# UNT-AT: A Robust Software to Predict the Outcome of Depression Therapies Using EEG Signals

Hesam Akbari[1(✉)], Wael Korani[1], Junhua Ding[1], Reza Rostami[2], and Reza Kazemi[2]

[1] Department of Information Science, University of North Texas, Texas, USA
{Hesam.Akbari,Wael.Korani,junhua.ding}@unt.edu
[2] Department of Psychiatry, University of Tehran, Tehran, Iran
{rrostami,rezakazemi}@ut.ac.ir

**Abstract.** Depression is a mental disorder that may lead to self-mutilation or suicide if left untreated. Selective serotonin reuptake inhibitors (SSRIs) and repetitive transcranial magnetic stimulation (rTMS) are among the most commonly prescribed therapies to treat depression. These therapies are prescribed and recommended to be taken over a period of time, and the main challenge is that about 50% of the patients might respond to these ways of treatments. In general, a psychiatric recommends one way of treatment based on his/her experience and waits for a period of time to evaluate the results. However, if the way of treatment is unsuccessful to decrease the depression level that might increase the risk of self-mutilation or suicide. This paper proposes a robust software called University of North Texas-Atieh Hospital (UNT-AT) to predict the outcomes of two different therapies for depressed patients based on recorded electroencephalogram (EEG) signals. The UNT-AT software utilizes phase space reconstruction (PSR) of EEG signals, a robust chaotic technique for tracking the brain's nonlinear dynamics, along with novel geometrical features (GFs) to decode the complex behavior of EEG signals. Initially, PSR of EEG signals is plotted in two-dimensional space, and GFs are used to quantify the PSR shape. Statistically significant features are selected using the Kruskal-Wallis test and are then fed into traditional machine learning algorithms and artificial neural network architectures for classification using 10-fold cross-validations to avoid bias. The UNT-AT software is evaluated using two different databases for SSRI and rTMS therapies, including data from 30 and 15 depressed patients, respectively. The results show that our proposed software achieves classification accuracies of 94.14% and 97.67% for predicting therapy outcomes for SSRI and rTMS, respectively. Our proposed software is the first system in literature to be used to choose the best course of treatments for depressed patients. The software is efficient and can be used in clinics and hospitals to assist neurologists and psychiatrists in prescribing the most effective course of treatment for depression.

**Keywords:** UNT-AT · SSRI · rTMS · depression · EEG


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## 1 Introduction

Depression might lead to self-harm and suicide if it is not treated [1]. The World Health Organization (WHO) reported that about seven hundred thousand people die by suicide every year [2]. There are around twenty suicide attempts for each death caused by suicide. This shows the importance of depression nowadays [3]. Selective Serotonin Reuptake Inhibitors (SSRI) therapy and Repetitive Transcranial Magnetic Stimulation (rTMS) therapy are among the best ways to treat the depression disorder [4].

The SSRI is a mode of action for several medications where SSRIs block the reuptake of serotonin into neurons. However, in rTMS therapy, a coil is used to generate magnetic pulses. The electromagnetic coil is placed close the scalp skin that generates electrical currents that enter the nerve cells. This process is repeated for a four to six weeks, five times a week. The effectiveness of both SSRI [5] and rTMS [6] therapies for the treatment of depression has been approved by the Food and Drug Administration (FDA). The response rate to SSRI therapy is around 50% [7], and for rTMS therapy is between 40% and 60% [8]. In some cases, the chosen therapy is unsuccessful, which might increase the risk of suicide to those patients.

The Electroencephalogram (EEG) signal is a neuroimaging technique that records brain activity by placing electrodes on the scalp [9]. The EEG recording is an inexpensive, easy, and real-time technique to record the brain activities. The EEG signals were used to detect depression disorder [10,11]. The promising performance of EEG signals in detecting depression encourages us to design a novel software named University of North Texas-Atieh Hospital (UNT-AT) to choose the best course of treatment for depression. This is the first time in the literature for a software to predict the best course of treatment for depression. In UNT-AT software, pre-treatment EEG signals are classified into either responder (R) or non-responder (NR) to different depression therapies. The UNT-AT software includes two different therapies for depression treatment (i.e. SSRI and rTMS). One task involves classifying pre-treatment EEG signals into R or NR for SSRI therapy, and the other involves classifying pre-treatment EEG signals into R or NR for rTMS therapy.

In the field of chaos science, phase space reconstruction (PSR) is applied to complex time series to decode their non-linearity [12]. EEG signals are non-stationary and exhibit non-linear characteristics. The complex and chaotic behavior of EEG signals has been decoded using the PSR technique to detect several mental disorders, such as depression [13], seizures [14], mental workload [15], alcoholism [16], and schizophrenia [9]. The PSR technique is used to plot the time series in higher-dimensional space to illustrate its complexity and non-linearity. Here, the performance of PSR on EEG signals is visualized in higher-dimensional space to decode brain function.

Several features have been defined to quantify the dynamics of the Phase Space Reconstruction (PSR) of time series, such as fractal dimension, entropy measures, Lyapunov exponents, and correlation dimensions. The main problem with these features is their complexity from both theoretical and computational

perspectives. In addition, several parameters are required to be set to decode the non-linearity of the information, which is a challenging task. Recently, geometrical features (GFs) have been proposed to quantify the nonlinear dynamics of PSR of EEG signals [9,10,14,16,17]. Unlike traditional chaotic-based features, GFs have an easy mathematical theory, which makes them quickly and easy to extract. Additionally, the concept of GF is based on geometry, which means there is no need to adjust any parameters. These advantages of GFs motivate us to apply GFs to the PSR of EEG signals to quantify the non-linearity of brain function.

The deep learning models showed acceptable performance in classification of EEG signals [18]. The main reason is that deep learning models have the ability to effectively learn and analyze complex patterns within the data. Additionally, deep learning models handle extensive amounts of information and many features simultaneously. The combination of these characteristics allows deep learning models to significantly identify generalized patterns in the dataset and use them for classification. In the literature, pre-trained architectures were used to classify images that were extracted from EEG signals [19]. Although the classification performance of pre-trained architectures was significantly high, these architectures had a complex structure with numerous layers and millions of neurons, requiring a lot of resources. On the other hand, custom architectures are designed to avoid using more computational resources. In the current work, a custom architecture is designed for classification.

In this paper, the UNT-AT software is proposed to predict the outcomes of different therapies for depression based on EEG signals. The EEG signals are plotted in a two-dimensional space using the PSR technique. Then, thirty-four GF are extracted to quantify the nonlinear dynamics of the EEG signals. The Kruskal-Wallis (KW) test selects features that are statistically significant. The selected features are fed into custom cascade-forward neural networks (CFNN). The binary classification task of R vs. NR is defined for both SSRI and rTMS therapies. The performance of the proposed UNT-AT software is evaluated using two databases: SSRI database and rTMS database.

The rest of the paper is organized as follows: Sect. 2 is about the materials of this study. Section 3 details the proposed UNT-AT software and PSR technique. Section 4 and Sect. 5 discusses GFs extraction, and classification methods. Section 6 presents the results and discussion. Finally, the paper is concluded in Sect. 7.

## 2 Materials

In this paper, two different databases: Mumtaz and Atieh that are used to evaluate the performance of the proposed UNT-AT software. Mumtaz database is a public database for SSRI therapy and Atieh Hospital database is a private database for rTMS database.

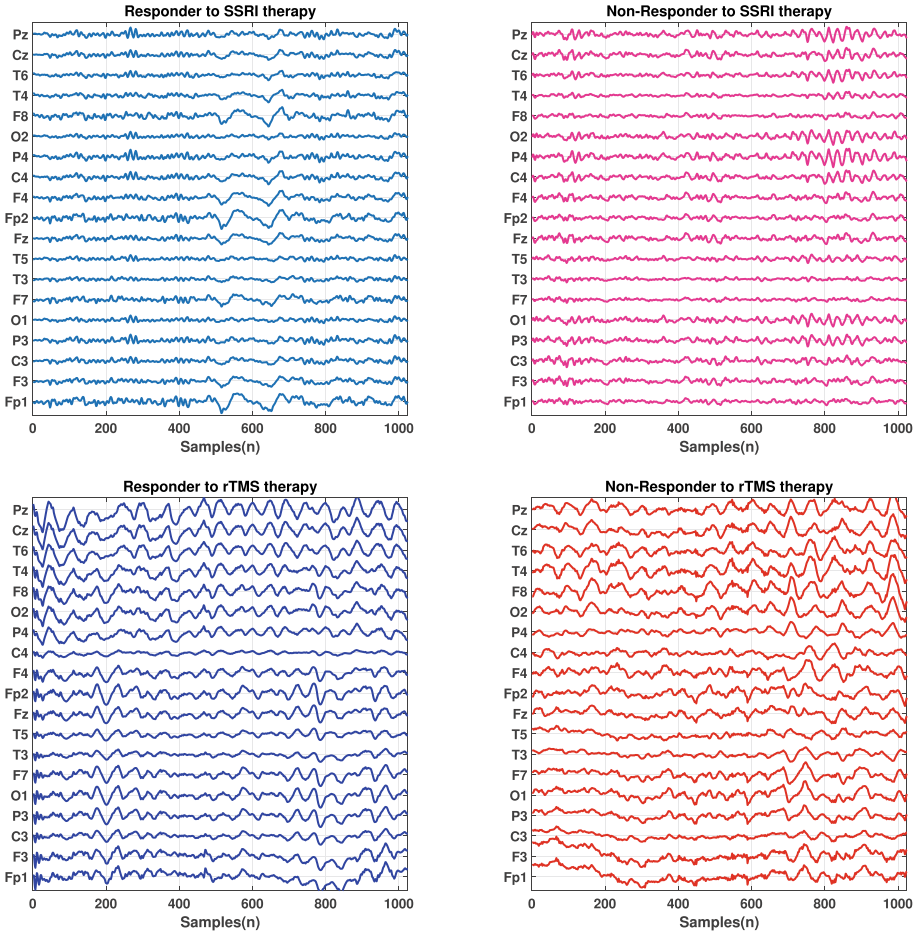



**Fig. 1.** A sample of R (left) and NR (right) EEG signals to SSRI (up) and rTMS (down), respectively.

### 2.1 Mumtaz Database

The Mumtaz database is a public database that contains the EEG signals of 30 major depressed patients who were selected for SSRI therapy [20]. The EEG signals were recorded for all patients before starting the SSRI therapy. The EEG signals were recorded using the 10–20 international standard system with 19 channels, and the sampling frequency of EEG recording 256 Hz as shown in Fig. 1. The location of channels on the scalp is shown in Fig. 2. In the experiment, Mumtaz used Escitalopram, Fluvoxamine, Sertraline, and Fluoxetine that have SSRI mode of action in different dosage for four weeks as described in [20]. After one month, the Beck Depression Inventory (BDI) score was evaluated for all patients. The EEG signals of patients who improved by more than 50% based

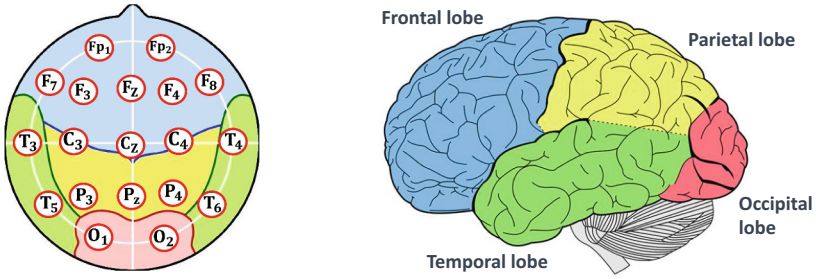



**Fig. 2.** The locations of the channels in the 10–20 system (left) and the brain lobes (right).

on the BDI score were categorized as R, and the rest were categorized as NR to SSRI therapy. The results show that 12 patients were R, and 18 patients were NR to SSRI therapy.

### 2.2 Atieh Hospital Database

The performance of the proposed UNT-AT software for predicting the outcomes of rTMS therapy is evaluated using a private database collected at Atieh Hospital, Tehran, Iran. Fifteen depressed patients received rTMS therapy. The diagnosis of depression disorder was evaluated by two psychiatrists Dr. Reza Rostami and Dr. Reza Kazemi at Atieh Hospital. The EEG signals were recorded for patients before starting the rTMS therapy, and the BDI scores were evaluated. The EEG signals were recorded at a sampling frequency 500 Hz as shown in Fig. 1. The international 10–20 standard system was used during the recording of the EEG signals. Then the rTMS therapy was recommended for four weeks. After one month, the BDI scores of the patients were evaluated once again. The patients who got improved over 50% based on the BDI score were considered as R, and the rest as NR to rTMS therapy. The results show that nine patients were considered R, and six patients were considered NR to rTMS therapy.

## 3 Proposed UNT-AT Software

This section describes the step-by-step process of our proposed UNT-AT software. After recording the data, the EEG signals are plotted in two-dimensional space using the PSR technique. Then, the GFs are extracted from all channels. Statistically significant features are selected by the Kruskal-Wallis (KW) test and fed into artificial neural network (ANN) architectures. The outcome of the classifier is R and NR to two different depression therapies: SSRI and rTMS. Finally, the UNT-AT will recommend how confidence medical care providers should be to prescribe each depression therapy as shown in Fig. 9. Figure 3 illustrates the

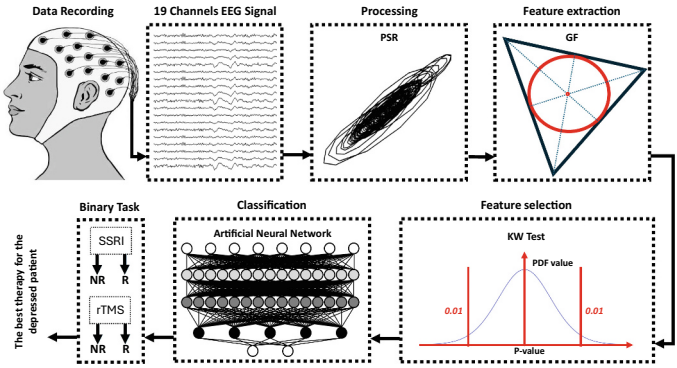



**Fig. 3.** Step by step of the proposed UNT-AT software.

step-by-step process of our proposed UNT-AT software. The design and implementation of our proposed UNT-AT are conducted using MATLAB software and Windows computer with i7-8700 CPU (3.20 GHz) and 3.2 GB RAM.

### 3.1 Phase Space Reconstruction

The PSR technique is used to discover the nonlinear dynamics of complex systems [21]. In the current work, the PSR of EEG signals is used to illustrate the non-linear nature of the brain in a depressed state. The PSR plots the EEG signals in a higher dimensional space to provide more information about the effects of depression on brain activity. The PSR has two parameters to be optimized called delay ($\tau$) and embedded dimension ($d$). Let us assume that a channel of EEG signal is represented as $E = [e_1, e_2, e_3..., e_n]$ where $n$ is the length of the signal. Then, the PSR is defined as follows:

$$PSR = \left(E_m, E_{m+\tau}, \ldots, E_{m+(d-1)\tau}\right) \tag{1}$$

where $m = 1, 2, \ldots, n - (d-1)\tau$. There are several techniques to estimate the $\tau$ and $d$ parameters. The leveling-off of the Average Mutual Information (AMI) function and the false nearest neighbor are the most common methods to approximate $\tau$ and $d$, respectively [22]. However, AMI and false nearest neighbor methods use more computational resources. Selecting the proper values for these two parameters directly impacts the information provided by the PSR. If these two parameters are set too high, the resulting PSR shape is more complex than the EEG signals themselves. On the other hand, if these two parameters are set too low, the resulting PSR is not able to decode the hidden nonlinear dynamics of the EEG signals. In [12], the values of $\tau = 1$ and $d = 2$ were recommended for analyzing EEG signals. In the current work, these two parameters are used to compute the PSR of EEG signals. Since $d = 2$, a two-dimensional space is defined to plot the PSR of EEG signals as follows:

$$X = E_m = [e_1, ..., e_{n-1}] \tag{2}$$

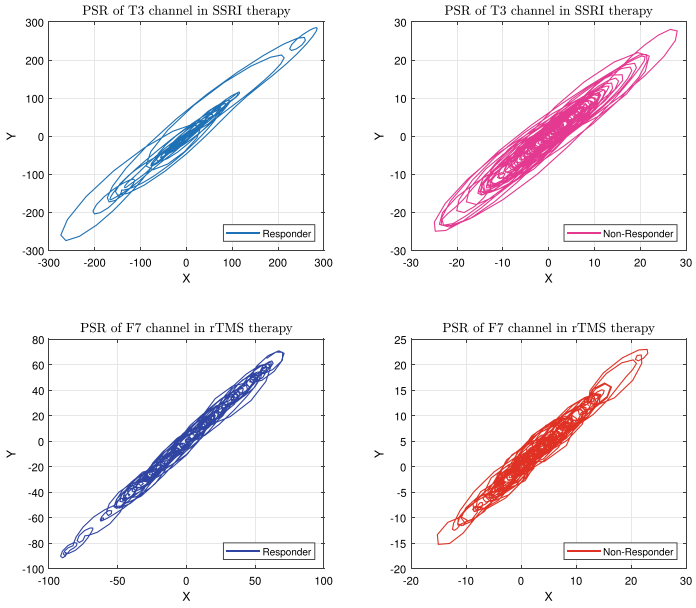



**Fig. 4.** PSR of CZ channel for R(left) and NR(right) to SSRI(up) and rTMS(down), respectively.

$$Y = E_{m+1} = [e_2, ..., e_n] \tag{3}$$

Plotting X versus Y is defined as PSR.

## 4 Geometrical Features

The quantification of behavior of the PSR can be obtained by nonlinear features such as Lyapunov exponent and fractal dimension. However, computing these features requires significant time and effort. The graphical features of EEG signals are used to show the complexity and variability of the PSR [9,10,16,17]. In this section, we aim to extract graphical features from EEG signals to differentiate between the R and NR classes. A total of 34 nonlinear graphical features are extracted utilizing PSR and Euclidean geometry. Summation of consecutive circles area (SCCA), summation of consecutive triangles area (SCTA), summation of Heron's circulars area (SHCA), summation of distances between Heron's circulars (SDHC), summation of the angles between Heron's circular (SAHC), summation of successive vector lengths (SSVL), shortest distance from each point relative to the 45-degree line (SH45), summation of shortest distance from each point relative to the 135-degree line (SH135), area of octagon (AOCT), summation of distances to a coordinate center (SDTD), summation of the angles between three consecutive points (SABP), summation of triangles area made successive points and coordinate center (TACR), summation of consecutive rectangular area (SCRA), two-dimensional standard descriptors (TDSD), elliptical

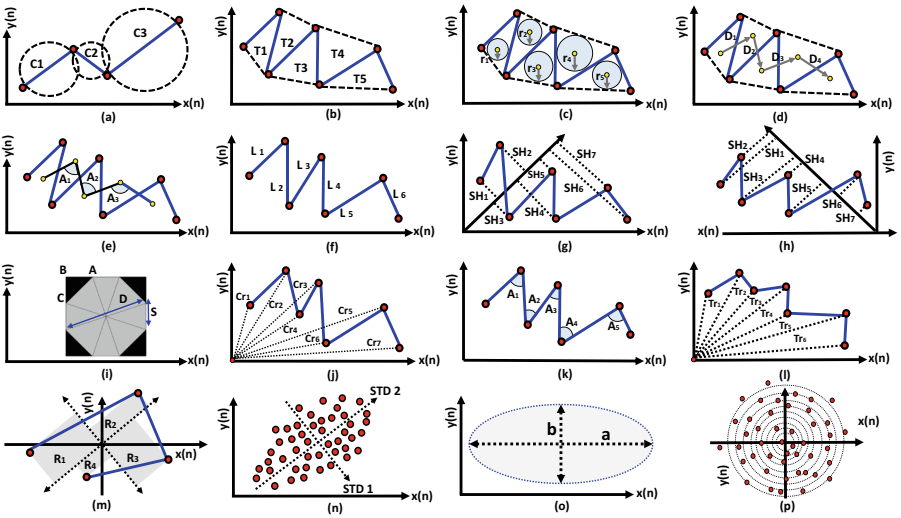



**Fig. 5.** Illustration of the geometrical features.

area (ELPA), central tendency measure (CTM) are extracted from the PSR. The detailed explanation and mathematical formulas for these graphical features are shown in Table 1 and Fig. 5 [9].

## 5 Classification

The cascade-forward neural network (CFNN) architecture is a kind of the feed-forward neural network (FFNN) architecture. In the proposed UNT-AH software, CFNN architecture is trained and tested using two different databases. The flow of the information is in a forward direction for both FFNN and CFNN architectures. Also, there is no connections between the neurons in the same layer. There are three main layers for any architecture: the input layer, hidden layers, and output layer. The number of neurons in the input layer is equal to the number of extracted features. In the same way, the number of neurons in the output layer is equal to the number of classes. CFNN architecture has connections from the input layer to the output layer directly and through the hidden layers as well. A CFNN learns any finite input-output relationship by setting a proper number of layers and neurons in the hidden layer [23]. The advantage of the CFNN architecture is that it maps any input to output, like the FFNN. Additionally, CFNN architecture finds the nonlinear relationships between the input and output layers while preserving the linear relationships between the layers.

In the current work, a CFNN architecture is used for the classification respondent and non-respondent patients. The performance of CFNN architecture is compared to an FFNN architecture with the same number of layers and neu-

**Table 1.** Description of the geometrical features.

| Feature | Definition |
|---|---|
| SCCA | The SCCA measures the degree of variability of PSR. Figure 5(a) illustrates the SCCA, where C represents the area of each circle: SCCA = C1 + C2 + C3 |
| SCTA | The SCTA measures the degree of variability of PSR by providing greater adaptability compared to the SCCA. Figure 5(b) presents the SCTA, where T denotes the area of each triangle: SCTA = T1 + T2 + T3 + T4 + T5 |
| SHCA | The SHCA measures the auto correlation of PSR. Figure 5(c) displays the SHCA, where $r$ is the radius of each circle: SHCA = $\pi r_1^2 + \pi r_2^2 + \pi r_3^2 + \pi r_4^2 + \pi r_5^2$ |
| SDHC | The SDHC measures the auto correlation and level of complexity of PSR. Figure 5(d) shows the SDHC, where D represents the distance between each successive Heron's circles: SDHC = D1 + D2 + D3 + D4 |
| SAHC | The SAHC measures the correlation of PSR to each other that refers to similarity in the time domain. Figure 5(e) illustrates the SAHC, where A is the angle between the centers of successive Heron's circles: SAHC = A1 + A2 |
| SSVL | The SSVL measures the degree of variation for PSR, which refers to amplitude variability in the time domain. Figure 5(f) depicts the SSVL, where L is the length of each vector formed by successive points: SSVL = L1 + L2 + L3 + L4 + L5 |
| SH45 | The SH45 measures the scattering of data points of PSR on the second and fourth quarters. Figure 5(g) shows the SH45, where the distance from each point to the 45-degree line is computed as follows SH45 = SH1 + SH2 + SH3 + SH4 + SH5 |
| SH135 | The SH135 measures the scattering of data points of PSR in the first and third quarters. Figure 5(h) illustrates the SH135, where the distance from each point to the 135-degree line is computed as follows: SH135 = SH1 + SH2 + SH3 + SH4 + SH5 |
| AOCT | AOCT measures the degree of spreading of PSR. Figure 5(i) shows the AOCT |
| SDTD | The SDTD measures the degree of variability of PSR according to the center of the coordinate. Figure 5(j) shows the SDTC, where Cr is the distance from each point to the coordinate center: SDTC = Cr1 + Cr2 + Cr3 + Cr4 + Cr5 |
| SABP | The SABP measures the fluctuation of angles, which refers to the degree of intricacy in time domain. Figure 5(k) presents the SABP, with A representing the angle between successive vectors formed by successive points: SABP = A1 + A2 + A3 + A4 |
| TACR | The TACR is a composite metric that integrates the SSVL and SDTD to measure both the variation and auto-correlation of PSR. Figure 5(l) shows the TACR, where Tcr is the area of each triangle formed by two successive points and the coordinate center: TACR = Tcr1 + Tcr2 + Tcr3 + Tcr4 |
| SCRA | The SCRA integrates the SH45, SH135, and SDTC features to measure the dispersion of data from the central point, 45°, and 135° lines with higher sensitivity. Figure 5(m) shows the SCRA, where R is the area of each formed rectangle by central points and 45°, and 135° lines: SCRA = R1 + R2 + R3 + R4 |
| TDSD | The TDSD measures the dispersion of points of PSR. Figure 5(n) shows the TDSD as a graphical feature, where STD1 and STD2 are the 45° and 135° lines |
| ELPA | The PSR shape exhibits an elliptical form. Figure 5(o) shows the ELPA, where the blue dotted ellipse represents the ELPA, and $b$ and $a$ are the minor and major axes of the ellipse, respectively |
| CTM | The CTM measures the variation level of PSR by computing the percentage of dispersed points on the coordinate plane as shown in Fig. 5(p). The range of CTM is [5: 5: 95], where the start radius is 5, and the incremental is 5, the end radius is 95. Thus, CTM extracts 19 features from PSR |

rons to show the effectiveness of the CFNN architecture. Additionally, the performance of the CFNN is compared to other traditional machine learning techniques: k-nearest neighbors (KNN), support vector machine (SVM), and random forest (RF). The 10-fold cross-validation (CV) strategy is employed to avoid bias in the our results. Table 2 shows the parameter setting of the classification methods.

**Table 2.** Parameters setting of classification methods.

| Classification method | Parameter | Value |
|---|---|---|
| CFNN and FFNN | Architecture | [,20,20,2] |
| | Maximum number of epochs | 50 |
| RF | Number of trees | 20 |
| SVM | Kernel Function | linear |
| KNN | Distance metric | Euclidean |
| | Number of neighbors | 5 |
| CV | Number of folds | 10 |

## 6 Results and Discussion

The EEG signals from both the Mumtaz and Atieh hospital databases are split into segments. The length of each segment is 1024 samples. The size of each segment is $(19 \times 1024)$. A total of 2185 segments are obtained from the Mumtaz database, including 1323 segments for NR and 862 segments for R to SSRI therapy. On the other hand, a total of 2193 segments are obtained from the Atieh Hospital database, including 831 segments for NR and 1362 segments for R to rTMS therapy. Two binary classification tasks are defined for distinguishing between R and NR EEG signals based on the therapy: R to SSRI vs. NR to SSRI using the Mumtaz database, and R to rTMS vs. NR to rTMS using the Atieh Hospital database, respectively.

Figure 3 shows the proposed UNT-AT software step-by-step to predict the outcomes of two depression therapies using EEG signals. In the process of extracting the GFs, EEG channel is plotted on two-dimensional space using the PSR technique. Figure 4 shows that the complex and nonlinear dynamic behavior of the EEG signals can be tracked by PSR technique. In Fig. 4, the PSR of R signals narrower than NR EEG signals in both therapies. It shows that the PSR scattering behavior of R group is higher than NR group. Also, it shows that the data points of PSR in NR groups are more closer to each other than R group.

In order to distinguish between the PSR of R and NR EEG signals in the SSRI and rTMS therapies, geometrical features are extracted. A total of 34 features are extracted from the PSR of each channel, resulting in $34 \times 19 = 646$

features for each segment. As a result, the extracted feature matrix for the R and NR groups is $862 \times 646$ and $1323 \times 646$ for SSRI therapy, respectively. On the other hand, the extracted feature matrix for the R and NR groups is $1362 \times 646$ and $831 \times 646$ for rTMS therapy, respectively.

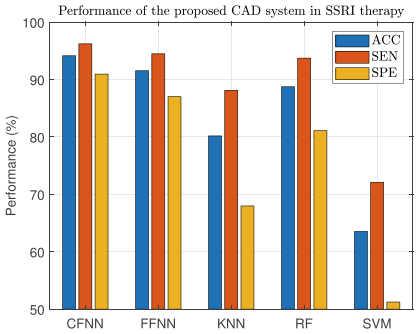
KW test is applied to the extracted features to select the statistically significant features [24]. Features with a p-value less than 0.01 are selected as proper features. The size of the feature matrix after applying the KW test for the R and NR groups is $862 \times 506$ and $1323 \times 506$ for SSRI therapy, respectively. On the other hand, the size of the feature matrix after applying the KW test for the R and NR groups is $1362 \times 579$ and $831 \times 579$ for rTMS therapy, respectively. Usually, KW test is used as feature selection algorithm, approximately 21.68% of features are dropped in SSRI therapy, while around 9.51% of features are dropped in rTMS therapy. This reduction in features improve the performance of the trained classifier. The selected features are fed into several classifiers using 10-fold CV strategy. The performance of the classifier will be evaluated using Accuracy, Sensitivity, and specificity. The accuracy (ACC) is computed to classify R and NR patients. Sensitivity (SEN) is computed to show how confident the patient will be NR to specific therapy. Specificity (SPE) is computed to show how confident the patient will be R to specific therapy.

**Table 3.** Performance of classification methods.

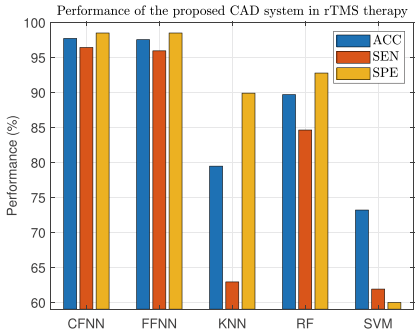
| | SSRI therapy | | | | |
|---|---|---|---|---|---|
| | CFNN | FFNN | KNN | RF | SVM |
| ACC (%) | 94.14 | 91.53 | 80.18 | 88.74 | 63.54 |
| SEN (%) | 96.22 | 94.48 | 88.13 | 93.73 | 72.11 |
| SPE (%) | 90.95 | 87.01 | 67.98 | 81.09 | 51.24 |
| | rTMS therapy | | | | |
| | CFNN | FFNN | KNN | RF | SVM |
| ACC (%) | 97.67 | 97.49 | 79.43 | 89.64 | 73.16 |
| SEN (%) | 96.38 | 95.90 | 62.89 | 84.59 | 61.87 |
| SPE (%) | 98.45 | 98.45 | 89.86 | 92.73 | 59.96 |

Table 3 shows the results of five different classifiers. Figure 6a and Fig. 6b show the performance of all classifiers for SSRI and rTMS therapies. The results show that the CFNN architecture achieves the best classification performance compared to other classification methods. The performance of RF algorithm is better than KNN and SVM. Although FFNN outperforms other traditional classifiers (i.e., KNN, RF, SVM), the CFNN architecture outperforms the FFNN.

Identifying specific locations in human brain that show significant response to specific depression therapy may help psychiatrists to choose the best course of treatment. In order to evaluate the effectiveness of each channel in predicting the outcome of a depression therapy, the performance of the UNT-AT software




(a) Performance of classification methods on SSRI therapy.




(b) Performance of classification methods on rTMS therapy.

**Fig. 6.** Comparison of the performance of classification methods on SSRI and rTMS therapies.

is evaluated using a single channel EEG signal. The evaluation is repeated for each channel using the best classifier CFNN. Figure 7 shows the performance of each channel for SSRI and rTMS therapies. The results indicate that T3 and F7 are the best channels for predicting the outcomes of SSRI and rTMS therapies, respectively. T3 and F7 are located in the left side of the brain next to each other as shown in Fig. 2.

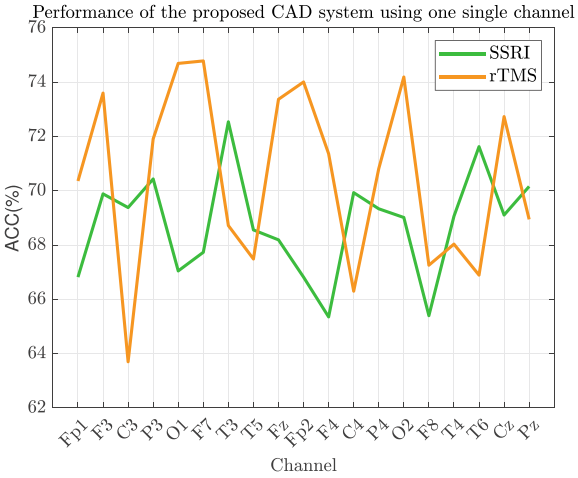



**Fig. 7.** Performance of the proposed UNT-AT software for each single channel.

The performance of the T3 and F7 channels in the SSRI and rTMS therapies are statistically evaluated (mean and standard deviation) for the extracted GFs

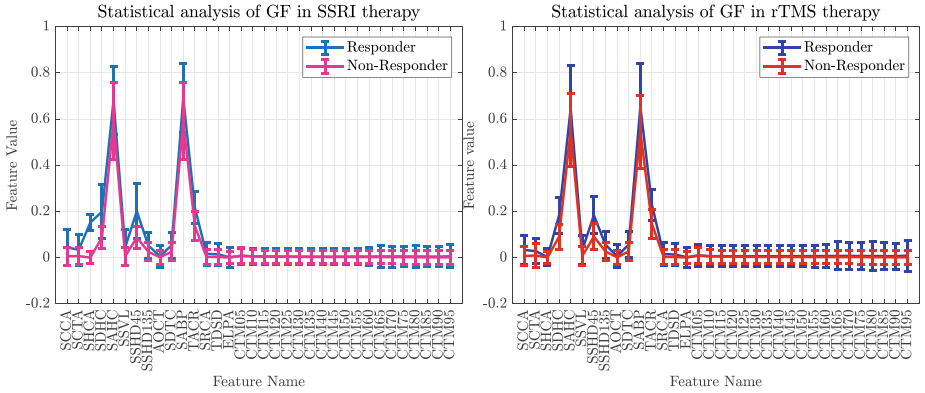



**Fig. 8.** Statistical analyzing the extracted GFs from the T3 and F7 channels in the SSRI (left) and rTMS (right) therapies, respectively.

to understand the dynamics of these channels in R and NR situations as shown in Fig. 8.

The results demonstrate that the mean values of the GF in the R group are higher than in the NR group in both SSRI and rTMS therapies. This means that the PSR of the R EEG signals occupies more area than the NR EEG signals. Additionally, the higher value of the standard deviation indicates that the PSR of EEG signals in the R group is more complex, irregular, and unpredictable than in the NR group. This fact can be seen in Fig. 4 for the T3 and F7 channels of EEG signals in SSRI and rTMS therapies, respectively. In fact, the PSR of the T3 and F7 channels can be used as a biomarker to visually inspect brain function in SSRI and rTMS therapies, respectively.

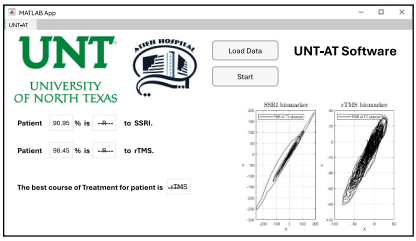
There are few number of studies to predict the outcome of depression therapies including SSRI and rTMS. Table 4 lists a comparison of our proposed UNT-AT software and recently methods for predicting the outcomes of SSRI and rTMT therapies. The proposed UNT-AT software achieves better performance in terms of ACC, SEN, and SPE compared to other previous studies. Our results outperforms the results in [20], where the authors used the same Mumtaz database for SSRI therapy. In addition, our results outperforms the results in [8]; however, the author used different private rTMS database.

The UNT-AT software is a novel tool that can be utilized in hospitals and clinics to predict the outcomes of depression therapies, and it is the first in the literature. Figure 9 shows the developed UNT-AT software and the results of all four possible outcomes. The proposed UNT-AT software is built on the PSR technique and extracts GFs, which aligns with a CFNN with a simple architecture. The proposed UNT-AT software is reliable and fast due to its simplicity. In addition, the developed UNT-AT software does not require much computational resources and can be run a standard computer available in clinics and hospitals.

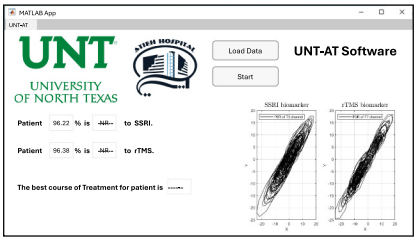
The contributions of the proposed UNT-AT software are listed as follows:

**Table 4.** Comparison of the performance of the proposed UNT-AT software with previous works.

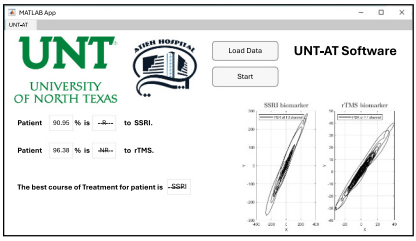
| Ref. | Database | Therapy | ACC (%) | SEN (%) | SPE (%) |
|---|---|---|---|---|---|
| [20] | 12 R vs. 18 NR | SSRI | 91.60 | 90.00 | 90.00 |
| Ours | 12 R vs. 18 NR | SSRI | 94.14 | 96.22 | 90.95 |
| [8] | 23 R vs. 23 NR | rTMS | 97.10 | 97.30 | 97.00 |
| Ours | 9 R vs. 6 NR | rTMS | 97.67 | 96.38 | 98.45 |



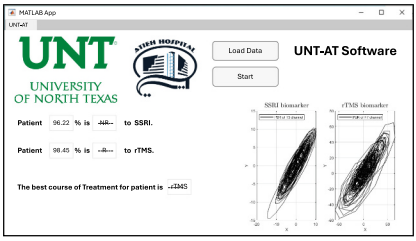

(a) R to both SSRI and rTMS therapies.




(b) NR to both SSRI and rTMS therapies.




(c) R to SSRI therapy and NR to rTMS therapy.




(d) NR to SSRI therapy and R to rTMS therapy.

**Fig. 9.** The developed UNT-AT software.

- First time to predict the outcome of two different depression therapies: SSRI and rTMS.
- The GFs is used for the first time to predict therapy outcomes, rather than detecting mental disorders.
- A fast and reliable software is developed using simple CFNN architecture.
- The proposed UNT-AT software is tested using two databases with different sampling frequencies that shows it is not sensitive to sampling frequency.
- The 10-fold CV strategy is implemented during training and testing to avoid bias in the results. This shows the effectiveness of the proposed UNT-AT software in the real-world applications.
- Offering a cost-effective, highly accurate, and efficient UNT-AT software that utilizes pretreatment EEG signals to predict the outcomes of SSRI and rTMS therapies for depressed patients. All design and implementation of the UNT-AT is implemented in MATLAB that makes it a significant software tool for use in hospitals and clinics to predict therapy outcome for depressed patients.

## 7 Conclusion

Suicide and self-harm are results of depression when it is not treated properly. SSRI and rTMS therapies are two courses of treatment for depression disorder. The FDA approved the effectiveness of these two therapies for depression. However, the response rate to these therapies for depressed patients is around 50%. If the treatment is unsuccessful that will increase the possibility of suicide and self-harm for depressed patients. In the current work, the UNT-AT software is developed based on GFs of EEG signals in the PSR domain and aligned with a CFNN architecture to predict the outcome of SSRI and rTMS therapies.

The proposed UNT-AT software is evaluated using EEG signals of 45 depressed patients, of whom 30 were candidates for SSRI therapy and 15 were candidates for rTMS therapy. The results show a classification accuracy of 94.14% and 97.67% in predicting the outcomes of SSRI and rTMS therapies, respectively. In addition, the results show that the PSR of EEG signals for R patients is more complex and wider than NR. On the other hand, the PSR of EEG signals in NR patients is more predictable and has lower irregularity, which might be due to the decrease in neuronal connections in NR patients' brains. The best channels to predict the outcomes of SSRI and rTMS therapy are located T3 and F7, respectively. In addition, the PSR of these two channels can be used as biomarkers to predict the outcomes of depression therapy. In the future, the performance of the proposed UNT-AT software will be evaluated for psychological treatments such as tricyclic antidepressants (TCAs), Monoamine oxidase inhibitors (MAOIs) as well as somatic treatments such as electroconvulsive therapy (ECT), vagus nerve stimulation (VNS), deep brain stimulation (DBS), transcranial direct current stimulation (tDCS), light therapy, ketamine, and esketamine.

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