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Deep Convolutional Neural Network Model for Automated Diagnosis of Schizophrenia Using EEG Signals

EEG Sinyallerini Kullanarak Şizofreninin Ayırıcı Tanısı için Derin Konvolüsyonel Sinir Ağı Modeli

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Deep Convolutional Neural Network Model for Automated Diagnosis of Schizophrenia Using EEG Signals

ABSTRACT

Objective: One of the serious mental disorders in which people interpret reality in an abnormal situation is schizophrenia. A combination of extremely disordered thoughts, delusions, and hallucinations occurs due to schizophrenia, and the person's daily functions are seriously impaired due to this disease. For general cognitive activity analysis, electroencephalography signals are widely used as a low-resolution diagnostic tool. This study aimed to diagnose schizophrenia using the transfer learning method by including the EEGs of 73 patients diagnosed with schizophrenia, and 67 patients from the healthy group.

Material and Method: In the first step of the study, digital electroencephalography signal data was converted into spectrograms to make them usable. In the classification phase, ResNet18, ResNet50 and EfficientNet models, which are FastAI, and Convolutional Neural Network (CNN) based deep learning models, were used.

Results: Despite the complexity of electroencephalography data, CNN-based models in the study were successful in capturing different aspects of neurophysiological activity. The best performance was obtained from the ResNet-50 model with an accuracy rate of 97%. Afterwards, the classification process was finalized with 95% ResNet-18, and 83% EfficientNet models, respectively.

Conclusion: It is thought that the classification performance of the result obtained in the application is promising and may be a guide for future studies.

Keywords: Artificial Intelligence, EEG, FastAI, Schizophrenia, transfer learning.

ÖZET

Amaç: İnsanların gerçekliği anormal bir durumda yorumladığı ciddi zihinsel bozukluklardan biri de şizofrenidir. Şizofreni nedeniyle aşırı derecede düzensiz düşünce, sanrı ve halüsinasyonların birleşimi ortaya çıkmakta ve bu hastalık nedeniyle kişinin günlük işlevleri ciddi şekilde bozulmaktadır. Genel bilişsel aktivite analizi için elektroensefalografi sinyalleri, düşük çözünürlüklü bir teşhis aracı olarak yaygın olarak kullanılmaktadır. Bu çalışmaya şizofreni tanısı almış 73 hasta ile sağlıklı grubuna ait 67 hastanın EEG'si dahil edilerek transfer öğrenme metodu ile şizofreni teşhisi gerçekleştirmek amaçlanmıştır.

Gereç ve Yöntem: Çalışmanın ilk adımında sayısal elektroensefalografi sinyal verilerini kullanılabilir hale getirmek amacıyla spektogramlara dönüştürme işlemi gerçekleştirilmiştir. Sınıflandırma aşamasında FastAI ile Convolutional Neural Network (CNN) tabanlı derin öğrenme modelleri olan ResNet18, ResNet50 ve EfficientNet modelleri kullanılmıştır.

Bulgular: Elektroensefalografi verilerinin karmaşıklığına rağmen çalışmada CNN tabanlı modeller, nörofizyolojik aktivitenin farklı yönlerini yakalamada başarılı olmuştur. En iyi performans %97 doğruluk oranı ile ResNet-50 modelinden elde edilmiştir. Sonrasında sırasıyla %95 ResNet-18 ve %83 EfficientNet modelleri ile sınıflandırma işlemi sonuçlandırılmıştır.

Sonuç: Uygulamada ulaşılan sonucun sınıflandırma performansının umut verici olduğu ve bundan sonraki yapılacak çalışmalar için yol gösterici nitelikte olabileceği düşünülmektedir.

Anahtar Sözcükler: EEG, FastAI, şizofreni, transfer öğrenme, yapay zekâ.

Introduction

Schizophrenia is a mental illness accompanied by disorders of perception, cognition, thought, behavior, and mood that affects approximately 1% of the world's population (1,2). Today, the diagnosis of schizophrenia is based solely on interviews, and observations of patient behavior by a trained psychiatrist. The diagnosis is made by subjective evaluations between different doctors, and/or centers (3). For this reason, the underlying organic causes (such as drug use that causes psychotic symptoms, brain tumours, susac syndrome, demyelinating diseases) may be missed. Omission of organic causes may lead to failure of the treatments given and progression of the underlying disease.

Since schizophrenia shares many clinical features with other psychiatric disorders, difficulties are encountered in the diagnosis phase. For this reason, biomarkers are sought to help diagnose and monitor schizophrenia. Biomarker evaluation is performed not only in the fields of genetics, morphology/anatomy, but also in the fields of functional imaging, perceptual physiology, and electrophysiology (4-9). In the diagnostic process, performing magnetic resonance imaging or biomaker studies in every patient presenting with schizophrenia symptoms increases the cost considerably. For all these reasons, it would be an appropriate approach to develop methods that are not used routinely but are easy to obtain in case of necessity, economically feasible but can also prevent subjective evaluation. EEG is the most appropriate study for this definition. EEG is an accessible, cheap, and easy-to-use technology. For this reason, EEG is frequently preferred and used in the differential diagnosis of psychiatric diseases (10).

In the literature, EEG studies have been conducted comparing patients diagnosed with schizophrenia based on anamnesis, and mental status examination with other patient groups, and controls. In general, an increase in non-specific abnormalities has been reported in patients with schizophrenia (11). Some studies have stated that EEG abnormalities, and paroxysmal arrhythmias may have a positive effect on prognosis in schizophrenia (12). Using a classification system similar to DSM-IV, Abrams, and Taylor showed that patients with schizophrenia had twice as many left-sided temporal EEG abnormalities as patients with affective disorders (13).

EEG waves may show waveform changes due to physiological artefacts such as blink artefacts, muscle artefacts, movement artefacts, pulse and respiration artefacts, which may adversely affect interpretation or cause misinterpretation. Although it is possible to eliminate environmental artefacts, it is often not possible to eliminate physiological artefacts. This limitations in traditional methods, and special results in EEG data lead to the need to use artificial intelligence, and deep learning methods. With the increasing emphasis on the role of artificial intelligence in medical diagnoses, analysis of EEG data offers significant hope for better understanding and treating psychiatric diseases. This study aims to identify EEG features that may be helpful in diagnosing schizophrenia. By examining the EEG records of schizophrenia patients, the data of the healthy, and control groups were tried to be distinguished using artificial intelligence methods. In the first step, EEG data was converted into spectrograms to make them usable. In the classification phase, Pytorch-based FastAI, and CNN-based ResNet18, ResNet50, and EfficientNet models were used. Despite the complexity of EEG data, CNN-based models have been successful in capturing different aspects of neurophysiological activity.

Material and Method

In the study, EGG data of patients who applied to Binali Yıldırım University Mengücek Gazi Education and Research Hospital Psychiatry Clinic were used. These EEG data, which were taken while the patients were under the follow-up of the psychiatrist for consultations requested from the Neurology Department to rule out organic pathologies, were collected retrospectively between January 1, 2022 and November 1, 2022. EEG data obtained from 73 patients diagnosed with schizophrenia, and 67 individuals from the healthy group constitute the main data source of the study. Local ethics committee approval was obtained on 13.10.2022, number 03/9, and the study was conducted in accordance with the ethical standards specified in the 1983 revision of the Declaration of Helsinki. EEG recordings were made with longitudinal montage on a Micromed branded SD plus 38-channel device with a high transmittance of 70 hertz, and a low transmittance of 0.53 hertz. EEG recordings were taken from FP1, FP2, F3, F4, C3, C4, P3, P4, O1, O2, F7, F8, T3, T4, T5, T6, A1, A2 channels. The naming, and locations of these channels are determined according to the international 10-20 system. Figure I shows the placement of electrodes according to the 10-20 system (14).

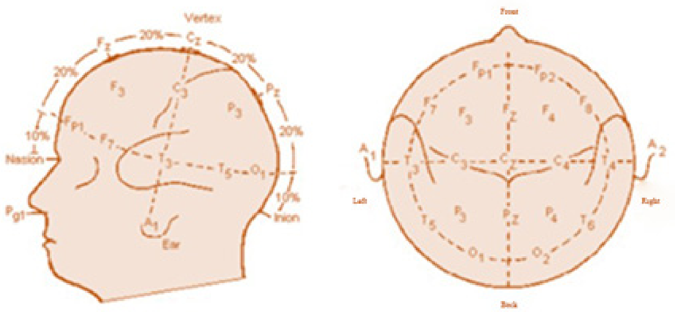

Figure I International 10-20 electrode placement system

Method

The study aimed to detect schizophrenia, and healthy individuals with deep learning methods using EEG data of schizophrenia patients. EEG is a method used to measure brain activity and was used in this study to identify potential differences between healthy, and schizophrenic individuals. The study process flow consists of data collection, data pre-processing, model selection, and model training stages. The process flow of the study is given in Figure II.

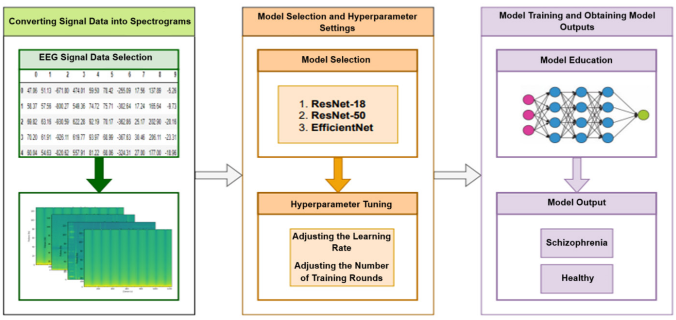

Figure II Working Flow Process

The first step of the study aims to make digital EEG signals more meaningful, and processable. At this stage, the signal data is converted into spectrograms. Spectrograms are matrices that visually express the frequency components of the EEG signal over time (15). These matrices are represented by colored graphs that represent time on the horizontal axis, and frequency on the vertical axis. This approach helps us better understand the complexity of EEG data, and track changes in activity at specific frequencies. Figure III shows an example of a spectrogram of the transformed healthy, and schizophrenia groups.

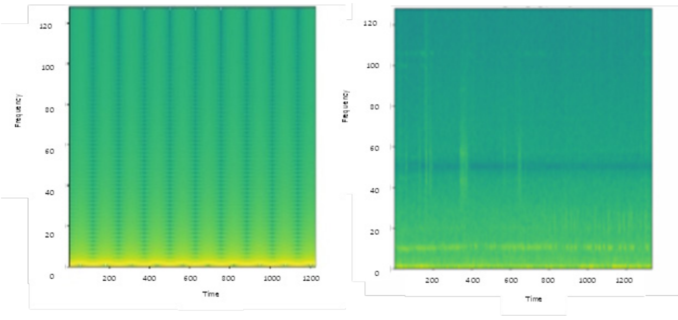

Figure III (a) Transformed spectrogram example for the schizophrenia group (b) Transformed spectrogram example for the healthy group

In the second step, model selection, and hyperparameter settings were carried out by adopting the transfer learning approach. The principle of transfer learning is based on the fact that the general properties, and patterns of the models have previously been examined in a large dataset (16). The convolutional neural network (CNN) is nowadays developing as a reliable method for image classification. Many models in CNN (such as ResNet, DenseNet, EfficientNet, Inception-v3 and others) are used for image classification. CNN can improve its performance by adding layers. However, adding layers can lead to increased layer complexity and loss of gradient. Since this phase greatly affects the success of the study, several different deep network models were evaluated. Depending on the complexity, and nature of the data, ResNet-18, ResNet-50, and EfficientNet neural networks were selected for model training, and classification. Learning rate, number of epochs, and batch-size hyperparameters were adjusted by trial, and error method. Setting these parameters correctly helps the model understand the information better and make better generalization. A summary containing model descriptions of selected deep networks is given in Table I.

Table I Descriptions of pre-trained models

Model	Layer Depth	Input Image Size	Feature Size	Parameters
0ResNet-18	18	224 × 224 × 3	512	11.7 M
ResNet-50	50	224 × 224 × 3	2048	25.6 M
EfficientNet0	0	224 × 224 × 3	1280	(variable)

ResNet

ResNet is a CNN model that has the ability to quickly classify various image types. ResNet is a good solution to eliminate the layer complexity and gradient loss problems caused by adding layers to CNN. ResNet-18, and ResNet-50, which are the most preferred models of the ResNet family, which includes different models according to the number of layers, were preferred within the scope of the study. In both models, batch size 32, and epoch number 100 were used. Using FastAI's lr_find function, the learning rate was determined as 1.3e-3 for ResNet-18, and 1.4e-3 for ResNet-50. While ResNet-18 consists of 18 layers, ResNet-50 has a 50-layer structure. The most important feature of ResNet is that as the network gets deeper, it can learn better by using skipped connections to prevent information loss. This provides the ability to create much deeper networks, and successfully complete more complex visual tasks (17).

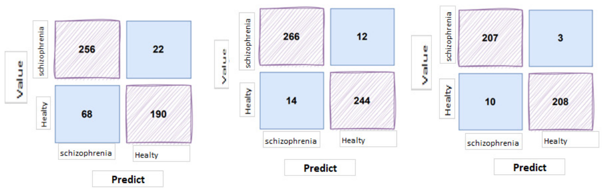

Figure IV (a) Complexity matrix for EfficientNet (b) Complexity matrix for ResNet-18 (c) Complexity matrix for ResNet-50

EfficientNet

EfficientNet is a lightweight, and efficient CNN model. It is optimized using a learning approach that automatically scales network depth, width, and resolution. However, since it is a customizable model, it can be easily adapted to various tasks or data sets. EfficientNet is used successfully in many visual processing tasks such as image classification, and object detection. At the same time, the high level of accuracy shows that EfficientNet also works well on large, and complex datasets (18,19). In the study, EfficientNetB0 was chosen because of its ability to scale CNNs as well as achieving better precision and efficiency. EfficientNetB0 was used with batch size 32, and epoch number 100. With the lr_find function, the learning rate was determined as 1.3e-4. The final step involves training B0 Efficient Networks on the augmented dataset. Transfer learning is used using pre-trained weights from the ImageNet dataset. This approach utilises the knowledge gained by the model on a large-scale dataset (ImageNet). After model selection, and hyperparameter adjustments were completed, the training process was started using FastAI, a PyTorch-based framework. This framework is simple to use, provides fast model training, comprehensive data cleaning, etc. It was preferred for the study due to its features (20). EEG spectrograms, which were part of the training data, were associated with the correct labels (healthy or schizophrenia). In other words, the model accomplished the task of distinguishing between schizophrenic patients, and healthy individuals. As a result of this step, success metrics measuring the performance of the model were evaluated mutually for each model. Table II gives the success metrics used in the study, and explanations of these metrics.

Table II Performance evaluation metrics

Metric	Explanation	Calculation
Truth	Percentage of samples classified correctly	(TP + TN) / (TP + TN + FP + FN)
Sensibility	Ratio of predicted positives to true positives	TP / (TP + FP)
Sensitivity	Ratio of true positives to predicted positives	TP / (TP + FN)
F1 Score	Harmonic mean of precision and sensitivity	2 * (Sensitivity * Sensitivity) / (Sensitivity + Sensitivity)

True Positives (TP): The number of true positives, examples that the model predicts as healthy, and those that are actually healthy,
True Negatives (TN): The number of true negatives, the number of examples that the model predicts as schizophrenia, and those that actually have schizophrenia,
False Positives (FP): The number of false positives, examples that the model predicts as healthy but actually have schizophrenia,
False Negatives (FN): The number of false negatives

represents samples that the model predicts as having schizophrenia but are actually healthy.

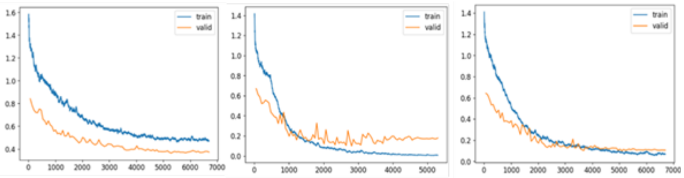

Figure V (a) Loss graph for EfficientNet (b) Loss graph for ResNet-50 (c) Loss graph for ResNet-18

Performance metrics are used to measure how well a model or system processes data, and how reliable the decisions are. These measurements determine the quality, and reliability of the results by evaluating a model's accuracy, precision, sensitivity, and other performance indicators. Application requirements provide a fundamental tool in the decision support phase by determining which metric to use. The results obtained at the end of the study process show how well which model Works, and its ability to diagnose schizophrenia.

Table III Operating performance results

Model	Class	Precision (%)	Sensitivity (%)	F1 Score (%)	Average Accuracy (%)
EfficientNet	Schizophrenia	79	92	85	83
	Healthy	90	74	81	
ResNet-50	Schizophrenia	95	99	97	97
	Healthy	99	95	97	
ResNet-18	Schizophrenia	95	96	95	95
	Healthy	95	95	95	

Power of delta, theta, alpha and beta bands (DP, TP, AP and BP)

Common EEG characteristics primarily include the time-domain features, frequency-domain features and entropy features. The frequency features of EEG are simple and intuitive, and some studies confirmed that frequency features could be effective for recognition of human emotion. Power spectral analysis is a conventional method in EEG analyses. It is based on decomposing the signal, using Fourier transform, into functionally distinct frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz) and beta (12–30 Hz). Then an estimation of the power spectral density of the signal is performed, from which the average band power is computed for each frequency band (DP, TP, AP and BP).

Results

The study aimed to distinguish schizophrenia, and healthy patients with high accuracy using deep learning methods using EEG signal data from a total of 67 healthy and 73 schizophrenia patients. Digital EEG signal data converted into spectrograms were classified with pre-trained CNN models EfficientNet, ResNet-18, and ResNet-50. The performances of deep networks were evaluated using accuracy, sensitivity, precision, and F1-Score metrics. The metric performances obtained because of the study are given in Table III.

When Table III is examined, it can be seen that the targeted high-performance classification process has been successfully carried out. According to Table 3, according to the high sensitivity, sensitivity, and F1 score values in the three models, it is understood that the model has the ability to both accurately identify the disease, and correctly classify healthy individuals. When the average accuracy values are examined, it is seen that the most successful model is ResNet-50 with an accuracy rate of 97%. This success is followed by ResNet-18, and EfficientNet models with 95%, and 83% respectively. Complexity matrices, which express the number of correct, and incorrect predictions in the classification process of the models used, are given in Figure IV.

It can be seen that the complexity matrices given in Figure IV support the accuracy rates given in Table III. When the complexity matrix for the ResNet-50 model, which shows the most successful performance, is examined, it is understood that the prediction rate for the schizophrenia group is higher. In addition to performance metrics, and complexity matrices, loss graphs showing incorrect predictions, and error rates of validation data were also examined. The graphs in Figure V clearly show that the ResNet-50 model exhibits higher performance compared to other models.

The loss graphs given in Figure V are an important tool to closely monitor the training process of the model and evaluate its performance. The observed steady decrease indicates that the model is effectively learning the data and improving the overall accuracy. Without overfitting, the model will adapt to new, and unseen data. This shows that the performance evaluation standards determined to achieve the objectives of the study are compatible with each other.

Discussion

Millions of people worldwide experience a complex psychiatric disorder known as schizophrenia. Correct diagnosis of this disorder, whose diagnosis, and treatment is a long, and difficult process, is of critical importance. In recent years, the use of EEG data has attracted great attention in both clinical, and neurological evaluations for the diagnosis of schizophrenia. The EEG method used to record brain activity helps diagnose neuropsychiatric disorders such as schizophrenia earlier. In this context, artificial intelligence methods play a supporting role by assisting the physician in the analysis of EEG data.

Aslan et al. presented an artificial intelligence-based method to automatically detect schizophrenia from EEG recordings. In the first step, they converted the EEG signals to 2D using Continuous Wavelet Transformation to obtain the time-frequency properties of the EEG signals. They used the VGG16 model of CNN architecture to classify the resulting scalogram images. As a result of the study, they achieved a correct prediction success rate of 99.5% for the healthy group, and 98% for the patient group (21).

Shalbaf et al. proposed a transfer learning-based method using EEG signals to distinguish schizophrenia patients from healthy people. In this study, they converted EEG signals into images with time-frequency analysis, and then applied pre-trained CNN models (AlexNet, ResNet-18, VGG-19 and Inception-v3). They classified the deep features obtained from the convolution, and pooling layers of these models using the SVM classifier. As a result of the study, by combining the frontal, central, parietal, and occipital regions on the ResNet-18-SVM model, the highest performance metrics were accuracy (98.60 ± 2.29%), sensitivity (99.65 ± 2.35), and specificity (99.65 ± 2.35), respectively. It was obtained as 96.92% ± 2.25) (22).

Khare et al. aimed to develop an automatic model that automates the diagnosis of schizophrenia using EEG signals, instead of manual, time-consuming, subjective, and error-prone traditional diagnostic methods. They created an automatic model combining Robust Variational Mode Decomposition (RVMD) and Optimized Extreme Learning Machine (OELM) classifier. Whale Optimization Algorithm was used to optimize the α, and L values of RVMD, and the hyperparameters of the OELM classifier. They stated that this method increased the classification accuracy of the OELM classifier for each mode, while also reducing the root mean square error for RVMD. They were evaluated with the ten-fold cross-validation technique of the OELM classifier, in which the features selected by the Kruskal Wallis test were used. As a result of this evaluation, sensitivity (93.94%), specificity (91.06%), F-1 measure (94.07%), sensitivity (97.15%), and Cohen's Kappa (85.32%) performance measurements were obtained (23).

Padayatty et al. presented a method to distinguish EEG signals in patients with schizophrenia using wavelet transform, and machine learning. They included data from a total of 81 patients, 32 healthy, and 40 schizophrenics, in the study. They obtained frequency, and time data by decomposing non-linear, and non-stationary EEG signals into wavelet coefficients. They performed the classification process by applying KNN, LDA, QDA, and SVM classifiers on the feature set. At the end of the study, they achieved the highest success rate of 90.14% with the SVM classifier. They stated that EEG is an effective biomarker in the diagnosis of schizophrenia, depending on the success rate they achieved (24).

Zulfikar et al. aimed to develop a Computer Aided Diagnosis (CAD) system to support experts for the automatic diagnosis of schizophrenia. They included two different data sets in the study. The first data set used in the study consists of 19-channel EEG signals obtained from 28 participants (14 SZ patients, and 14 healthy controls), and the second data set consists of 16-channel EEG signals obtained from 84 participants (45 SZ patients, and 39 healthy controls). First, they created Hilbert Spectrum (HS) images of the first four Intrinsic Mode Function (IMF) components by applying Empirical Mode Decomposition (EMD) to EEG signals. They then classified these images with VGG16, a pre-trained CNN model. As a result of the study, they reached an accuracy rate of 98.2% for the first data set, and 96.02% for the second data set (25).

Weikoh et al. aimed to automatically diagnose schizophrenia using EEG signals. A total of 1142 EEG recordings, 626 schizophrenic, and 516 normal, were included in the study, collected with a 19-channel electrode array. They used decision tree, support vector machine, and k-nearest neighbor algorithms to classify normal, and schizophrenia groups. They achieved the highest performance with 97.20% with the KNN algorithm (26).

Das et al. proposed a method that examines multivariate EEG signals and extends the univariate iterative filtering (IF) technique to detect schizophrenia. The proposed approach to separate EEG signals into different spectral bands Frequency is a new technique known as multivariate iterative filtering (MIF). They evaluated schizophrenia, and healthy EEG groups with KNN, linear discriminant analysis (LDA), and support vector machine (SVM) classifiers. As a result of the study, they achieved 98.9% accuracy with the SVM (Cubic) classifier (27).

In a study conducted by Bagherzadeh et al. they identified 2 databases including 14 adult schizophrenia and 45 pediatric schizophrenia patient groups. In this study, they used EfficientNetB0, ResNet-50 and NasNet-Mobile models in combination and increased the accuracy rate by 3% compared to other methods and reached 96.67% (28).

The designed system aims to provide support to experts in the decision-making phase with its calculation, and prediction capabilities. The findings show that the system can be used as a reliable tool and can provide significant assistance to healthcare professionals in clinical practice.

Limitations

Small number of patients and healthy control groups, neurological examination, medical history, medical history and medication information were not included in the study, the fact that it has not been evaluated whether the accuracy rate can be increased by combining the available data with several different machine learning methods (such as EfficientNetB0ResNet-50, ResNet-50/NasNet-Mobile).

All these limiting parameters can be overcome by recording patient data in more detail, using several machine learning methods in combination in the same study and performing meta-analyses.

Conclusion

This study investigates the effect of deep learning methods to distinguish between schizophrenia patients, and healthy individuals using EEG data. As a result of the classification process performed using the transfer learning method within the scope of the study, it is seen that ResNet-based models are superior to the EfficientNet model. The results obtained in all three models show that artificial intelligence, and EEG data have a high potential to be used in schizophrenia diagnosis, but the study performance can be improved considering the information available in the literatüre, and the complexity of schizophrenia diagnosis. It is thought that this potential can be further increased in future research by using larger data sets, creating more sensitive algorithms, and integrating neurological examinations. The use of machine learning methods, which are determined to have a high accuracy rate in the diagnostic process, reduces the rate of change in diagnoses according to the evaluating physician. In addition, it enables early detection of underlying organic pathologies and early initiation of the treatment process. The results show that this method can speed up the diagnosis process of schizophrenia, and help obtain more accurate results, and will shed light on future studies in this field.

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