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PREDICTING SOCIAL NETWORK ADDICTION USING VARIANT SIGMOID TRANSFER FEED-FORWARD NEURAL NETWORKS (FNN-SNA)

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ABSTRACT

Researchers have reflected on personal traits that may predict Social Networking Sites (SNS) addiction. However, most of the researchers involved in the findings of personality traits predictor for social networking addiction either postulate or based their conclusions on analytical tools. Moreso, a review of the literature reveals that the prediction of social networking addiction using classifiers have not been well researched. We examined the prediction of SNS addiction from a well-structured questionnaire consisting of sixteen (16) personality traits. The questionnaire was administered on the google form with a response rate of 95% out of the 102-sample size. Additionally, a three (3) variant sigmoid transfer feed- forward neural networks was developed for the prediction of SNS addiction. Result indicated that pertinence ($\beta = 0.251$, $p < 0.01$) was the most powerful predictor of social networking addiction in general and less obscurity addiction ($\beta = 0.244$, $p < 0.01$). Experimental results also showed that the developed classifier correctly predict SNS addiction with 98% accuracy compared to similar classifiers.

Keywords: Social Networking Sites, Personality traits, Feedforward Neural Networks, Sigmoid transfer function, Logistic function

INTRODUCTION

Information and Communication Technologies (ICT) have turned out to be a vital part of human behavior. The upsurge in novel technologies and virtual communication involving personal computers, tablets, and mobile phones is triggering alterations in individuals' daily habits and behaviors (King *et al*., 2013; Soror *et al*., 2015). With greater than before accessibility of Internet, social networking addiction is turning a serious problem worldwide, among teens and young adults (Wu *et al*., 2016; Holmgren and Coyne, 2017). It has been advocated that social networking addiction can cause several unsolicited consequences, such as academic dysfunction, anxiety, depression, sleeplessness, weakening family and peer relations, and substance use (Greydanus and Greydanus, 2012; Radovic *et al*., 2017). Moreso, Social Networking Sites (SNS) form a big part of Internet usage enabling people to harness the usefulness of the Internet to achieve certain objectives and needs. However, the proportion of people who experience negative consequences from an excessive use of the Internet and its specific online applications has been on the increase. SNS are virtual networks where people can create a profile and link that profile to others to form a vibrant personal network (Brewer *et al*., 2016; Shah *et al*., 2016).

Social networking addiction is an integral part of Internet addiction operationally defined as behavioral addiction that involve human– machine interaction (Griths *et al*., 2014; Ifinedo, 2016; Carillo, Scornavacca, & Za, 2017). Some researchers' view (Griffiths, 1996) is that Internet addiction are a subset of behavioral addiction. The Big six behavioral addiction (Griffiths, 2005; Griffiths *et al*., 2016) project the basic components of addiction (i.e., salience, mood modification, tolerance, withdrawal, conflict and relapse), but findings indicate that social networking addictions are not limited to these Big six behavioral addiction demanding the need for this study to design a structured questionnaire to identify current personality traits that can best predict social networking addiction.

Researchers, recognizing the probable significance of SNS use to young generations development, have been occupied with findings to ascertain the personality traits that best predict social networking addiction (Deng, Liu, Li, & Hu, 2013; Lee, Ahn, & Kim, 2014; Nadkarni & Hofmann, 2012; Seidman, 2013; Wang *et al*., 2015; Radovic *et al*., 2017). Most of the researchers involved in the findings of personality traits predictor for social networking addiction either postulate or based their conclusions on analytical tools. Moreso, a review of the literature reveals that the prediction of social networking addiction using classifiers has not been well researched.

Artificial Neural Network (ANN) as a classifier consists of an interconnected collection of simple processing units (nodes) with internal connection strengths (weights). These networks has the ability to learn from observed knowledge expressed through inter -links connection strengths, and can make such knowledge available for human use (Kalogirou, 2001; Sharma, Vishal and Singh, 2017). However, one of the key challenges in neural network research is on learning algorithms and architectures (Liu *et al*., 2017; Bengio, 2009). Finding a suitable network architecture with less computational complexity in weight values create challenges in the use of artificial neural networks for classification problems. A Feed-forward Neural Network (FNN) is an artificial neural network where connections between the nodes is without any loops or feedbacks (Corte-Valiente *et al*., 2017; El-Dahshan *et al*., 2014). The FNN structure of artificial neural network is favored because of its modularity, i.e., nodes in the same layer have the same functionality or generate the same level of abstraction about input vectors. The FNN is considered a more suitable structure for complex classification and prediction problems based on its numerous properties.

Back propagation is the traditional algorithm for training FNN, with reasonable training time (Brajevic and Tuba, 2013; Sollazzo, Fwa and Bosurgi, 2017). Back propagation is a variant of gradient search and back propagation is a method for computing the approximate gradient of the error with respect to the connection strengths for a given input by propagating error backwards through the network (Brajevic and Tuba, 2013; Sollazzo, Fwa and Bosurgi, 2017). However, getting trapped in local minima and computational complexity are some downsides to back propagation. In this paper, a variant sigmoid transfer function was used to the training of FNN used in the prediction of social networking addiction and based on some personality traits. The idea in this paper was motivated based on the fact that the choice of transfer functions may strongly guide the performance of neural networks back propagation algorithm (Brajevic and Tuba, 2013; Ascione *et al*., 2017; Sollazzo, Fwa and Bosurgi, 2017; Yao, 1999). The rest of the paper is organized as follows. In Section 2, review on social networking addiction is described. In Section 3, FNN and sigmoid transfer function concepts is presented. Section 4 presents the developed method of predicting social networking addiction based on variant sigmoid transfer function FNN. The results and evaluation of the developed method is described in Section 5. Section 6 conclude the work.

LITERATURE REVIEW

The SNS is a global occurrence. Besides Google and YouTube, SNS is presently the third most frequently used Internet application in the world (Kaplan and Haenlein, 2010; Labovitz *et al*., 2010; Wartella *et al*., 2016; Singh *et al*., 2017; Wozniak *et al*., 2017). As a result of SNS popularity, most school of thoughts believe that SNS can become addictive especially to the young generations. Basically, addiction is most related and thought of as abuse upon ingested substances (Brenner, 1997), but some researchers have long argued that it is also probable to develop addictions to behaviors. SNS addiction can therefore be seen as addictive forms of behavior that occur in the absence of an addictive substance and can be described as a form of Internet addictions (Albrect *et al*., 2007; Griffiths, 1999; 2000). Ryan *et al*. (2016) carried out a qualitative exploration of Facebook addiction using seven essential indicators of Internet addiction (negative consequences, loss of control, online social enhancement, preoccupation, mood alteration, withdrawal, and excessive use) and the authors results have help move Facebook addiction study nearer to construct validity for more focused study. Scholars have advocated that too much use of novel online social networking may be particularly problematic to young people (Echeburua and de Corral, 2010). In accord with the biopsychosocial framework for the etiology of addictions (Griffiths, 2005) and the syndrome model of addiction (Shaffer *et al*., 2004), it is claimed that those people addicted to using SNS feel indications related to those encountered by people who undergo substances addictions or other behaviors (Echeburua and de-Corral, 2010). Moreso, some scholars have postulated that young susceptible people with egotistical tendencies are predominantly prone to engaging with SNS in an addictive manner (La Barbera, La Paglia, & Valsavoia, 2009). In order to clarify the occurrence of SNS addiction, Turel and Serenko (2012) summarized three all-embracing hypothetical viewpoints that may not be mutually exclusive. Based on these three hypothetical viewpoints, Xu and Tan (2012) propose that the shift from normal to problematic social networking use arises when social networking is regarded by the individual as an exclusive mechanism to release stress, loneliness, or depression. They argued that those who often involve in social networking addiction are naturally shy at mingling in real life. The swift increase of online social networking, principally in relation to the growing amounts of time people spend online has led some to assertion that excessive SNS use may be addictive to some individuals (Kuss and Griffiths, 2011; Andreassen *et al*., 2017; Tang and Koh, 2017; Hou *et al*., 2017; Elhai *et al*., 2017). Donelly and Kuss (2016) conducted a cross-sectional online study on a sample of 103 young adults. The study intended to recognize associations between SNS usage, SNS addiction and depression (Tang and Koh, 2017; Primack *et al*., 2017; Foerster and Röösli, 2017). The results of the authors study recommend that Instagram use and SNS addiction were important predictors of depression. Seabrook *et al*. (2016) performed a multidatabase search to identify and summarize study inspecting depression and anxiety in the domain of SNS. The evidence suggests that SNS addiction connects with mental illness and well-being. Oberst *et al*. (2017) use structural equation modeling to examine the role of fear of been left out and passion of SNS use for explaining the connection between psychopathological symptoms and negative consequences of SNS addiction through mobile devices. It was found that both fear and passion reconcile the relationship between psychopathology and negative consequences of SNS addiction through mobile devices, but by different devices.

In this Study, Internet addictions can be technically defined as personality traits exhibited towards the use of social networking sites involving human– machine interaction. Griffiths (1996) expanded upon the core components of Internet addictions (i.e., salience, mood modification, tolerance, withdrawal, conflict and relapse). The following SNS addiction predictors are considered.

Salience

This arises once the activity becomes the most essential activity in the person's life and dominates his or her philosophy, moods, and actions.

Mood modification

This depicts an arousing "buzz" or a "high" or illogically sedative feel of a person for engaging in the activity and can be perceived as a coping strategy.

Tolerance

This is the process whereby more of the activity are required to attain the previous effects. For instance, a gambler may have to slowly increase the size of the bet to feel the joy initially derived by a much smaller bet.

Withdrawal symptoms

The personality traits of shakes, moodiness, or irritability exhibited by a person when the activity is discontinued or rapidly reduced.

Conflict

This refers to the clashes between the addict and close ones (interpersonal conflict) or from within the addict themselves (intrapsychic conflict) that are related with the activity.

Relapse

This is the propensity for recurring returns to earlier forms of the activity and for even the most extreme forms defining the summit of the addiction to be quickly returned after a long abstinence or control.

Measured personality traits: SNS addiction

In this paper, social networking addiction was measured based on expert opinions and current happenings in the domain of Internet addictions. The attributes for this measurement are in the form of a questionnaire considered a representative of personality traits on SNS addiction. These personality traits of 16 attributes are highlighted in Table 1.

MATERIALS AND METHODS

First, a multivariate regression analyses were performed to examine the contribution of the measured personality traits to social networking addictive behaviors and secondly, the developed variant sigmoid function with three parameters and a layered feedforward network was used to accurately predict social networking addiction using the measured personality traits as inputs.

Feedforward neural network

The basic FNN arrives at its output through processing that propagates from input data to the output side unanimously without any feedbacks (Brajevic and Tuba, 2013; Sollazzo, Fwa and Bosurgi, 2017). In this paper, a layered representation of the feedforward neural network was adapted as depicted in Figure 1. In a layered feedforward, neural network there are no links between nodes in the same layer; outputs of nodes in a specific layer are always connected as inputs to nodes in succeeding layers (Ojha, Abraham and Snášel, 2017; Montana and Davis, 1989). This representation is ideal because of its modularity, i.e., nodes in the same layer produce the same level of abstraction about input vectors. Although, many neural-network models have been proposed, feed-forward network with a back propagation-learning algorithm, is the most extensively used model in terms of real-world applications. As mentioned earlier, back propagation algorithm is computationally complex and needs better transfer function to reduce its limitations.

In FNN, the processing propagates in only one direction, forward, starting from the input nodes, through the hidden nodes (if any) and to the output nodes. Output of the i^{th} neuron can be described by Equation 1.

$$y_i = f_i\left(\sum_{j=1}^{n} w_{ij}x_j + \alpha_i\right) \qquad (1)$$

Where y_i is the output node, x_j is the j^{th} input to the node, w_{ij} is the connection weights between the node and input x_j, α_i is the bias of the node, and f_i is the node transfer function.

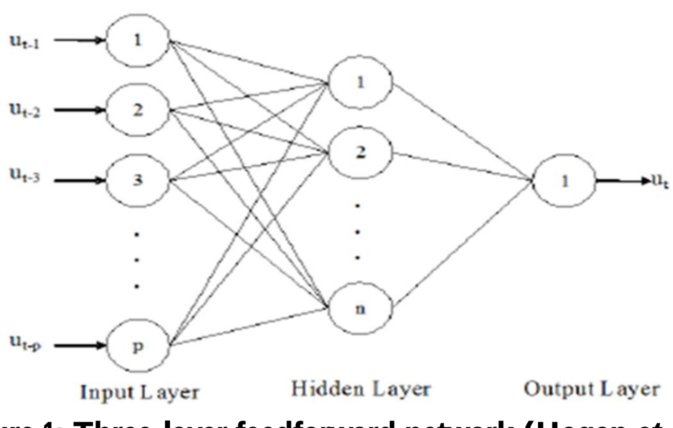

Figure 1: Three-layer feedforward network (Hagan *et al*., 1994)

Sigmoid transfer function

A sigmoid transfer function is a bounded differentiable real function that is defined for all real input values and has a positive derivative at each point (Han and Moraga, 1995). Sigmoid function is the most commonly recognized function used in neural networks because of its nonlinearity and the computational ease of its derivative. A sigmoid transfer function refers to the derivative of the logistic function (Verhulst, 1845). A logistic function or logistic curve is a common "S" shape (sigmoid curve), as shown in Equation 2 below.

$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}} \qquad (2)$$

Where e is the Euler's number, x_0 is the x-value of the sigmoid midpoint, L is the curve's maximum value and k the gradient of the curve. The values of x ranges between $-\infty$ and $+\infty$.

The standard logistic function is the logistic function with parameters (k = 1, x_0 = 0, L = 1) which yields the sigmoid transfer function of Equation 3.

$$f(x) = \frac{1}{1+e^{-x}} \qquad (3)$$

Dataset

The dataset used for the developed feedforward neural network with variant sigmoid transfer is a structured questionnaire based on personality traits that defines social networking addiction. The dataset is the result of 102 questionnaires administered on the google form. The final dataset formatted in the ARFF format contains 97 instances with 16 attributes representing the number of returned responses and measured variables respectively. The attributes defined in the dataset (questionnaire) was because of the knowledge of experts in the domain of Internet addictions. The ARFF dataset was divided into training set and testing set having 70% and 30% respectively.

Data analysis

Multivariate regression analyses were performed to examine the contribution of the measured personality traits to social networking addictive behaviors. To determine the unique contribution of each independent variable, the squared semi-partial correlation coefficients (sr^2) were examined as in Table 1.

The sample consisted of 58 males (59.8%) and 39 females (40.2%) of all 97 participants. The results (Table 1) indicated that Pertinence ($\beta = 0.251$, $p < 0.01$), Obscurity ($\beta = -0.244$, $p < 0.01$) and Masculine ($\beta = 0.242$, $p < 0.01$) were significantly associated with social networking addiction. The amount of variance explained by personality traits for the dependent variable (social networking addiction) was small, ranging from 0.0% for control to 0.4% for frequency, restraint and agitation as indicated by sr^2 values. Pertinence was the most powerful predictor of social networking addiction in general ($\beta = 0.251$, $p < 0.01$) and less obscurity addiction ($\beta = 0.244$, $p < 0.01$).

Table 1: Multivariate regression analyses

	Social networking addiction*		
	Beta	***p* value**	s r^2
Frequency	.065	.533	.004
Location	-.077	.442	.005
Introversion	-.119	.254	.012
Restraint	.077	.512	.004
Agitation	.076	.509	.004
Timespan	.140	.193	.015
Abatement	-.056	.592	.003
Masculine	.242	**<.001**	.046
Feminine	-.026	.815	.001
Age	-.113	.335	.008
Attitude	-.047	.665	.002
Pertinence	.251	**<.001**	.045
Activeness	.151	.170	.017
Surrogate	-.203	.078	.029
Control	-.024	.820	.000
Obscurity	.244	**<.001**	.042

Statistically significant values (p < 0.05) are indicated in bold

The designed approach

In this paper, we use a variant sigmoid function with three parameters that represent the dynamic range, symmetry and slope of the function respectively and a layered feedforward network. The designed feedforward network with variant sigmoid function and with different parameters configuration in different layers was developed to accurately predict social networking addiction.

The regulation of these three parameters in different layers can reduce the local minima and computational complexity problem that contribute to the slowness of back propagation learning. The formula of the variant sigmoid function is given as Equation 4.

$$f(x, b_1, b_2, b_3) = \frac{b_1}{1 + e^{-b_2(x)}} - b_3 \qquad (4)$$

Where b_1 is parameter for the dynamic range of the function, b_2 is the parameter for the slope of the function and b_3 represents the parameter for the bias of the function. The dynamic range of the function denotes a greater capacity of the neuron to differentiate among the widely different intensities of input which it receives.

In this study, the developed feedforward network with variant sigmoid function was trained by minimizing an error function. The error function used is the Mean Squared Error (MSE), which is given by Equation 5.

$$MSE(w_{ij}) = \frac{1}{bm}\sum_{i=1}^{b}\sum_{j=1}^{m}(f_{ij} - d_{ij})^2 \qquad (5)$$

Where b denotes the number of training instances, m the number of FNN outputs, f_{ij} the target, d_{ij} the actual value, both for the input j and the i output instances.

The architecture for the developed social networking addiction model based on feed-forward neural network with variant sigmoid transfer function (FNN-SNA) is as shown in Figure 2. The training set contains the dataset described in Figure 3 with samples formatted into the ARFF consisting of the SNS addiction attributes. The training set was used to build the developed FNN classifier.

The resultant classifier was trained with three variant sigmoid transfer functions and MSE error function. The resulting classifier based on the testing set is then used for predicting social networking addiction.

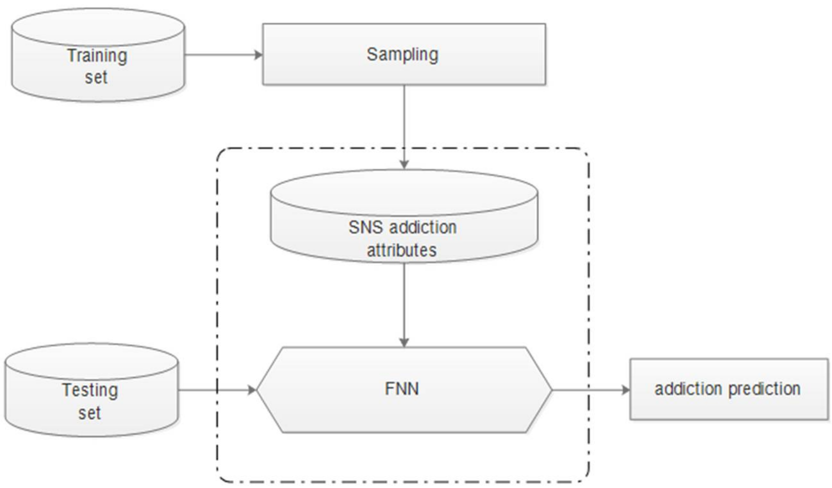

Figure 2: Designed FNN-SNA model

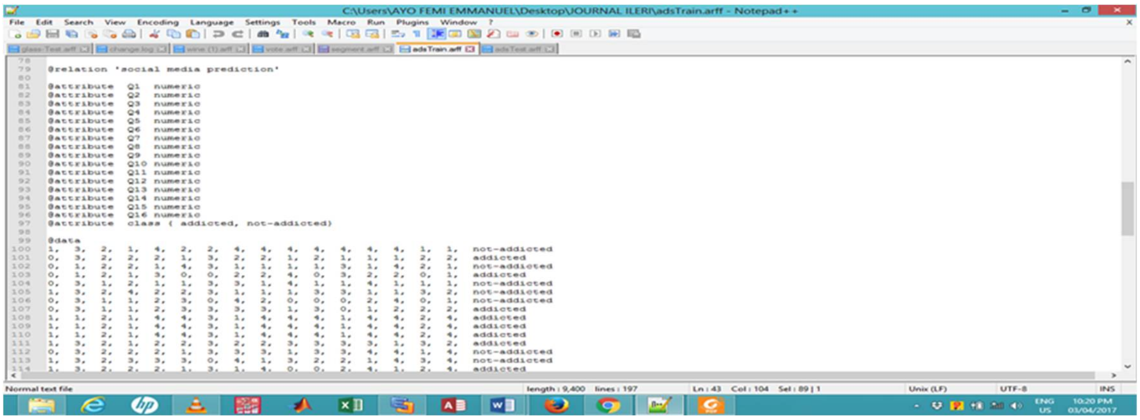

Figure 3: Dataset preparation

SYSTEM IMPLEMENTATION

The Java programming language and FNN weka API was used to load the dataset in the ARFF format for the training, building and prediction of social networking addiction. In this paper, a three-variant sigmoid transfer function was deployed to the improvement of the limitations identified with the backpropagation algorithm. This approach was justified on the knowledge that the choice of transfer functions may strongly guide the performance of neural networks backpropagation algorithm. The screenshot showing the dataset preparation in the ARFF format is shown in Figure 3. Next, we present the algorithm for the developed three variant sigmoid transfer function FNN model for the prediction of social networking addiction (See Table 2). The attributes in the dataset is defined in Table 3.

Neural network GUI

The interface for the Java and Weka API for the developed variant sigmoid transfer FNN for predicting social networking addiction is as shown in Figure 4. The interface consists of controls such as the Start button, and Accept button.

Training the system

The *Start button* in Figure 4 was used for the training of the system. On clicking the button, the training process begins with the following pre-defined parameters:

For the system, the following parameters were used:

Number of Epoch = 500
Learning rate = 0.3
Momentum = 0.2
No of hidden nodes = 8
No of inputs = 16
No of output nodes = 2

Similarly, the *Accept button* was designed to display the output of the predicted classes. The predicted classes can either be addicted or non-addicted to social networking sites.

Table 2: FFN-SNA algorithm

Input: input patterns, x_j

Output: output function, y_i

Begin
// Initialize weights
$w_{ij} \leftarrow random(0,1)$
for all $j \in x_j$ **do**
  // choose a pattern γ_j^{μ} and apply it to the input layer ($n = 0$)
  do
  $\Gamma_j^0 \leftarrow \gamma_j^{\mu}$ such that $\gamma_j^{\mu} \in x_j$
  //propagate the signal forward through the network
  for each i and n **do**
    $f(x, b_1, b_2, b_3) = \frac{b_1}{1+e^{-b_2(x)}} - b_3$ // variant sigmoid function
    $y_i = f\left(\sum_{j=1}^{n} w_{ij} x_j + \alpha_i\right)$
  // compute the error function
    $\delta_{ij} = \frac{1}{bm} \sum_{i=1}^{b} \sum_{j=1}^{m} \left(y_{ij} - d_{ij}\right)^2$
  end for each
  //Compute the deltas for the preceding layers by propagation the errors backwards
  for all n = n-1 to 1 **do**
    $\gamma_i^{n-1} = f(h_i^{n-1}) \sum_j w_{ij}^n \delta_j^n$
    $\Delta w_{ij}^n = \eta \delta_i^n \gamma_j^{n-1}$
    for all n **do**
      //update all nodes according to the new weights
      $w_{ij}^{new} = w_{ij}^{old} + \Delta w_{ij}^n$
    end for all
  end for all
  until (stopping criteria = true) // end ***do***
end for all
return y_i // SNS predictions
End

RESULTS AND EVALUATION

The developed model was implemented using a personal computer with 2.10GHz Intel Pentium(R) 4 CPU and 4GB of memory under Windows 8. NetBeans was used as the Integrated Development Environment (IDE) while Weka API and Java was used as the programming language. To show the accuracy of the developed model, the earlier version of the work was compared with other data mining approaches such as Naive Bayes, KNN and J48 decision tree.

As a way of extension, the current version, included more data mining approaches for performance evaluation of the developed model. These data mining approaches includes Neural Network (NN), Logistics, Sequential Minimal Optimization (SMO), Random Forest, Simple Cart, Simple Logistics, Random Tree, and Decision Table (See Table 4).

All the data mining approaches under comparison was implemented in WEKA 3.9 application. The reviewed literature revealed that the prediction of social networking addiction using classifiers have not been well researched, hence, the justification for using the data mining approaches under comparison.

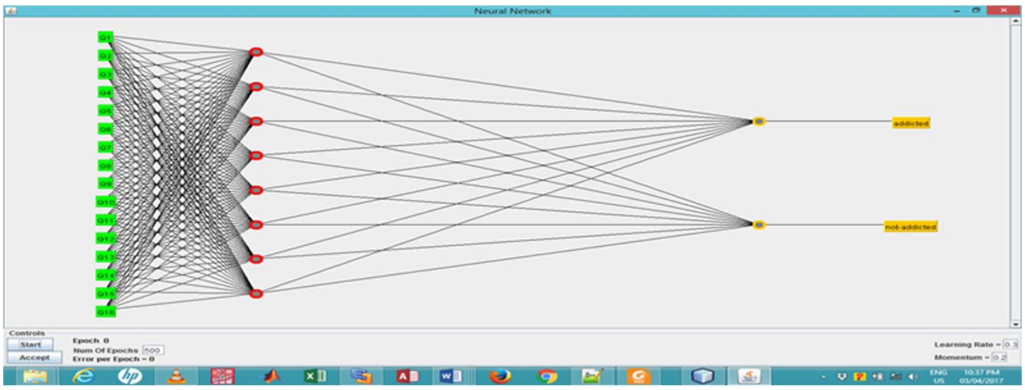

Figure 4: Graphical interface for FNN-SNA

Table 3: Measured Personality Traits

Personality traits	**Features selected**
Frequency	The number of times a person visits social networking sites during a period of time or in a day.
Location	The preferred log location of an individual for social networking sites. For instance, an individual addiction to SNS may increase gradually based on the location they are at that time (e.g. home, school, work, anywhere).
Introversion	Refers to the number of friends a person has on the profile of a social networking site compared to real life. For instance, an individual that is shy in real life may get addicted to SNS due to its virtual communication arrangement.
Restraint	Total abstinence of a person from major responsibilities due to the frequent use of social networking sites.
Agitation	Distraction but not complete abstinence from major responsibilities due to the frequent use of social networking sites.
Timespan	This is when the number of hours spent online is more than the number of hours spent offline.
Abatement	This refers to the decline in an individual productivity due to social network engagements.
Masculine	This refers to attribute that measures the propensity for a male gender been a personality trait that can increase social networking addictions.
Feminine	This refers to crave for social connections being a female personality trait that lead to social networking addiction.
Age	This refers to age been a personality trait that may likely increase the use of social networking sites. For instance, it was discovered that young generations are more inclined to the use of SNS than the older generations.
Attitude	This refers to a measure of the attractiveness or lack of excitement to social networking use especially as people grow older. Young people tend to show more desires towards the use of social networking sites.
Pertinence	This is the attribute that measures the relevancy of social network to people of older generation than younger generation.
Activeness	This is the attribute that measure restlessness to use of social networking sites (i.e., younger generations are the most likely active users of social networking sites).
Surrogate	This attribute measures preference in the use of social network for keeping in touch with friends. For instance, some people tend to use social networking sites more for establishing relationship with friends than other medium such as calls and messaging.
Control	This refers to the attribute that measures preference to checking out social networking sites while on duty or place of work. The lack of self-control towards the use of social networking sites during work hours is a strong personality trait measuring social networking addiction.
Obscurity	This depicts the willingness to stay up late or get up early to spend more time on social networking sites. For instance, a person that keeps late nights for connecting with friends on Facebook or chatting up friends on WhatsApp etc.

Table 4: Experimental Results

Algorithm
FFN-SNA
NN
Logistics
SMO
RandomForest
SimpleCart
Simple Logistics
RandomTree
Decision Table
Naive Bayes
KNN
J48

It was observed from Table 4 that FFN-SNA is a better predictor of social networking addiction based on the personality traits in the dataset. It was also established that NN, Logistics, SMO, Random Forest, Simple Cart, J48, Simple Logistics, and KNN are other good predictors in that order. Naïve Bayes was found to be the least predictor of social networking addiction.

CONCLUSIONS AND FUTURE WORK

In this study, a three (3) variant sigmoid transfer FNN was developed for the prediction of social networking addiction. We investigated the personality traits that helps predict the social networking addiction through a well-structured questionnaire administered on the google form. The administered questionnaire presented 16 personality attributes for the prediction of social networking addiction. These sixteen (16) personality traits were subjected to multivariate regression analyses to determine the unique contribution of each personality traits. The results showed that Pertinence ($\beta = 0.251$, $p < 0.01$), Obscurity ($\beta = 0.244$, $p < 0.01$) and Masculine ($\beta = 0.242$, $p < 0.01$) were significantly associated with social networking addiction. The amount of variance explained by personality traits for the dependent variable (social networking addiction) was small, ranging from 0.0% for control to 4.6% for masculine as indicated by s r^2 values. Pertinence was the most powerful predictor of social networking addiction in general ($\beta = 0.251$, $p < 0.01$) and less obscurity addiction ($\beta = 0.244$, $p < 0.01$).

Our approach to social networking predictions was benchmarked with other algorithms. The experimental results showed that our approach, FNN-SNA achieved 98% prediction accuracy better than similar algorithms. The FNN-SNA approach to the prediction of social networking addiction showed that a good choice of transfer functions in neural network training can greatly improve its classification performances and reduce training time complexities.

It should be noted that the three (3) variant sigmoid transfer function approach used in this paper can reduce the local minima and computational complexity problems that contribute to the slowness of back propagation learning. However, for some typical structure only half of the weights from the input to the hidden layer will be adjusted, if b_3 = 0 in Equation 4.

This work could be improved to produce more quality results. First, evolutionary algorithms can be deployed to train FNN by minimizing the error function. This will greatly improve the local minima and computational complexity of the neural networks. Secondly, a multiobjective particle swamp optimization approach can be used with neural networks to improve the training time and reduce computational complexities. Finally, the ideas in this work can be adapted, modified, and applied in other domains of study.

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