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Providing Intelligent Software to Diagnose the Type and Severity of Mental Disorders Based on QEEG: A Comparative Study between the Statistical Method and the Intelligent Method

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ABSTRACT

Background: Identifying mental disorder biomarkers is one of the leading goals of the clinical science.
Objectives: This study aimed to provide an artificial intelligence based solution and software program to diagnose the type and severity of mental disorders according to the quantitative electroencephalogram (QEEG) of patients.
Materials and Methods: The QEEG data collected from 45 patients addicted to one of the substances (crystal-glass methamphetamine [n=15], tramadol [n=15], heroin/opium [n=15]) and 15 healthy people. They were entered into SPSS version 20 and analyzed by Discriminant Analysis (DA) function and simultaneously used as the Training Group of the artificial neural network (ANN) of the diagnosis software. In order to test and validate the software, in the following, QEEG was also recorded from the remaining 60 subjects (45 addicted and 15 healthy people).
Results: The results obtained from the software were 0.836, 0.884, 7.21, 0.19, 0.712, and 0.890, respectively. Meanwhile, the values of these parameters for DA were 0.677, 0.66, 1.99, 0.49, 0.363, and 0.739, respectively. The results of the software significantly improved the diagnosis. Totally nine discriminant functions were obtained for the frontal, parietal and central lobes was obtained according to the delta, Theta, Alpha and Beta variables.
Conclusion: As a result, intelligent diagnosis software provided can be used with a high sensitivity and great specificity rather than Paper-Pencil tests for accurate diagnosis of the type of disorder and expressing its severity at a confidence level that is scientifically computed and displayed.

Keywords: Artificial Intelligence; Diagnosis; Electroencephalography; Neurolinguistic Programming; Discriminant Analysis

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Introduction

Each mental disorder is thought to be a clinically important behavioral or psychological pattern or syndrome that manifests in one person and is associated with a discomfort (a painful sign) or a disability (disorder in one or more important

functions), or with a considerable increase in the risk of death, pain, discomfort, disability, or the lack of freedom [1]. In addition, this syndrome or pattern should not merely be an expected and approved cultural response against a particular event, such as the death of a loved one. Whatever the main cause, it should be now considered as a behavioral or psychological biological functional disorder in an individual [2].

This type of diagnosis is based on the views of a clinical psychologist or psychiatrist using DSM-5 [3]. A diagnosis can be also made through testing [4]. Considering the common disagreements among experts in some diagnostic cases and as the paper-pencil tests are self-reported and the subjects may pretend to be good or bad (fake bad and fake good), as well as the effect of pre-learning (the effect of pre-test) on the subjects, and that the diagnostic criteria are not based on biomarkers, all deteriorate the validity and reliability of the diagnosis [5].

Previous studies have also been conducted to diagnose mental disorders using artificial intelligence techniques [6]. Imianvan and Obi [7] developed a diagnostic system for bipolar disorder using Neuro-fuzzy tools. The Neuro-fuzzy logically uses neural network techniques to find the parameters of the fuzzy system. Yousif *et al.* [8] developed and implemented a multi-layer perceptron (MLP) to categorize voice samples and identify mental health problems. The proposed categorization system determined whether the voice sample was created by a person with mental problems or not. Schizophrenia and mania are among these mental problems. The project had 99% accuracy. Lopes *et al.* [9] tried to find the common component of mental illnesses by a multilayer perceptron (MLP). The MLP was optimized by Ant Colony Algorithm.The project intended to identify variables that occur more frequently. The accuracy of the method was 89.2%. Abusaa *et al.* [10] created a text mining system to identify psychiatric problems with clustering and categorization methods. Their goal was to differentiate voice samples made by mental patients or healthy people. That study achieved an accuracy of over 92%. Kazas and Margaliot [11] followed an algorithmic approach to visualizing the topology of mental illnesses using a Self-Organizing Feature Map (SOFM). They trained the SOFM for the production of a two-dimensional map of 24 well-known psychiatric patients. Each disorder was represented by a vector containing 82 entries that included the symptoms of the disorder. This map showed the final clusters of mental illnesses. Each cluster contained similar disorders and the map discriminated them from other clusters. This provided a method for visualization and transparent graphing of the topology of mental disorders.

The common feature of previous studies is their limited ability to detect only one or at most two disorders without identifying the severity of the disease and the probable confidence level of intelligent diagnosis. In those instances, there is no possibility of the neural network evolution over time with new data. Therefore, they always offer static results. In the current software, in addition to this possibility, it is possible to define a new disorder without programming. As a distinctive feature of this comprehensiveness software, it can support most mental illnesses in the case of available training samples. In this software, identifying the severity of the mental disorder in addition to its type is a major distinctive success in the field of

diagnosis and tracking clinical outcomes of treatment. Another important point about the severity of the disease is the coincidence of the severity provided by the software for each particular disease in accordance with an objective gold standard. For example, if depression is diagnosed, the severity of depression is expressed in terms of Beck Depression Inventory (BDI-S) and is clinically interpretable. Therefore, the aim of the present study was to provide a software program for diagnosing the type and severity of mental disorders according to QEEG.

The present study tried to use a researcher-made software program and method based on QEEG biomarker to intelligently diagnose the type of mental disorder by expressing the confidence level. In addition, it quantitatively expresses the severity of the disorder in order to track the clinical outcomes of various types of medical and psychological treatments.

Materials and Methods

In this paper, for benchmarking the test results, a case-by-case test was carried out on four types of drug addiction and the results of the software were compared with the results of data Discriminant Analysis (DA) in SPSS version 20 and then reported.

Data from the Neuroguide Training software that is capable of providing a QEEG in three distinct assemblies (19-channel) was used as the data in this research. The data was collected through brain mapping of 45 addicted patients (crystal-glass, tramadol, heroin/opium) and 15 healthy people as a source of statistical analysis in SPSS, as well as four training groups of artificial neural intelligence network within the diagnosis software. In order to test the software, 60 other subjects including 45 addicts and 15 healthy people were enrolled. The parameters of sensitivity, specificity, diagnosis, area under the ROC Curve (AUC), Kappa coefficient, positive likelihood ratio, and negative likelihood were obtained comparatively with the conventional DA method.

Samples of this study were collected through convenience sampling from two psychology and psychiatry centers in Tabriz, both of which provided neurofeedback treatment based on QEEG. Summarize the demographic data of the participants in the study as follows: The mean, standard deviation and age range of tramadol- addicted patients (n=30) were 28.93, 2.96, 21-33 respectively. The same descriptive indicators for heroin and opium addicted patients (n=30) were 29.93, 1.43, 28-34 respectively; also for crystal-glass addicted patients (n=30) were 30.40, 1.80, 27-34. Finally, these descriptive indicators for healthy controls (n=30) were 29.53, 2.35, 25-33 respectively.

Half of the aforementioned participants were used to test and validate the diagnostic software. The variables of this research were the absolute power of the 8 bands, brain encephalogram include (alpha, beta, theta, delta, high beta, beta 1, beta 2, and beta 3) with Frequency range (1.0-3.5 Hz, 4.0-7.5 Hz, 8.0-12.0 Hz, 12.5-25.0 Hz, 25.5-30.0 Hz., 25.5-30.0 Hz, 12.0-15.0 Hz, 15.0-17.5 Hz, 18.0-25.0 Hz) was prepared in a 19-line matrix with 8 brain positions and 8 frequency bands. Furthermore, the following 19 points were recorded in accordance with the International 10–20 system (*C3, C4, P3, P4, O2, O1, P4, P3, P4, F8, F8, T3, T4, T5, Fz, Cz, Pz, F7).*

After recording and deletion of artifacts, the absolute power of the 8 bands (alpha, beta, theta, delta, high beta, beta 1, beta 2, and beta 3) was prepared in a 19-line matrix with

8 brain positions and 8 frequency bands, which is a huge mathematical matrix for each individual. This was done for all the subjects and used in the software training phase. For the diagnosis and evaluation of a new patient, the software reads data of the EEG simply from the data input menu and performs the network simulation phase and provides the output that is the type and severity of the disorder. The data of the first 60 people were analyzed in SPSS and the 4 groups were significant. Then 3 diagnostic equations were determined. The results of the analysis in SPSS will follow and then the results of the current statistical method and the new diagnostic software were compared. Summary of methodology and comparison of two different methods of statistical diagnosis and clinical auto-diagnosis in this study in the table 1 is presented:

Table 1. A summary of the methodology of this research and how to assign subjects to groups

	Experimental group	Number	Role and function	The kind of analysis applied to the data	The calculated parameters of the outputs for comparing the gold standard group and the AI group
Method 1 (statistical and clinical)	Addicted to tramadol	15	Gold standard group (The score and its resulting diagnosis are from an objective valid parallel test. Here the diagnosis is of a clinical psychology expert, that is, both the QEEG and diagnosis of the clinician are obtained for each individual in the group and the diagnostic functions are ultimately obtained by the statistical method)	Discriminant Analysis	Sensitivity, specificity, diagnosis, and calculation of the area under the ROC curve (AUC), Kappa coefficient, positive likelihood ratio, negative likelihood ratio
	Addicted to heroin and opium	15			
	Addicted to crystal-glass	15			
	Healthy controls	15			
Method 2 (intelligent)	Addicted to tramadol	15	Validation Group (The test, evaluation, and validation group of the neural network in the software. Both the QEEG and the clinical diagnosis were obtained for the people of this group, too, but they were finally used as data from the neural network training group)	Learning algorithms after the emergence of artificial neural network and genetic evolutionary algorithms	Sensitivity, specificity, LR+, LR-, Kappa statistics, area under the ROC curve
	Addicted to heroin and opium	15			
	Addicted to crystal-glass	15			
	Healthy controls	15			
	Total subjects	120			

Results

Results section of this research has three sub-sections:

The first section examines the significance of the difference of means of brain frequency bands of the four groups.

The second section examines the eight frequencies bands and the frontal, parietal and central lobes of the brain to determine whether it is possible to determine the type of abused substance through his brain waves or not. The discriminant analysis function are then created (for brevity, the frontal and parietal calculations are excluded and only their results are presented in this paper, the statistical computation of the central areas [C4-CZ-C3], is however fully described).

In the **third section**, the results from applying EEG of the remaining 60 subjects who did not participate in the software learning neural network process were entered into the software and compared with the statistical results.

Section one: hypothesis: It appears that a significant difference exists between the

absolute power of the bands in the frontal, central and occipital brain areas of the four groups of subjects addicted to heroin and opium, tramadol, crystal-glass, and the healthy controls.

Table 2 shows the descriptive statistics in the central area of the brain for the four groups (healthy controls and addicted to tramadol, addicted to heroin and opium, or addicted to crystal-glass).

Table 2. Descriptive statistics for the absolute power of the bands in the four groups in the Central area of the brain

Groups	Waves -	Mean absolute power -	SD -	Minimum -	Maximum
Addicted to tramadol	Delta	107.193	77.027	25.992	206.314
	Theta	163.128	138. 689	23. 493	333. 482
	Alpha	149. 875	151. 248	2. 572	329. 427
	Beta	296. 568	306. 740	1. 140	660. 345
	High Beta	20. 892	21. 769	0. 021	46. 846
	Beta1	110. 615	113. 444	0. 810	244. 974
	Beta2	89. 308	92. 421	0. 316	198. 865
	Beta3	128. 314	133 .356	0. 245	286. 541
Addicted to heroin and opium	Delta	21. 789	11 .165	8. 508	39. 662
	Theta	11. 595	5. 745	7. 258	28. 539
	Alpha	5.792	1.816	3.910	10.049
	Beta	3.930	2.123	1.829	9.660
	High Beta	0.149	0.155	0.052	0.617
	Beta1	2.283	0.715	1.294	3.205
	Beta2	1.031	0.569	0.496	2.444
	Beta3	1.267	1.251	0.459	5.093
Addicted to crystal-glass	Delta	188.363	16.495	166.842	206.314
	Theta	307.618	29.231	267. 272	333. 482
	Alpha	306. 752	26. 647	269. 804	329. 427
	Beta	614. 556	55. 256	537. 757	66. 345
	High Beta	43. 474	4. 073	37. 812	46. 846
	Beta1	228. 181	20. 436	199. 758	244. 974
	Beta2	185. 123	16. 482	162. 226	198. 865
	Beta3	266.569	24.093	233.083	286.541
Healthy controls	Delta	11.213	5.120	5.676	20.212
	Theta	9.390	4.766	6.405	24.494
	Alpha	19. 322	13. 517	10. 368	61. 401
	Beta	9.983	5.678	4.661	20.598
	High Beta	1.163	0.689	0.485	2.523
	Beta1	5.336	3.661	1.874	11.772
	Beta2	2.525	1.193	1.383	5.099
	Beta3	3.571	1.726	1.888	6.398

In the frontal area, the absolute power of the bands in the group abusing crystal-glass was more than that of the group addicted to tramadol. In the heroin and opium addicted and the healthy controls groups, the absolute power of the bands was lower and there was no significant difference in the SD of the two groups.

In the central area, the absolute power of the bands in the group abusing crystal-glass was more than that of the groups addicted to tramadol. In the heroin and opium addicted and the healthy controls groups, the absolute power of the bands was lower and there was no significant difference in the SD.

In the occipital area, the absolute power of the bands in the group abusing crystal-glass was more than that of the groups addicted to tramadol. In the heroin and opium addicted and the healthy controls groups, the absolute power of the bands was lower and

the absolute power of the bands was more than the frontal and central brain areas.

Equivalence testing for covariance matrix was statistically significant (Box's M=7843.996, p=0.0001). The amount of Box did not reach the significant level of 0.05. The output was interpreted as there was no significant violation of the homogeneity hypothesis of the variance covariance matrix in these two populations.

The Wilks' lambda multivariate test showed that the effect of groups is significant in the frontal, central and occipital brain areas on the absolute power of the bands (f =26.069, p<0.05). The Levene's test of Equality of Error Variances is significant for all groups in all dependent variables (p<0.01); But the output was interpreted as there was no significant violation of the homogeneity hypothesis of the variance matrix in these two populations.

The Tukey's test was performed for the four groups in the absolute power of the bands. There was a significant difference among the groups in the absolute power of the delta band. The between-group difference was 81.84 for the tramadol/heroin and opium groups; -69.11 for tramadol/crystal-glass groups; 102.20 for tramadol/healthy groups; -150.96 for heroin and opium/crystal-glass groups; 20.35 for heroin and opium/healthy groups, and171.32 for crystal-glass /healthy groups.

There was a significant difference between the groups in the absolute power of theta band, except for the heroin and opium/healthy groups (p<0.01). The between-group difference was 159.95 for tramadol/heroin and opium groups; -127.57 for tramadol/crystal-glass groups; 163.22 for tramadol/healthy groups; -287.52 for heroin and opium/crystal/glass groups, 3.26 for heroin and opium/healthy groups, and 190.79 for crystal-glass/healthy groups. The difference in the absolute power of theta band was insignificant in heroin and opium/healthy groups.

There was a significant difference among the groups in the absolute power of the Alpha band, except for the heroin and opium/healthy groups (p<0.01). The between-group difference was 156.73 for tramadol/heroin and opium groups; -134.13 for tramadol/crystal-glass groups; 140.22 for tramadol/healthy groups; -290.86 for. Heroin and opium/crystal-glass groups; -16.70 for heroin and opium/healthy groups and 274.16 for crystal/glass /healthy groups.

There was a significant difference among the groups in the absolute power of the beta band, except for the heroin and opium/healthy groups (p<0.01). The between-group difference was 317.35 for tramadol/heroin and opium groups; -268.54 for tramadol/crystal-glass groups; 311.98 for tramadol/healthy groups; -585.89 for heroin and opium/crystal-glass groups, -5.36 for heroin and opium/healthy groups, and580.53crystal-glass /healthy groups.

There was a significant difference among the groups in the absolute power of the high beta band, except for the heroin and opium/healthy groups (p<0.01). The between-group difference was 22.26 for tramadol/heroin and opium groups; -18.58 for tramadol/crystal-glass groups; 21.34 for tramadol/healthy groups; -41.11 for heroin and opium/crystal-glass groups; 0.919 for heroin and opium/healthy groups, and40.20 for crystal-glass /healthy groups.

There was a significant difference among the groups in the absolute power of thebeta1 band, except for the heroin and opium/healthy groups (p<0.01). The between-group

difference was 117.77 for tramadol/heroin and opium groups; -99.78 for tramadol/crystal-glass groups; 115.04 for tramadol/healthy groups; -217.56 for heroin and opium/crystal/glass groups; -2.73 for heroin and opium/healthy groups, and 214.83 for crystal-glass /healthy groups.

There was a significant difference among the groups in the absolute power of the beta 2 band, except for the heroin and opium/healthy groups (p<0.01). The between-group difference was 95.68 for tramadol/heroin and opium groups; -80.90 for tramadol/crystal-glass groups; 94.41 for tramadol/healthy groups; -176.58 for heroin and opium/crystal-glass groups; -1.27 for heroin and opium/healthy groups, and 175.31 for crystal/glass/healthy groups.

There was a significant difference among the groups in the absolute power of thebeta3 band, except for the heroin and opium/healthy groups (p<0.01). The between-group difference was 137.61 for tramadol/heroin and opium groups; -116.44 for tramadol/crystal-glass groups; 135.44 for tramadol/healthy groups; -254.05 for heroin and opium/crystal-glass groups; -2.16 for heroin and opium/healthy groups; 251.89 for crystal-glass/healthy groups.

The absolute power of delta band of the addicted to tramadol group did not show any significant difference in any areas of the head with a significance level greater than 0.01.In the addicted to heroin and opium group, there is no significant difference in the frontal/central areas (p>0.01). There was a significant difference in the frontal/occipital and central/occipital with a significance level of p<0.01 and a mean difference of -17.855 and -26.56, respectively. The mean difference in the addicted to crystal-glass group in the frontal/central areas (-16.707), frontal/occipital (-38.576), and central/occipital areas (-21.86) was significant in the absolute power of delta band at the significance level of less than 0.01.

The mean difference in the healthy controls group in the frontal/central areas was not significant at the significance level of more than 0.01, but in the frontal/occipital (7.39), and central/occipital areas (6.11) was significant in the absolute power of delta band at the significance level of less than 0.01.

The mean difference in the addicted to tramadol group in the frontal/central areas was not significant in the theta band at the significance level of greater than 0.01, but it was significant in the frontal/occipital (-91.48), and central/occipital areas (-15.84) at the significance level of less than 0.01.

The mean difference in the addicted to heroin and opium group in the frontal/central areas was not significant in the theta band at the significance level of more than 0.01, but in the frontal/occipital (-19.24), and central/occipital areas (-16.73) was significant at the significance level of less than 0.01.

The mean difference in the addicted to crystal-glass group in the frontal/central (-36.30), frontal/occipital (-120.36), and central/occipital areas (-21.86) was significant at the significance level of less than 0.01.

The mean difference in the healthy controls group in the frontal/central areas was not significant at the significance level of more than 0.01, but in the frontal/occipital (5.36), and central/occipital areas (3.81) was significant at the significance level of less than 0.01.

Figure 1 shows the final results of the mean absolute power of the bands in the four groups in 12 points on the head. It shows that the absolute power of the bands in the occipital area (O2) was more than other areas.

There was a smaller difference in the mean absolute power of the bands between the addicted to heroin and opium group and the healthy controls. There was a significant difference in the mean absolute power of the bands between the addicted to tramadol and crystal -glass groups and addicted to heroin and healthy controls groups.

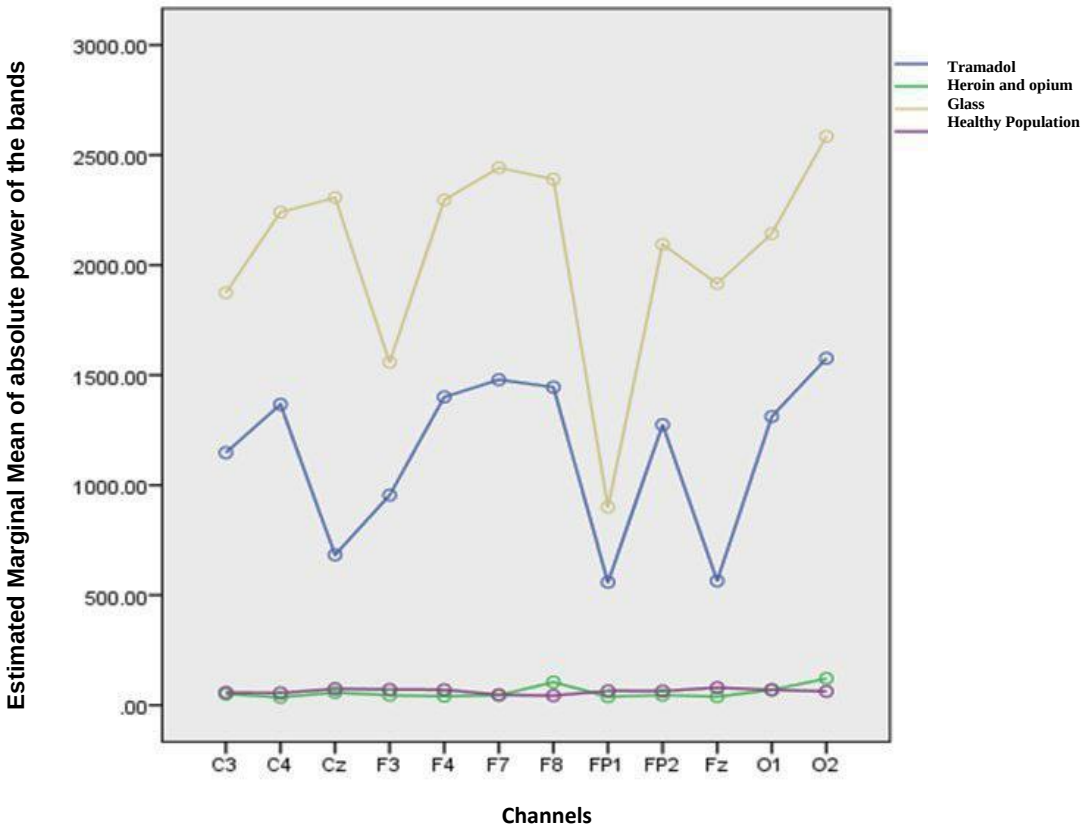

Figure 1. The differentiation of mean absolute power of the bands in the four groups in 12 points on the head.
(C: Central, F: Frontal, FP: Prefrontal, O: Occipital, Fz: Frontal ziro)

The Discriminant Analysis was simultaneously performed to determine whether the absolute power of central 8 band waves can predict the membership in the addicted to tramadol, heroin/opium, crystal-glass , or healthy controls group, or not.

The Wilks' Lambda of all three functions was significant. λ=0.040, χ^2=565.162, p=0.0001 and λ=0.451, χ^2=139.261, p=0.0001 and λ=0.769, χ^2=45.962, p=0.0001 show that the predictor variables generally distinguished the performance of groups of addicted to tramadol, addicted to heroin and opium, addicted to crystal-glass, and healthy controls.

Table 3 shows the intragroup correlation between the predictor variables and the discriminant function as well as the standardized weights in the central areas.

Table 3. Standard and correlation coefficients of the discriminant function variables in the central areas

Predictor variables	Standard coefficients of the function			Correlation coefficients of the function		
	1	2	3	1	2	3
Delta	0.913	-2.865	5.028	0.532	0.620	0.573
Theta	16.253	-0.148	-14.368	0.508	0.693	0.511
Alpha	-6.975	7.458	-2.542	0.447	0.740	0.503
Beta	-7.907	-3.865	12.464	0.462	0.699	0.540

The absolute power of the beta, beta 1, beta 2 and beta 3 bands were eliminated from the discriminant function1. Based on these

coefficients, in the first function of the tramadol group equation, the absolute power of the delta band had the greatest relationship with the discriminant function with the coefficient of 0.532; in the second function of the heroin and opium group equation, the absolute power of the alpha band with a coefficient of 0.740; and the third function of the equation of crystal-glass and opium group equation, the absolute power of the delta band with a coefficient of 0.573 had a good and moderate relationship with the discriminant function in the central areas. The equations of functions are as follows.

- (Tramadol) D1 = delta (0.532) + Theta (0.508) + Alpha (0.447) + Beta (0.462)
- (Heroin and opium) D2 = delta (0.620) + Theta (0.693) + Alpha (0.740) + Beta (0.699)
- (crystal-glass) D3 = delta (0.573) + Theta (0.511) + Alpha (0.503) + Beta (0.540)

Table 4 shows the classification of discriminant function for the central areas where the discriminant function has classified 81.1% of all cases correctly.

Table 4. Classification of discriminant function for the central areas

		Group membership prediction				Total
		Tramadol	Heroin	Crystal-glass	Healthy	
Count	Tramadol	23	0	22	0	45
	Heroin and opium	4	33	0	8	45
	Crystal-glass	0	0	45	0	45
	Healthy controls	0	0	0	45	45
%	Tramadol	1.51	0	9.48	0	100
	Heroin and opium	8.9	73.3	0	17.8	100
	Crystal-glass	0	0	100	0	100
	Healthy controls	0	0	0	100	100

Note: 81.1% of original grouped cases correctly classified.

The discriminant function correctly predicted the tramadol addicts by 51.1%, heroin and opium addicts by 73.3%, crystal-glass addicts by 100% and healthy controls by 100%.That is, in the central area, the performance of absolute power of delta, theta, alpha and beta bands in the prediction of the crystal-glass addicts and the healthy people groups was better than the rest of the groups. This performance was lower in the tramadol addicts group (51.1%) and 48.9% of them were mistakenly classified in the crystal-glass addicts group.

The third section of results is the comparison results from diagnosis software and the mean of the results of the three brain lobes with statistical manner and artificial intelligent manner:

These results show that the intelligent software had a better performance with 88% correct diagnosis accuracy rate compared to the DA statistical method with 75.2% accuracy rate (table 5).

Table 5. The mean accuracy rate of DA and the diagnosis software for the four groups

Lobe	The DA method (%)	The results of the software (%)
Occipital	73.3	85
Frontal	71.2	39
Central	81.1	90
Mean Accuracy Rate	75.2	88

The interpretation of the area under the ROC curve (AUC):

One of the diagnostic criteria is the area under the ROC curve in which the values of 0 to 0.5 represent random classification, and values of 0.5 to 1 represent the overall diagnostic capability of the model. According to table 6, the area under the ROC curve in the test group for the intelligent diagnosis software and DA was 89 and 73.9 percent,

respectively. In addition, the results of the comparison of diagnostic functions (DA method) and the ANN intelligent diagnosis software models with 95% confidence showed that the area under the ROC-curve and accuracy rate for diagnostic analysis (DA) were 73.9 and 75.9% (p<0.0001), respectively, while the same values for the ANN intelligent diagnosis software were calculated 89 and 88% (p<0.0001) respectively. Figure 2 shows the ROC curve for both models.

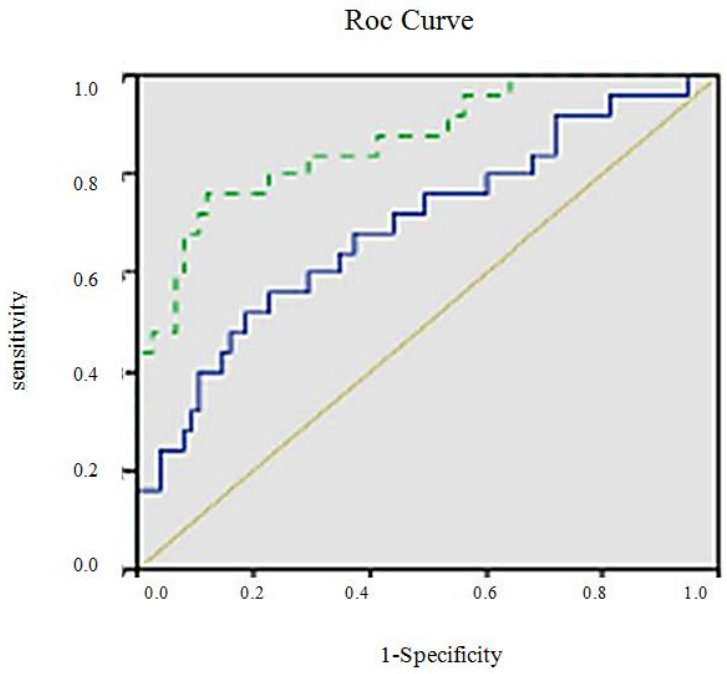

Figure 2. ROC curve based on the DA method and the presented artificial intelligence diagnosis software. Green: The presented artificial intelligence software; Blue: The DA method; Gray: Reference Line.

Table 6. Sensitivity, Specificity, Positive likelihood ratio, Negative likelihood ratio, Kappa statistics, and the area under the ROC curve for the two models

Model	Sensitivity	Specificity	*LR+	†LR-	Kappa statistics	AUC **
Discriminant analysis	0.677	0.66	1.99	0.49	0.363	0.739
Intelligent diagnosis software	0.836	0.884	7.21	0.19	0.712	0.890

* Positive likelihood ratio, †Negative likelihood ratio, ** (Area under the ROC curve)

Accuracy rate index

Another indicator of fitness is the accuracy rate. That is a ratio of cases correctly classified in each category in which the values of 0 to 1 represent the diagnostic capabilities of models at a level. The correctly predicted ratios in the table above indicate the correct classification of the network in the training group. According to the table, the percentage of correct predictions for the intelligent diagnosis software was 88% and for the DA method was 75.2%.

Discussion

Finding the severity of the mental disorder in addition to finding its type for tracking the clinical outcomes of the interventions is a

major concern in this field that is answered by the developed software.

In Comparing the results of the DA method and previous studies results about the types of substance addiction, Bayrami *et al.* [12], for instance concluded that chronic abuse of psychoactive substances damages ever all brain areas, such as the prefrontal cortex and the hippocampus, and thus disrupts the cognitive functions of these areas.

Their results were consistent with the present study. The increase in fast waves in the frontal lobe represents a type of pathological hyperactivity in the area. LO examined the issue of relapse based on QEEG and suggested that the ANCOVA of the power spectral density of EEG in previously defined excitation bands showed that there was an increase in the high frequency (5.19-8.39 Hz) of the beta activity among the 48 patients who relapsed abusing drugs recently compared with 59 cases that did not relapse, as well as the 22 healthy subjects. The important point is that in logistic regression which was followed up, the power parameter (FAST Beta POWER) was found as the only predictor of severity of disorder, depression level and childhood conduct disorder in predicting relapsing drug abuse with sensitivity, specificity, positive predictive power (PPP) parameter, and negative predictive power (NPP) on discriminate between the results with the values of 61%, 85%, 75% and 74%, respectively. Increased FAST Beta EEG activity in patients who will eventually relapse is due to the subtle pre-disease and dysfunction factors in the frontal areas of the brain [13]. As noted in this diagnosis analysis study, the high power of fast waves in the frontal areas represents the alignment of the results.

In this study, in addition to the above-mentioned comparisons, two different models, with two different methodologies (statistical and artificial intelligence), were used to diagnose and predict mental disorders in the individuals and their results were compared. According to the findings, the intelligent diagnosis software model, programmed by the authors had the highest sensitivity. Examining the characteristics indicates that the intelligent diagnosis software is more powerful to recognize the right healthy people than the statistical DA method.

Kappa statistic also indicates that the intelligent diagnosis software model had a better performance. Although other studies have been conducted on statistical modeling and artificial intelligence modeling for the diagnosis of mental disorders - a number of which were briefly mentioned in the introduction- they mainly aimed to identify the effective demographic factors such as age sex, and race. The purpose of this study, however, was to compare the accuracy and predictive accuracy of a statistical model and compare it with the accuracy of the proposed intelligent diagnosis software model. In this way, the mental disorders diagnosis software can be used as a biomarker-based method rather than self-reported psychological tests, with a high sensitivity and specificity in diagnosing the type and severity of mental disorders. Moreover, this diagnosis software, in addition to identifying the type of mental disorder, intelligently diagnoses the severity of mental disorders - for the first time - only using QEEG, without the need for Paper-Pencil tests, and with the scoring of valid subjective scales for each disorder. For instance, depression was scored based on the

Beck Depression Inventory for subsequent clinical interventions outcome tracking. Indicating the correct probability of confidence in the accuracy of diagnosis, i.e. confidence level is also another distinctive feature of the software.

Conflict of Interest

The authors have no conflict of interest.

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