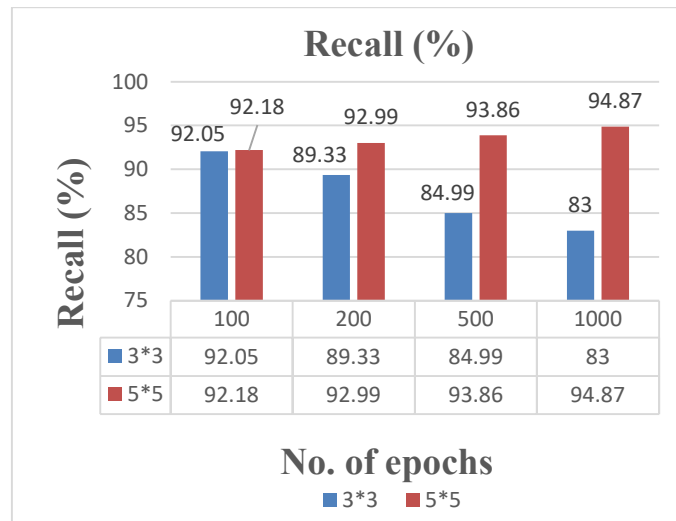


Fig.18.Average recall rate of alcohol consumption effects in magnetic resonance images of the brain in different window sizes and IPAC numbers.

The comparison of the F1 score criterion in different kernel sizes of 3*3 and 5*5 is shown in figure 19. Like the other two evaluation criteria, the F1 score also decreased with increasing kernel size. While the F1 score improved with increasing number of IPAKs. The reason for the superiority in smaller window sizes is better feature engineering and learning. The results obtained from the evaluation phase demonstrate the high effectiveness of the proposed CNN architecture in detecting alcohol-induced brain abnormalities in MRI images. The model achieved an overall accuracy of 99.2%, a recall rate of 95%, and an F1 score of 85.95%, outperforming many previously reported methods. These performance metrics indicate that the model is not only capable of correctly identifying positive cases (i.e., individuals with alcohol use disorder) but also efficient in minimizing false negatives. Furthermore, the analysis of different hyper parameter settings such as learning rate and the number of training iterations showed that the model maintained high stability across varying configurations. Even when the kernel size was increased from 3×3 to 5×5, the decline in accuracy remained within an acceptable range, confirming the robustness and flexibility of the model in diverse scenarios.

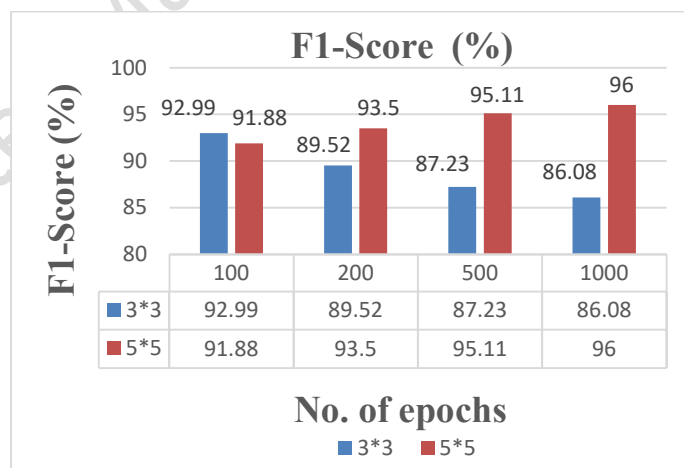


Fig.19.Average F1 score in detecting the effect of alcohol consumption in magnetic resonance images of the brain in different window sizes and numbers of IPAKs.

In addition, the lightweight and computationally efficient structure of the proposed CNN makes it well-suited for deployment in real-world settings, including resource-limited clinical environments or remote diagnostic applications. Collectively, the quantitative and qualitative findings of this study strongly suggest



that the proposed deep learning system is a reliable, accurate, and practical tool for the early detection of alcohol-related brain damage using MRI data.

3.5. Comparison to other methods

As illustrated in the comparison in table4, the proposed model demonstrates superior performance in terms of accuracy, efficiency, and practical the ability deploy compared to previous methods. Many earlier studies relied on non-imaging data such as EEG signals or neuropsychological features, or utilized deep learning models that were computationally intensive and difficult to implement in real-world settings. In contrast, our method employs an end-to-end approach based on MRI images with a lightweight CNN architecture, achieving an accuracy of 99.2%, the highest among the compared studies. Importantly, this is accomplished without the need for heavy computational resources, indicating an effective balance between performance and practicality a key strength of the proposed work.

Table 4. Comparison to other methods.

Study / Method	Type of Model	Dataset Used	Accuracy (%)	Comments
Lee et al. (2024), Logistic Regression [14]	Traditional ML	EEG + NF features	71.2	Best result with combined EEG and neuropsychological features; limited generalizability.
Sun et al. (2023), NMF (Unsupervised ML) [15]	Unsupervised ML	MRI (657 adolescents)	Not reported	Focused on cortical thinning patterns; uses unsupervised approach.
Vergara et al. (2022), Neural Network [16]	Neural Network	rsFNC (102 subjects)	79.0	Focus on functional connectivity features; moderate classification accuracy.
Kumari et al. (2023), CNN LSTM [17]	Hybrid Deep Learning	UCI Alcohol EEG	92.8	High accuracy, but requires heavy computational models.
Kim et al. (2021), Deep Learning [18]	Deep Learning	K-NHANES Survey	87.0	Used for risk prediction; not directly based on MRI image data.
Zhu & Brown (2021), 8 layer CNN [19]	Custom Deep CNN	MRI (dataset size unknown)	96.2	Strong performance, but computational demands and architecture not detailed.
Wang et al. (2019), AlexNet (Transfer) [20]	Transfer Learning CNN	MRI with fine tuned AlexNet	97.3	Excellent accuracy; requires high computational cost.
The Proposed Model	Optimized Light weight CNN	MRI (379 slices)	71.2	Highest reported accuracy; efficient architecture with low resource demand.

3.6. Limitation

Despite the strong performance of the proposed model in detecting alcohol-induced brain damage, several limitations should be acknowledged. First, the dataset used in this study was relatively small and derived from a single source, which may limit the generalizability of the results to broader populations. Second, no explicit statistical control was applied to potential confounding variables such as age, gender, or psychological status, which could have influenced the outcomes. Third, the interpretability of convolutional neural networks (CNNs) remains limited due to their “black-box” nature, making their direct use in clinical decision-making somewhat challenging. To enhance the reliability and applicability of future research, we recommend using larger, multi-center datasets, incorporating explainable AI techniques



to improve model transparency, and integrating complementary statistical analyses to account for possible confounders.

4. CONCLUSION

This study designed and analyzed a deep convolution neural network to detect the effects of alcohol consumption in brain MRI images. The proposed model is capable of automatically extracting features from images without the need for predefined features or manual processing. The efficiency of the model was investigated by changing parameters such as convolution kernel size, learning rate, number of epochs, and activation functions, and after optimally adjusting these parameters, 96% accuracy in classification was achieved. This high accuracy indicates the ability of the model to accurately detect brain changes caused by alcohol consumption in diverse MRI datasets. The results indicate that this model performs better than traditional methods and other deep learning models and confirm its usability as an accurate and reliable tool in clinical settings and medical research. One of the main limitations of this study is the use of a relatively small and single-center dataset, which may reduce the generalizability of the results. Additionally, potential confounding factors such as individual differences in age, gender, mental health status, and variations in MRI scanners could influence brain structures in the images and, consequently, affect the model's outcomes. Although efforts were made to minimize these effects through rigorous data pre processing and cross-validation, future research should consider using larger, more diverse, and multi-center datasets to enhance the model's robustness and external validity. Moreover, incorporating statistical analyses to control for confounding variables can further strengthen the reliability of the findings.

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