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Fuzzzy Neural Network Application for Determining the Presence of Social Media Consumption

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Abstract:

A decision-making model for social media addiction is established. Fuzzy mathematics and BP neural networks are used in the model. There are chosen six judging directories. Quantitative directories' subsidiary grade functions are organised. Expert scoring confuses the qualitative directories. College students who use networks are randomly chosen as samples. The trial demonstrates that the procedure could effectively and accurately carry out the choice on Social Media dependence.

Keywords: Social Mediadependence; decision; fuzzy mathematics (FM); Back Propagation (BP)neural network

1. Introduction

Experts in education and psychology have become more interested in social media addiction [1]. An alienist in New York [3] and a psychiatric expert at the University of Pittsburgh have confirmed that the existence of social media addiction after it was first proposed. Those impulsive and erratic online behaviours are referred to as social media addiction. Currently, persons are evaluated using a questionnaire based on the Social Media Addiction Scale. High accuracy, however, cannot be achieved [5].

Although fuzzy mathematics can improve accuracy, they cannot learn on their own [6]. Neural networks mimic the fundamental brain activities. It has been used in analytical prediction and pattern recognition. An error of the back propagation neural network, often known as the BP neural network, has been widely employed up to this point. Harvard University donated the BP neural network in 1974.Without a prior description, An arbitrary input and output of the non-linear representation relationship could be realised. Other benefits of the BP neural network include fault tolerance, parallel processing, ability, classification and self-learning. In this study, a new way for determining social media addiction was provided by the neural network.

2. THE FUNDAMENTALS OF NEURAL NETWORKS CONCEPTS

Input, output, and hidden layers make up the BP neural network. The neurons in one layer are linked to those in the one below it. And mass exhibit the connections. Figure 1 depicts the three-layer BP neural network's topology. In actuality, the network may contain numerous hidden layers. Three-layer neural networks may realise any complex representation relation, according to research. In the model, this type of three layer was chosen.

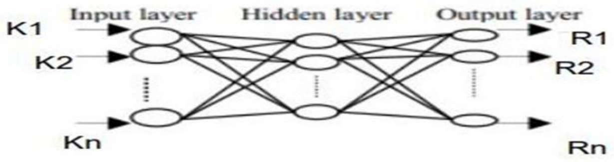

Figure 1: BP neural network - Structure

Forward and back propagation are the two main components of the learning process of the BP neural network. The model's input has sent from the input layer then passing through hidden layer, lastly output layer during the forward propagation process. The mass and the thresholds will be modified to reduce the error if desired output has not been achieved in the output layer, and an error signal shall be transferred from the output layer to the input layer, until mistake is smaller than a minor integer, the process will loop.

3. THE DEVELOPMENT OF A FUZZY NEURAL NETWORK-BASED DECISION-MAKING MODEL FOR SOCIAL MEDIA ADDICTION

It was decided to use a three-layer fuzzy neural network figure 3.1 shows prototype.

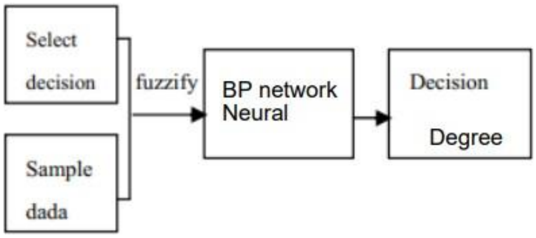

Figure 2

3.1. Selects Directories

The primary aspect that can affect a child's behaviour about addiction to social media is the parents' educational approach [8]. The goal of using social media (PUSM), the frequency of use (NUTEW), the average amount of time spent on each use (ADET), the relationship with peers (RSMTS), telekinesis (Ts), and a relationship with parents (Rp) chosen as the social media addiction evaluating directories [9] and the directories divided into three categories such as behaviour aspect, internal values, and external values. In figure 3, this is displayed. ADET and NUTEM are included in the quantitative directories.

Others are listed in high-quality directories. Secure, average, and low-resolution Ts were separated. PUSM was separated into playing games or making friends and playing games or gathering messages. RSMTS was categorised as excellent, ordinary, and subpar. Rp was classified as neutral, mediocre, and repulsive.

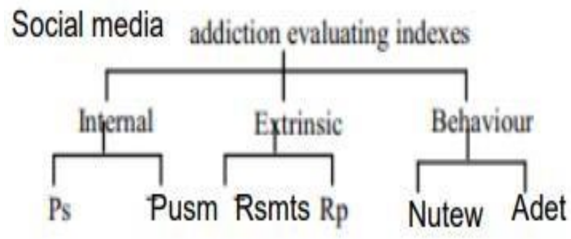

Figure 3: Assessing directories and social media addiction

4. CLARIFIES THE DIRECTORIES AND DEFINES THE FUNCTIONS OF THE SUBSIDIARY GRADES

Grades 1, 2, and 3 are equivalent to independent, average, and dependent, respectively, on the scale used to assess social media addiction. Lower semi-trapezoid distribution functions transform the quantitative directories. For instance, the ADET subsidiary grade (SG) functions appear as in:

$$\mu_1(M) = \begin{cases} 1 & (m \le 2) \\ \frac{(6-m)}{4} & (2 < m \le 6) \\ 0 & (m \ge 12) \end{cases} \tag{1}$$

$$\mu_2(M) = \begin{cases} 0 & (m \le 2) \\ \frac{(m-2)}{4} & (2 < m \le 6) \\ \frac{(12-m)}{6} & (6 < m \ge 12) \\ 1 & (m > 12) \end{cases} \tag{2}$$

$$\mu_3(M) = \begin{cases} 0 & (m < 2) \\ \frac{(m-6)}{6} & (2 \le \mathrm{m} < 6) \\ 1 & (m \ge 12) \end{cases} \tag{3}$$

Expert grading techniques transform qualitative directories. The professionals use 10-minute systems to evaluate each index. The division of the grades is 10. The subsidiary degree are the quotients. The SG of each directory is displayed in Table 1.

Table 1: The quality directories' SGs.

Directories / SG	Evaluation 1	Evaluation 1	Evaluation 1
Ts	0.8	0.3	0.1
	0.28	0.68	0.41
	0.02	0.2	0.90
PUSM	0.75	0.12	0.02
	0.2	0.7	0.44
	0.12	0.3	0.86
RSMTS	0.78	0.3	0.02
	0.24	0.6	0.25
	0.12	0.20	0.70
Rp	0.85	0.3	0.02
	0.3	0.7	0.26
	0.2	0.3	0.89

The neural network's architecture Three output nodes and 25 input nodes make up the BP neural network and the assessing directories are represented by the 25 input nodes. To calculate the test value using lower semi-trapezoid distribution functions yields the SG for quantitative directories. For instance, the ADET is replaced with formulas 1, 2, and 3 and takes around 3 hours.

$$\mu_1(3) = \frac{6-3}{4} = \frac{3}{4} = 0.75$$

$$\mu_2(3) = \frac{3-2}{4} = \frac{1}{4} = 0.25$$

$$\mu_3(3) = 0$$

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then we will get the SG (0.75,0.25,0).
The ADET is inserted into formulas 1, 2, and 3 and lasts for around 2 hours.

$$\mu_1(2) = 1$$
$$\mu_2(2) = 0$$
$$\mu_3(2) = 0$$

Afterwards, the SG (1,0,0) will be discovered.
The ADET lasts for roughly 6 hours3 and is used in place of formulas 1, 2, and 3.

$$\mu_1(6) = 0$$
$$\mu_2(6) = 1$$
$$\mu_3(6) = 0$$

the SG (0,1,0) will then be discovered.
The ADET lasts for roughly 12 hours3 and is used in place of formulas 1, 2, and 3.

$$\mu_1(12) = 0$$
$$\mu_2(12) = 0$$
$$\mu_3(12) = 1$$

then we will get the SG (0,0,1).
By referring to table 1, the SG of the qualitative directories can be found. One student's

Ps, for instance, is considered secure.

$$\rho_1(M) = \begin{cases} 1 & (m \leq 2) \\ \frac{(6-m)}{5} & (2 < m \leq 6) \\ 0 & otherwise \end{cases} \tag{4}$$

$$\rho_2(M) = \begin{cases} 1 & (m \leq -2) \\ \frac{(m-2)}{5} & (-1 < m \leq 1) \\ \frac{(5-m)}{10} & (2 \leq m \leq 12) \\ 0 & otherwise \end{cases} \tag{5}$$

$$\rho_3(M) = \begin{cases} 1 & (m < 2) \\ \frac{(3-m)}{10} & (2 \leq \mathrm{m} < 6) \\ 0 & otherwise \end{cases} \tag{6}$$

the SG (0.8,0.3,0.1) will then be discovered. The predicted output values (1,0,0), (0,1,0), and (0,0,1) are represented by 3 output nodes.

The "2P+1" approach, proposed by Hecht-Nielsen, can be used to choose how many nodes are in the hidden layer. The hidden layer nodes in the neural network have a total of 12 in terms of learning time.

5. THE NEURAL NETWORK'S TRAINING METHODS

R is the samples' figure. Every sample's input direction is given by the formula $M=[M_{r1},M_{r2},\ldots,M_{rm}]$.The output direction is most likely to be $L=[L_{r1},L_{r2},\ldots,L_{rn}]$.$A_1=[A_{r11},A_{r12},\ldots,A_{r1k}]$is the hidden layer's input direction, while $A_2=[A_{r21},A_{r22},\ldots,A_{r2k}]$is its output vector.$B_1=[B_{r11},B_{r12},\ldots,B_{r1n}]$serves as the input for the output layer, while $B_2=[B_{r21},B_{r22},\ldots,B_{r2n}]$serves as the layer's output. The mass of the K_{Oi} input layer neuron K_{Ot} hidden layer neuron i.e. Wit. The ratio of the hidden layer's K_{Ot} and output layer's KOj neurons' masses is V_{tj}. The output layer j and the threshold of the nodes in the hidden layer t, then $(1\leq r\leq R,1\leq i\leq m,1\leq j\leq n,1\leq t\leq k)$

The first sample entered into the input layer initially, and the hidden layer's input value can be computed as,

$$K_{s/x} = \sum_{i=1}^{n} Q_{ix} X Z_{is} - \delta_x \ldots \ldots ..$$

The hidden layer's output value is as follows:

$$K_{s2x} = f(K_{s2x})(f(y) = \frac{1}{1+e^{-y}})$$

The output layer's input value is:

$$D_{s1j} = \sum_{i=1}^{k} L_{ij} X K_{s2x} - \mathsf{P}_j \ldots \ldots ..$$

Actually, the output value is:

$$D_{s2\,j} = f\,(D_{s1j})$$

The total error will be obtained after all the samples have been entered:

$$P_{.} = 1/2 \sum_{s=1}^{q} \sum_{j=1}^{n} (R_{ij} - C_{s2j})2 \ldots\ldots..$$

The learning process will end only if the calculated error value is greater than a specified value or the learning circle is greater when compared to the specified value; if not, alignment error value of output layer and hidden nodes can be calculated:

$$N_{sj} = (R_{si} - D_{s2j}) \text{ X } D_{s2j} \text{ X } (1 - D_{s2j})$$

$$U_{sj} = \sum (N_{si} - V_{ij}) \text{ X } (Z_{s2j} \text{ X } (1 - Z_{s2j})$$

The next time, the mass and the thresholds will be regulated:

$$V'_{tj} = V_{tj} + \alpha \times N_{sj} \times Z_{s2x}$$

$$\sigma'_{j} = \sigma_{j} + \alpha \times N_{sj}$$

$$W'_{it} = W_{it} + \beta \times d_{sx} \times x_{si}$$

$$\theta'_{t} = \theta_{t} + \beta \times d_{sx}$$

It is the same as before when the learning process begins a second time. The mass and thresholds were trained using the MATLAB 7 neural network toolkit.50 students were chosen at random to complete the questionnaire; 20% served as the testing set and 3% as the training set. Every student participated in the training process as a sample, and the method described above was used to collect a collection of input and output values. The error is less than 0.0001, and the first learning rate is 0. 0001.The training process came to an end when 983 circled. The fluctuation of the error convergence curve is depicted in Figure 4.

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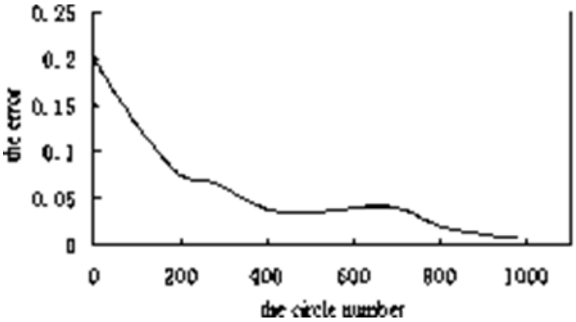

Figure 4: The curve of error convergence

6. THE MODEL'S EVALUATION THE TRAINED NETWORK EVALUATED THE 25 SAMPLES

The directories of the 5 participants are shown in Table 2

Table 2: The directories of the 5 participants:

Directories / Sample	Ps	PUSM	RSMTS	Rp	NUTEW	A
1	Low decision	creation friends orplaying games	Upright	balanced	3.3	3.3
2	Low decision	creation friends or playing games	Middling	odious	10.1	7.2
3	secure	making friends or playing games	Poor	middling	6.2	3.3
4	low-resolution	Collecting messages or making friends	Upright	middling	8.2	6.1
5	secure	collecting messages	Upright	harmonious	5.1	2.2

Table 3 compares the real circumstance with the outcome of the judgement. The grade was determined in accordance with the maximum membership grade law. The decision's outcome matches the facts of the case.

Table 3: Comparison between the real circumstance and the outcome of the choice.

Sample	The actual grade	The decision grade
1	Individualistic	(0.9,0.01,0.02)
2	Individualistic	(0.9,0.01,0.03)
3	Middling	(0.02,0.9,0.01)
4	Reliant	(0.003,0.02,0.9)
5	Reliant	(0.03,0.002,0.9)

7. CONCLUSION

The Social Media addiction determination used a combination of fuzzy mathematics and BP neural network. The entire error will be transformed back during the training phase when all the samples have been supplied, speeding up convergence. This approach can provide solid proof for the psychosocial treatment of patients with social media addiction.

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