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PSYCHOLOGY WITH SOFT COMPUTING METHOD: FORECASTING OF ANGER EXPRESSION OF THE HUMAN USING THE DEVELOPED MODEL BASED ON SUPPORT VECTOR MACHINE

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Anger is a natural emotion that activates self-defense mechanisms to protect oneself in stressful situations. However, if stress level is excessive, or the intensity, frequency, or duration of anger expression is not controlled, it can have negative effects on one's physical health and cause emotional problems like depression, anxiety, lowered quality of life, and interpersonal problems. The purpose of the present study is to forecast the anger expression from the anger state and trait using the developed model based on support vector machine (SVM) in a group of nonclinical individuals. To this end, 3,443 participants including students (60%), university staff (20%) and hospital staff (20%) are examined. After removing the missing data (443 participants), 3,000 data were considered in the analysis. The distribution of gender in the present study was 48% males and 52% females. The mean age of participants was 35.42 years (*SD* = 8.41, range 18-60 years). The proposed model is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. In the developed model, the training step is performed using a series of data through the known input and output data, and after the validation and testing steps, unknown output data corresponding to the known input data are predicted. The state, feeling, verbal, physical, trait, temperament, and reaction of anger are the inputs of the developed model. The anger expression scales including anger expression-out, anger expression-in, anger control-out, anger control-in, and anger index are forecasted as the output data from the developed model. Results indicate that the developed model based on SVM forecasts anger expression with acceptable accuracy. Therefore, it can be used as an appropriate model to predict how to express people's anger with acceptable accuracy.

Key words: Anger; Forecasting; Support vector machine; Anger expression; Anger experience.

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Anger is a clinically relevant emotion and has been usually defined as a unitary construct, but during the past 30 years a multifaceted conceptualization of anger, according to Spielberger's theory, has spread (Spielberger, Krasner, & Solomon, 1988). Spielberger pointed out that anger can be understood as a momentary state (i.e., how people feel at the moment) and as a trait (i.e., how people feel in general). The distinction between state and trait anger, referred to as the state-trait anger theory, has been repeatedly and empirically validated (Deffenbacher et al., 1996; Quinn, Rollock, & Vrana, 2014). Moreover, Spielberger recognized the importance of how these angry feelings are expressed and controlled.

Anger experience and its expression are distinct concepts. Anger experience refers to the emotional state one feels, in addition to the accompanying physiological responses. On the other hand, anger expression refers to the behavioral dimension that is one's way of dealing with the feeling of anger. Anger expression styles can be categorized into the following three types: anger-in, anger-out, and anger-control (Spielberger, Jacobs, Russell, & Crane, 1983). Anger-in is defined as redirection of the anger to the self, denial of thoughts or memories related to the situation that triggered anger, or denial of the emotion of anger itself. Anger-out is defined as expressing anger to another person or object in various ways including a physical act, criticism, insult, or verbal abuse. Anger-control is defined as making an effort to control and manage anger and express the feeling of anger while respecting the rights and emotions of the other person, using words that are not aggressive (Spielberger et al., 1983). The anger expression style of a person is influenced by both education and social context (Song, Hwang, & Jeon, 2009). Appropriate anger expression can help one regain calm after the physical and psychological imbalance caused by anger. However, inappropriate anger expression will result in negative influences on interpersonal relationships with others. Therefore, it is necessary to control anger in an appropriate manner to maintain physical and psychological health. Furthermore, appropriate anger expression techniques are also important for the interpersonal relationship adjustment as well as the social adaptation and development (Song et al., 2009). This type of dealing with negative emotions is called the emotion regulation.

Emotional self-regulation or emotion regulation is the ability to respond to the ongoing demands of experience with a range of emotions in a manner that is socially tolerable and sufficiently flexible to permit spontaneous reactions as well as the ability to delay spontaneous reactions as needed. Recently, research on anger regulation has received increasing attention in the past few decades (Gross, 2014). Some studies have examined cultural differences with regard to the use of anger regulation strategies, as well as how the relationships between these strategies and their key antecedents and consequences systematically differ across cultures (Mauss & Butler, 2010). Consistent with this view, three types of anger regulation have attracted particular attention: anger-in or anger suppression, anger-out or anger expression, and anger control (Spielberger, 1999). Research on emotion regulation has also considered how individuals are culturally motivated to pursue their life goals, since this factor may influence one’s handling of anger (Park et al., 2013).

According to Spielberger’s theory (1999), anger reflects a multidimensional phenomenon composed of internalized anger, externalized anger, and anger control. Internalized anger reflects the tendency to suppress angry thoughts and feelings. In contrast, externalized anger reflects the tendency to engage in aggressive behaviors towards objects or persons in the environment. Finally, anger control refers to the ability to monitor and prevent the experience or expression of anger. How anger out/anger expression influences one’s health and well-being has been another topic of study (Kitayama et al., 2015). Hence, differences across these dimensions of anger might help to distinguish between depressive, anxious, and hostile symptoms. Anger can be either adaptive or maladaptive. Adaptive anger is a mechanism for dealing with an obstructed goal or perceived threat. Maladaptive anger results in greater conflict and personal discomfort (Lench, 2004).

Because of the aforementioned contents and the importance of the expression of anger and its influence on individual behavior, it seems necessary to predict the expression of anger. The study of the relationship between experience and anger expression in the human can be helpful for clinical professionals and therapists about the emotion of anger. If a mathematical model is found to establish a connection between the input data (anger state and trait) and output data (anger expression-out, anger expression- in, anger control-out, anger control-in, and anger index), it will be very useful for calculation of anger expression scales. Unfortunately, because of the complexity of this problem, such a mathematical model has not been presented. As another approach, the human brain could be considered as a model for simulation and prediction of anger expression. Over the past 15 years, a view has emerged that computing based on models inspired by our understanding of the structure and function of the biological neural networks may hold the key to the success of solving intelligent tasks by machines. The new field is called artificial neural network (Abraham, 2005; Hopfield, 1988; Yegnanarayana, 2009), although it is more apt to describe it as parallel and distributed processing. A neuro-fuzzy system is another choice for the considered purpose. It is a fuzzy system that uses a learning algorithm derived from or inspired by neural network theory to determine its parameters (fuzzy sets and fuzzy rules) by processing data samples (Nauck, Klawonn, & Kruse, 1997). Combination of both techniques enhances the performance of control, decision-making, and data analysis systems. Foundations of neuro-fuzzy systems highlight the advantages of integration making it a valuable resource for graduate students and researchers in control engineering, computer science, and applied mathematics.

In the field study of psychology, the use of soft computing methods began in about 1975 and numerous studies have been done with these methods. Several researchers have reported the application of soft computing algorithms for the prediction of human emotion or behavior and its assessment. Some selected researches are summarized as follows:

- Levine (1989) introduced neural networks as an increasingly important tool for the mechanistic understanding of psychological phenomena. Three commonly used principles in neural-network design (associative learning, competition, and opponent processing) were outlined in this paper, and two examples of their use in behavior-modeling architectures were discussed.
- Kalghatgi and his colleagues reported the application of artificial neural networks to personality prediction based on the Big-Five model (Kalghatgi, Ramannavar, & Sidnal, 2015). This work analyzed social media data to predict significant personality traits, that is, qualities or characteristics specific to an individual, using the Big-Five model. The predictions could be applied to various domains like business intelligence, marketing, sociology, and psychology. The parallelism between an individual's personality traits and his/her linguistic information was explored for analytics.
- Potey and his colleagues published a paper to introduce the various approaches of user modeling, machine learning, and soft computing techniques that have successfully modeled human behavior (Potey & Sinha, 2015).
- Devi and his colleagues (Devi, Kumar, & Kushwaha, 2016) proposed design methodology and application of adaptive neuro-ffuzzy inference system (ANFIS) in the prediction of the anxiety of students using a hybrid learning algorithm to improve the prediction based on the conventional model using questioner. First order Sugeno fuzzy model was considered whose parameters are tuned through a hybrid learning algorithm. The performance of the proposed model is verified in terms of the prediction errors. It was found that both mean absolute percentage error (MAPE) and root mean square error (RMSE) were reduced significantly. The results established that the fusion of fuzzy logic and neural network with hybrid learning algorithm can be very useful in psychological research.
- Almeida and Azkune (2018) developed a multilevel conceptual model that describes the user behavior using actions, activities, and intra- and inter-activity behavior. Using this conceptual model, they created a deep learning architecture based on long short-term memory networks (LSTMs) that models the inter-activity behavior. The presented architecture offered a probabilistic model for prediction of next actions and identification of anomalous user behaviors.

In addition to the application of soft computing algorithms in the prediction of human emotion and behavior, there were some other applications of these algorithms in psychology and psychometrics. Some selected researches are summarized as follows:

- Nicole and Caprara (2005) described an attempt to assess the development of a stable aggressive behavior, by means of a neuro-fuzzy model of the relationships between sociometric predictors (popularity/refusal rates among peers, hyperactivity, prosocial behavior) and yearly variations in physical and verbal aggressive conduct in children. A hardly noticeable initial difference is sufficient to lead to relevant differences, such as resilience to change the judged aggressive level in the presence of changes of sociometric predictors for marginally aggressive children only.

- Sese and his colleagues described the neural networks principal components analysis (NNPCA) and the comparison of its results with the performance of classical PCA by means of a computer simulation study (Sese, Palmer, & Montano, 2004). Results indicated very important convergence between neural and classical PCA, even with simulated diffuse latent structures. NNPCA was performed under principles of neurobiology plausibility (learning neural architecture), useful to analyze latent psychometric structures adding more psychological significance. This new tool could be considered as another complementary way to assess measurement models, together with classical approaches. The pioneer character of this work also requires the development of further empirical evidence that allows advancement in the use of the NNPCA in the study of psychometric measurement models.
- Di Nuovo and his colleagues investigated the application of two well-known soft computing techniques, fuzzy logic, and genetic algorithms (GAs) in the psychopathological field (Di Nuovo, Catania, Di Nuovo, & Buono, 2008). The investigation started from a practical need: the creation of a tool for a quick and correct classification of mental retardation level, which is needed to choose the right treatment for rehabilitation and to assure a quality of life that is suitable for the specific patient condition.

The aforementioned examples show that the use of soft computing algorithms has been used extensively in psychology and is in development. In continuation of previous researches in the field of psychology using soft computing algorithms, in the present study, a model based on the support vector machine (SVM) is proposed to forecast the anger expression and control scales of humans in nonclinical individuals. To this end, data were collected from the 3,443 participants who filled in the State-Trait Anger Expression Inventory-II (STAXI-2; Spielberger, 1999). After removing the missing data, 3,000 data were considered in the analysis. The state, feeling, verbal, physical, trait, temperament, and reaction of anger are the inputs of the developed model. The anger expression scales including anger expression-out, anger expression-in, anger control-out, anger control-in, and anger index are the output of the model.

An outline of the remainder of the present paper is as follows: In Section "Methodology", we briefly introduce the mathematical formulation used to develop a model based on SVM for forecasting of anger expression of the human. The results of the calculation of the anger expression and control scales are presented in Section "Results." A discussion on the results and the merits of the proposed methods are presented in Section "Discussion." Finally, Section "Conclusion" gives the concluding remarks.

METHODOLOGY

Participants

Participants (*N* = 3,443) were individuals who had not received any clinical diagnosis and included students (60%), university staff (20%), and hospital staff (20%). The data of students and university staff were collected from some universities of the Islamic Republic of Iran including the Kharazmi University (35%), Sharif University of Technology (15%), Allameh Tabataba'i University (30%), Tehran University (10%), and Shahid Beheshti University (10%) between 2013 and 2018. Also, data of hospital staff were collected from the staff of Mostafa Khomeini, Taleghani, and Imam Hussein hospitals of Iran in the abovementioned time period. Each participant filled in the State-Trait Anger Expression Inventory-2 (STAXI-2; Spielberger, 1999). After removing the missing data (443 participants), the data of the remaining 3,000 participants were inserted into the SPSS 16.0 software (Norusis, 2008).

The distribution of gender in the present study was 48% males and 52% females. The mean age of participants was 35.42 years (*SD* = 8.41, range 18-60 years). Also, the cultural levels in the present study were scattered as follows: 75% Fars, 15% Turks, 5% ethnicity Lor, and 5% for other ethnicities present in the Islamic Republic of Iran. The normality of variables was investigated using Kolmogorov-Smirnov (K-S) test via adjusting the sample size. The results of Table 1 show that the distribution of study variables is normal.

TABLE 1
Conceptual model with two latent variables

Scales	*N*	Minimum	Maximum	*M*	*SD*	K-S test	*p*
S-ANG	3,000	15	60	21.08	8.078	1.10	.26
S-ANG/F	3,000	5	20	8.09	3.376	1.29	.19
S-ANG/V	3,000	5	20	6.96	3.182	1.20	.23
S-ANG/P	3,000	5	20	6.03	2.522	1.51	.15
T-ANG	3,000	10	40	20.39	5.605	1.21	.22
T-ANG/T	3,000	4	16	7.96	2.787	1.84	.10
T-ANG/R	3,000	4	16	9.53	2.707	1.67	.13
AX-O	3,000	8	32	16.36	4.149	1.13	.24
AX-I	3,000	8	32	19.05	4.094	0.91	.48
AC-O	3,000	8	32	20.24	5.259	0.71	.55
AC-I	3,000	8	32	20.58	5.440	0.61	.60
AX-index	3,000	5	96	42.59	13.191	0.65	.64

Note. S-ANG = state anger; S-ANG/F = state anger-feeling; S-ANG/V = state anger-verbal; S-ANG/P = state anger-physical; T-ANG = trait anger; T-ANG/T = trait anger-temperament; T-ANG/R = trait anger-reaction; AX-O = anger expression-out; AX-I = anger expression-in; AC-O = anger control-out; AC-I = anger control-in; AX-index = anger expression index.

Measures

State-Trait Anger Expression Inventory-2 (STAXI-2; Spielberger, 1999) includes the 57 items used to determine latent classes of anger (LCA) symptoms. The STAXI-2 measures anger as an emotional state, dispositional trait, as well as how individuals express and control their angry feelings. The state anger (S-ANG) scale assesses the intensity of anger as an emotional state at a particular time. It has three subscales, state anger-feeling angry (S-ANG/F), state anger-tendency to express verbal anger (S-ANG/V), and state anger-tendency to express physical anger (S-ANG/P). Each of the state anger subscales consists of five items. The trait anger (T-ANG) scale assesses how often angry feelings are experienced over time. It has two subscales, the trait anger-angry temperament (T-ANG/T), trait anger-angry reaction (T-ANG/R). Each of the trait anger subscales consists of four items. Items from the trait anger subscales use the stem "How I generally feel …" and examples include "Quick-tempered" (T-ANG/T) and "I get angry when I'm slowed down by others' mistakes" (T-ANG/R). The anger expression and anger control scales assess four relatively independent traits: anger expression-out (AX-O), anger expression-in (AX-I), anger control-out (AC-O), and anger control-in (AC-I). The anger expression and anger control subscales consist of eight items. Items from the anger expression subscales use the stem "How I generally react or behave when angry or furious …" and examples include "I strike out at whatever infuriates me" (AX-O; an index of the tendency to express anger outwardly toward other people/objects in the environment) and "I boil inside, but I don't show it" (AX-I; an index of the tendency to suppress the expression of angry feelings). Items from the anger control subscales also use the stem "How I generally react or behave when angry or furious …" and examples include "I take a deep breath and relax" (AC-I; an index of generally adaptive attempts to control one's angry feelings through calming down or cooling off), and "I am patient with others" (AC-O; an index of generally adaptive attempts to control the expression of angry feelings). In the end, anger expression index (AX-index) that provides an overall estimation of the anger expression and control scales. Subscales of the STAXI-2 (other than the state anger scale) use a 4-point Likert-type scale ranging from 1 (*Almost never*) to 4 (*Almost always*). Subscales of the state anger use a 4-point Likert-type scale ranging from 1 (*Not at all*) to 4 (*Very much so*). Administrations of the STAXI-2 have demonstrated excellent reliability and good convergent validity with measures of hostility, neuroticism, and psychoticism as measured by the Eysenck Personality Questionnaire (EPQ; Eysenck & Eysenck, 1975); as well as systolic and diastolic blood pressure (Spielberger, 1999). Divergent validity has been demonstrated by a lack of correlation between the STAXI-2 subscales and the State-Trait Personality Inventory curiosity subscale, and the EPQ extraversion subscale (Spielberger, 1999). Factor analysis supports the use of individual subscales (Spielberger, 1999; Spielberger & Reheiser, 2009). The subscales have also demonstrated adequate reliability and validity (Spielberger, 1999).

The internal consistency of the subscales used in the present study ranged from adequate to good: S-ANG (α = .91), S-ANG/F (α = .79), S-ANG/V (α = .79), S-ANG/P (α = .79), T-ANG (α = .85), T-ANG/T (α = .78), T-ANG/R (α = .78), AX-O (α = .85), AX-I (α = .73), AC-O (α = .89), and AC-I (α = .93).

Development of a Model Based on the SVM to Forecast Anger Expression

The purpose of the present paper is the development of a model to forecast the expression of anger using the anger state and trait indexes. To this end, SVM as a machine-learning approach has been selected. The SVM was developed first by Cortes and Vapnik (1995). At first, it was developed to solve a two-class linear discriminative problem by finding a *D*-dimensional hyperplane as a discriminator. For nonlinear classification problems, SVM introduces the kernel approach which transforms the data space into a higher dimension and makes a linear discriminative problem. Drucker and his colleagues (Drucker, Burges, Kaufman, Smola, & Vapnik, 1997) presented a new version of SVM algorithm for regression tasks known as support vector regression machine (SVRM). SVM algorithm has been used to solve many problems such as text categorization (Joachims, 1998), crack detection (Fisher, Camp, & Krzhizhanovskaya, 2016), gene selection for cancer classification (Guyon, Weston, Barnhill, & Vapnik, 2002), face detection (Osuna, Freund, & Girosit, 1997), control (Suykens, Vandewalle, & De Moor, 2001), and so forth.

As previously explained, SVM was developed to solve a two-class problem. Suppose n training data $\{x_i, y_i\}$ for i = 1, 2, …, n , are given in which x_i is a D dimensional input vector and y_i is the output with values of –1 or 1(bipolar coding for a two-class problem). All hyperplanes in D dimensional space can be represented as Equation 1.

$$\vec{\boldsymbol{W}}.\vec{\boldsymbol{X}} + b = 0. \tag{1}$$

Parameter $\vec{\boldsymbol{W}}$ is the vector orthogonal to the hyperplane and b is the offset. Here, $\vec{\boldsymbol{W}}.\vec{\boldsymbol{X}}$ denotes the dot product (standard scalar product) of $\vec{\boldsymbol{W}}$ and $\vec{\boldsymbol{X}}$ vectors. If a hyperplane $\{\vec{\boldsymbol{W}}, b\}$ can separate these data in two classes, function $f\left(\vec{\boldsymbol{X}}_i\right)$ can be defined as Equation 2.

$$y_i = f(\vec{\boldsymbol{X}}_i) = sign\left(\vec{\boldsymbol{W}}.\vec{\boldsymbol{X}}_i + b\right) = \begin{cases} 1 & \vec{\boldsymbol{W}}.\vec{\boldsymbol{X}}_i + b > 0 \\ -1 & \vec{\boldsymbol{W}}.\vec{\boldsymbol{X}}_i + b < 0 \end{cases} \tag{2}$$

To solve the noisy situations and outlier data, the comparison should be done with a value like $\varepsilon = 1$, so the function $f(\vec{\boldsymbol{X}}_i)$ should be rewritten as shown in Equation 3.

$$y_i = \begin{cases} 1 & \vec{\boldsymbol{W}}.\vec{\boldsymbol{X}}_i + b > 1 \\ -1 & \vec{\boldsymbol{W}}.\vec{\boldsymbol{X}}_i + b < -1 \end{cases} \tag{3}$$

which can be shown by $y_i(\vec{\boldsymbol{W}}.\vec{\boldsymbol{X}}_i + b) > 1 \quad \forall i$. For a given hyperplane $\{\vec{\boldsymbol{W}}, b\}$, all pairs $\{\lambda\vec{\boldsymbol{W}}, \lambda b\}$ define the same hyperplane, but each has a different functional distance to a given data point. To have a geometric interpretation, a normalization should be done with respect to magnitude of vector $\vec{\boldsymbol{W}}$. The formula used for calculation of the geometric distance is given as Equation 4:

$$d(\{\vec{\boldsymbol{W}}, b\}, \vec{\boldsymbol{x}}_i) = \frac{y_i(\vec{\boldsymbol{W}}.\vec{\boldsymbol{X}}_i + b)}{||\vec{\boldsymbol{W}}||} \geq \frac{1}{||\vec{\boldsymbol{W}}||}. \tag{4}$$

Parameters $\vec{\boldsymbol{W}}$ and b should be selected to maximize distance d to the nearest data points of the two different classes. This will be done by minimizing $||\vec{\boldsymbol{W}}||$ subject to distance constraints. The problem can be solved by Lagrange multipliers as Equation 5:

$$\begin{aligned} &\text{minimize:}\quad \mathrm{W}(\boldsymbol{\alpha}) = -\sum_{i=1}^{n} \boldsymbol{\alpha}_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i y_j \boldsymbol{\alpha}_i \boldsymbol{\alpha}_j (\vec{\boldsymbol{X}}_i.\vec{\boldsymbol{X}}_j) \\ &subject\ \text{to:}\quad \sum_{i=1}^{n} y_i \boldsymbol{\alpha}_i = 0 \\ &\qquad\qquad 0 \leq \boldsymbol{\alpha}_i \leq K(\forall i). \end{aligned} \tag{5}$$

where, $\boldsymbol{\alpha}$ is a D dimensional non-negative Lagrange multiplier which should be determined, and K is a constant value. The positive constant value K is not necessary in the separable case. Equation 5 can be rewritten as Equation 6 in a compact form:

$$\begin{aligned} &\text{minimize:}\quad W(\boldsymbol{\alpha}) = -\alpha^T.arrow(1) + \frac{1}{2}\alpha^T H \boldsymbol{\alpha} \\ &subject\ to:\quad \alpha^T y = 0 \\ &\qquad\qquad 0 \leq \boldsymbol{\alpha}_i \leq K. \end{aligned} \tag{6}$$

where, α^T denotes to transpose of $\boldsymbol{\alpha}$ vector. Also, H is a matrix with $H_{ij} = y_i y_j (\vec{\boldsymbol{X}}_i.\vec{\boldsymbol{X}}_j)$ and arrow (1) is a n-vector whose components are all equal to 1.

$$\begin{aligned} &\vec{W} = \sum_i \boldsymbol{\alpha}_i y_i \vec{\boldsymbol{X}}_i \\ &b = -\frac{1}{2}(\vec{\boldsymbol{W}}.\vec{\boldsymbol{X}}^+ + \vec{\boldsymbol{W}}.\vec{\boldsymbol{X}}^-) \end{aligned} \tag{7}$$

Where $\vec{\boldsymbol{X}}^+$and $\vec{\boldsymbol{X}}^-$ are the support vectors which satisfy equations $(\vec{\boldsymbol{W}}.\vec{\boldsymbol{X}}^+ + b) = 1$ and $(\vec{\boldsymbol{W}}.\vec{\boldsymbol{X}}^- + b) = -1$, respectively. The constant K will apply a soft margin which lets some training data be misclassified. The margin concept is shown in Figure 1.

For a nonlinear problem, using the kernel approach will transform the data into a linear problem whose concept is shown in Figure 2. Applying the kernel approach can be done by replacing the definition of $H_{ij} = y_i y_j (\vec{\boldsymbol{X}}_i.\vec{\boldsymbol{X}}_j)$ with $H_{ij} = y_i y_j (\Phi(X_i).\Phi(X_j))$ in the main problem. In this paper the Gaussian kernel is used in the simulation procedure as Equation 8:

$$K(\vec{\boldsymbol{X}}_i, \vec{\boldsymbol{X}}) = exp(-||\vec{\boldsymbol{X}} - \vec{\boldsymbol{X}}_i||^2/2\sigma^2) \qquad \text{for } \sigma > 0. \tag{8}$$

where, smaller values of σ leads to having a nearest neighbor classifier.

By modifying the loss function of Equation 5, the SVM approach can be applied in regression problems as done by Gunn (1998). Equation 5 shows the objective function for a two-class classification problem, and for a regression problem some modifications should be done (see Drucker et al., 1997).

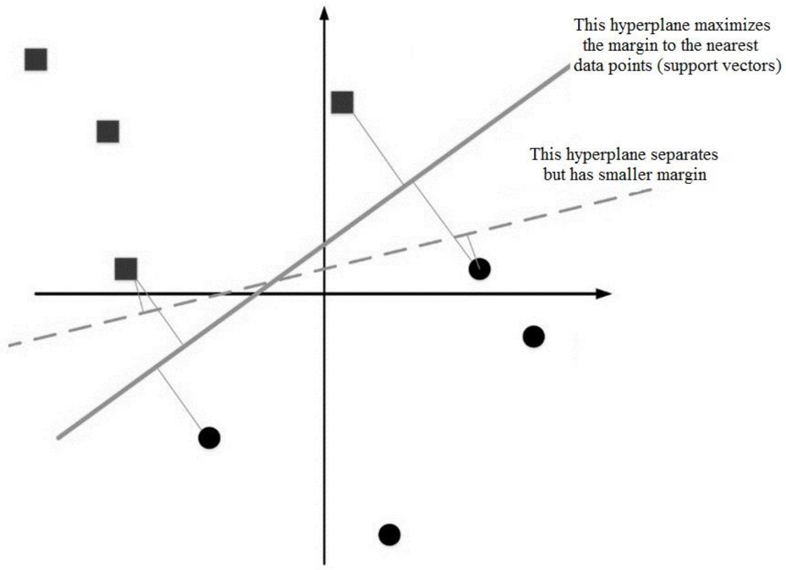

FIGURE 1
The best hyperplane maximizes the margin to the nearest data points.

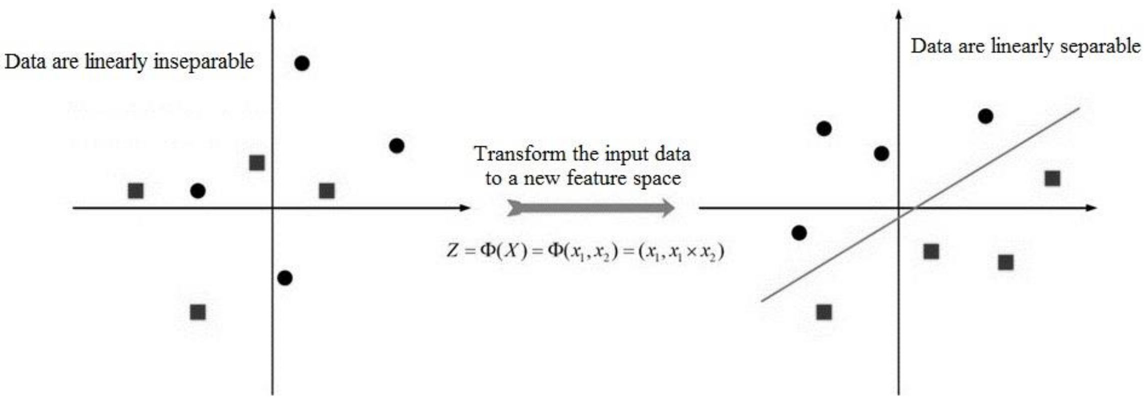

FIGURE 2
Utilizing the kernel approach will transform a nonlinear problem into a linear one.

RESULTS

The purpose of the present paper was to forecast the anger expression scales (AX-O, AX-I, AC-O, AC-I, and AX-index) when the S-ANG, S-ANG/F, S-ANG/V, S-ANG/P, T-ANG, T-ANG/T, T-ANG/R scales (anger state and trait) are known. In the developed model based on SVM, the data were used in the three steps (training, validation, and testing). Seventy percent of the considered data (3,000 data) are used for training step and the rest for validation and testing steps.

In training step, the model processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights which control the network. This process occurs over and over as the weights are continually tweaked. The set of data which enables the training is called the “training set.” During the training of a network the same set of data is processed many times as the connection weights are constantly refined. After the training of the developed model and validation step using 400 data, the application of the developed model was checked for remaining data (500 data). Validation set is different from test set. Validation set can actually be regarded as a part of training set, because it is used to build the model. It is usually used for parameter selection and to avoid over fitting. If the model is nonlinear and is trained on a training set only, it is very likely to get 100% accuracy and over fit, thus obtaining very poor performance on test set. Thus a validation set, which is independent from the training set, is used for parameter selection.

In the present paper, the features state, feeling, verbal, physical, trait, temperament, and reaction of anger are used as input data of the developed model to predict how to express anger (AX-O, AX-I, AC-O, AC-I, and AX-index). In Figures 3-7, as examples of results, the forecasted scales of anger expression (AX-O, AX-I, AC-O, AC-I, and AX-index) are compared with the actual ones for 100 randomly considered cases (selected cases from the 500 data). As shown, there is a good agreement between the forecasted anger expression scales and the actual ones.

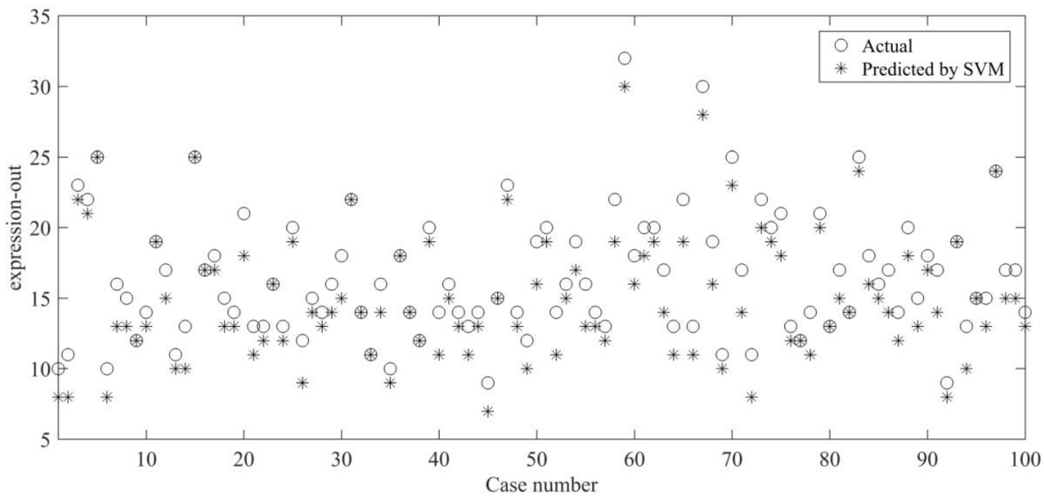

FIGURE 3
Comparison of actual and predicted values of the AX-O.

For comparison and efficiency evaluation, the fraction of variance unexplained (FVU) index which is defined in Equation 9 is used:

$$FVU = \frac{\sum_{i=1}^{N}(\hat{y}(\vec{x}_i)-y(\vec{x}_i))^2}{\sum_{i=1}^{N}(y(\vec{x}_i)-\bar{y}(\vec{x}_i))^2} \tag{9}$$

In Equation 9, y is the real output value, $\hat{y}$ is the output of SVM model, N is the number data point and $\bar{y} = \frac{\sum_{i=1}^{N} y(\vec{x}_i)}{N}$. FVU is a kind of normalized error index. In this index, the absolute value of error is important with respect to the amount of output variable's variation. The best modeling procedure will be for FVU = 0.

To investigate the robustness of the results, 10 different random subdivisions of the dataset in training/validation/test sets were selected and the average value of FVU and its variance were calculated for each scale. Table 2 shows the calculated FVUs of forecasted scales of AX-O, AX-I, AC-O, AC-I, and AX-index. As shown, the forecasting of anger expression and control scales in the considered cases have been performed with high accuracy using the developed model based on SVM.

TABLE 2
Calculated FVU for the output data in the performed forecasting using SVM

	AX-O	AX-I	AC-O	AC-I	AX-index
Mean	0.0082	0.0111	0.0092	0.0080	0.0075
Variance	1.4767E-07	7.2844E-07	1.5111E-07	1.4844E-07	1.4989E-07

Note. AX-O = anger expression-out; AX-I = anger expression-in; AC-O = anger control-out; AC-I = anger control-in; AX-index = anger expression index.

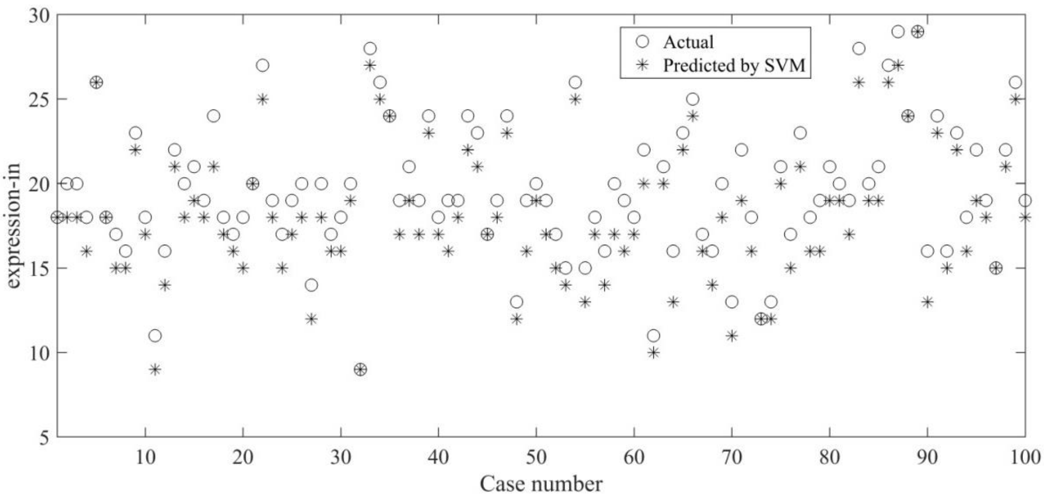

FIGURE 4
Comparison of actual and predicted values of the AX-I.

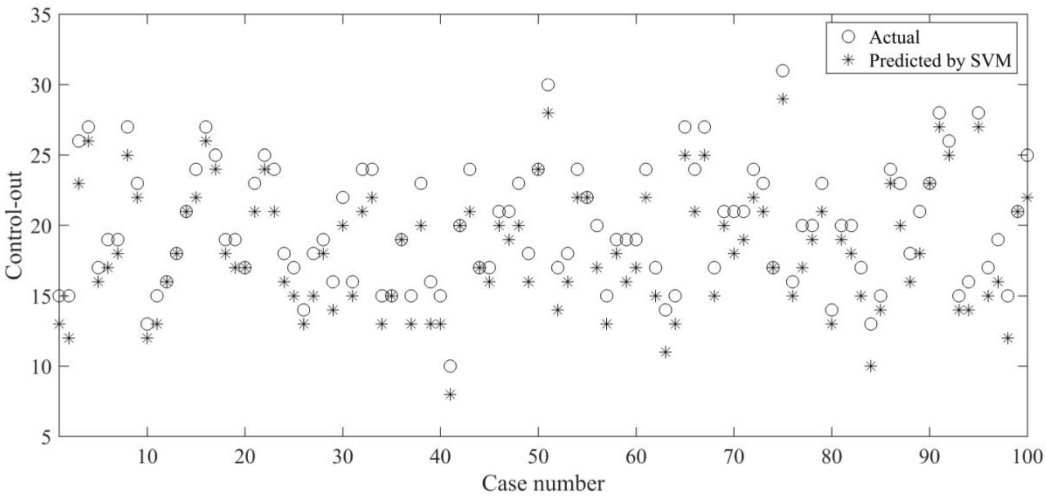

FIGURE 5
Comparison of actual and predicted values of the AC-O.

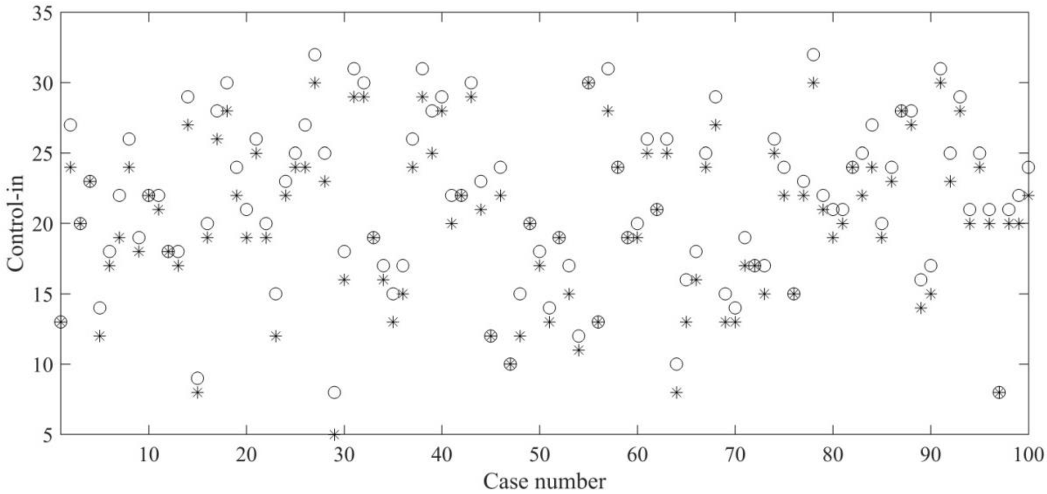

FIGURE 6
Comparison of actual and predicted values of the AC-I.

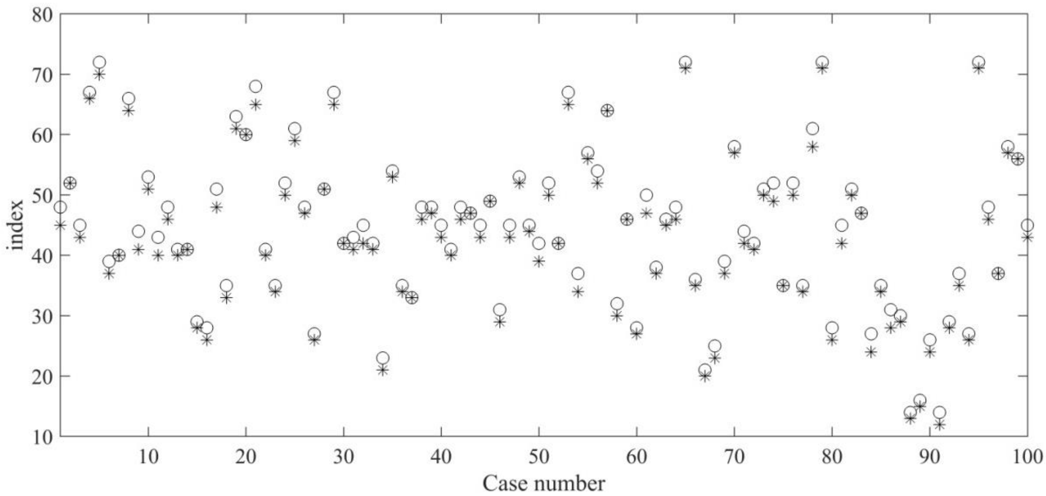

FIGURE 7
Comparison of actual and predicted values of the AX-index.

DISCUSSION

In the present study, the scales of anger expression and control were forecasted using the developed model based on the SVM. Seventy percent of the 3,000 collected data (2,100 data) were used for training step in the developed model. Also, 400 data were utilized in the validation step of the developed model based on SVM. For the 500 remaining data, S-ANG, S-ANG/F, S-ANG/V, S-ANG/P, T-ANG, T-ANG/T, T-ANG/R scales (anger state and trait) were the inputs of the developed computational model. The anger expression scales including AX-O, AX-I, AC-O, AC-I, and AX-index were forecasted using SVM. The FVU index that represents the error of forecasting of AX-O, AX-I, AC-O, AC-I, and AX-index were 0.0089, 0.0105, 0.0093, 0.0082, and 0.0073, respectively. In the literature review, the author did not find any research on the prediction of anger emotion using soft computing algorithms. However, some researchers have tried to recognize the human emotions using soft computing algorithms like artificial neural network and neuro-fuzzy systems. The accuracy of the predicted values using the SVM model as a machine-learning approach in the present study is in the range or even better than the previously published works using artificial neural network or neuro-fuzzy algorithms (Chatterjee & Shi, 2010; Devi et al., 2016; Ioannou et al., 2005; Kalghatgi et al., 2015; Lee et al., 2006; Malkawi & Murad, 2013; Nicholson, Takahashi, & Nakatsu, 2000; Potey & Sinha, 2015; Sprengelmeyer, Rausch, Eysel, & Przuntek, 1998; Subramanian, Suresh, & Babu, 2012). The main superiority of the soft computing algorithms like SVM in comparison to numerical methods is that it could be used for the modeling of any complex system to forecast or control the desired parameters.

As already mentioned, the accuracy of forecasting anger expression scales using SVM for 3,000 available data in the present paper is good. However, the number of available data for simulation may change the accuracy of the forecast. A higher number of data will result in better results.

Conclusion

In the present study, the anger expression scales were forecasted using the developed model based on the SVM. The state (S-ANG), feeling (S-ANG/F), verbal (S-ANG/V), physical (S-ANG/P), trait (T-ANG), temperament (T-ANG/T), and reaction (T-ANG/R) of anger scales were the inputs of the developed model. The scales of AX-O, AX-I, AC-O, AC-I, and AX-index were forecasted using SVM. The accuracy of forecasting the anger expression scales using SVM was high. FVU that presents error in forecasting AX-O, AX-I, AC-O, AC-I, and AX-index were 0.0089, 0.0105, 0.0093, 0.0082, and 0.0073, respectively. The most important point about anger is how a person expresses anger and controls it. Problems due to inappropriate expression of anger remain among the most serious concerns of parents, educators, and the mental health community. Given the accuracy of forecasting the anger expression scales in the present study, the developed model based on the SVM may be a reliable tool for the identification of the anger expression of a human and the subsequent control of this emotion.

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