IJBPAS, August, 2019, 8(8): 1479-1486

ISSN: 2277–4998

International Journal of Biology, Pharmacy and Allied Sciences (IJBPAS)

'A Bridge Between Laboratory and Reader'

www.ijbpas.com

PREDICTION OF DRUG ADDICTION USING ARTIFICIAL NEURAL NETWORK

FARID ALI MOUSA

Faculty of Computers and Information, Beni Suef University, Egypt

Farid.cs@gmail.com

Received 10th Jan. 2019; Revised 29th Jan. 2019; Accepted 9th Feb. 2019; Available online 1st Aug. 2019

https://doi.org/10.31032/IJBPAS/2019/8.8.4776

ABSTRACT

Drug addiction is one of the serious problems that worry the Egyptian government. A lot of problems have been appeared as a result from this type of addiction such as assault or rape which considered to be physical and sexual aggression. And its causes many risks and problems around the world like creating physical, psychological, social and economic problems that need local and international efforts to address them.During the last years, the focus in computer science was on a technique called machine learning; there is some facilities which are essential made this field to be an important one. In the past, the medically diagnosis field is separated from case description. In this paper we use artificial neural network to identify the addiction status of people.

Keywords—Drug Addiction;Neural Network; Medical Diagnosis; Backpropagation neural network.

I. INTRODUCTION

Identifying whether a patient is a drug addict or not is considered a serious problem that faces investigators and families. There are different factors affecting the identification of patient's status such as body, reactions and social behaviour change; but these factors can be used for the diagnosis of other diseases. Therefore, this way is so difficult for the identification.

The risk of this addiction raises meaningfully during the last years. A lot of reasons for adults may lead to the direction toward this addiction for example divorce or job loss; on the other hand for adolescents, moving or changing schools may be the reason behind this way. So, it is urgent to move for stopping their spreading and control the addictive cases.[1]

Machine learning technology is now useful in medical data analysis. Several types of research have been carried out for the diagnosis of these cases medically. Some specialized hospitals save correct diagnostic data in the form of medical records. The entry of the corrected records is the only step needed to run a learning algorithm[2].

Step wise this diagnosis data can be taken easily from the descriptions of previous described cases. The derivative work can be used to assist physicians

in diagnosing new patients to improve accuracy, speed and / or reliability of the diagnosis, or to prepare students or physicians in diagnosing patients in certain diagnostic problems.
The main core of this research is to find a model for the identification of these cases. The ANN has been used to identify if the person is an addict or not; this is done by studying a number of addicts' cases in Egypt.

A. Artificial Neural Network (ANN)

The Artificial Neural Network (ANN) technique is employed in classification step because it is used to resolve complexness issues. Artificial network adapts itself by consecutive training algorithmic program and its design and connected between weights. The neural network of the brain is signification by a man-made neural network (ANN), which may be delineated as connected nodes. They're used extensively in literature because of their ability to find out complicated patterns. The artificial neural network consists of nodes (shown as circles in Figure 1), ANN input layer drawn as $(x_1, x_2, \ldots., x_n$, ANN hidden layer, ANN with an output layer y. The aim of ANN is to outline a collection of weights w (between input nodes, hidden nodes, and output nodes) that minimize the mean square errors. These weights are modified per the parameter of learning $\lambda \in [0, 1]$ throughout training, till the results are per the output. Terribly radical changes in weight are often created once value of λ is huge, whereas additional iterations number (called epochs) are often required if the worth is simply too little before the model learns enough from the training knowledge. An issue of exploitation artificial neural networks is finding parameters that learn from the training knowledge while not over fitting (i.e., memorizing training knowledge) that lead to poor performance on invisible data. The system will cover current knowledge from data if there are several hidden nodes in the model, whereas it should block the system to create it higher for input values if there are too few. Moreover, the selection of deed the criterion ought to be designated. This might involve stopping as long because the total error of the network is a smaller amount than the already planned error or once a particular range of epochs has been completed [3].

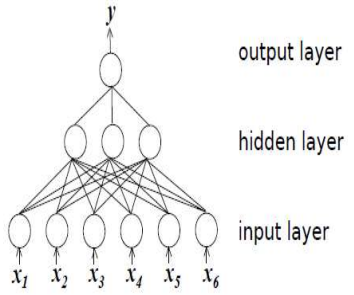

Figure 1: Multi-layer neural network

B. Addiction

Addiction can be defined as a prolonged, often a lapsing brain disorder that causes obsessive sought and usage of drugs, in spite of the negative consequences for both the addict and those around him/her. Although the initial use of drugs is voluntary for most people, the brain changes overtime inhibiting individual's self-control and ability to resist strong attacks that pushes them to use drugs.

Fortuitously, the treatments are available to help people avoid harmful effects of drugs. Research suggests that combining addiction therapy and behavioural therapy is the best way to ensure success in many patients. Therapeutic techniques tailored for each drug abuser and any other co-emerging medical, mental, and social problems can lead to permanent evacuation and a life free of drug addiction.[4]

Like other chronic, recurring diseases, such as diabetes, asthma, or heart disease, drug addiction can be managed effectively. And similar to other chronic illnesses, relapsing and re-abuse of drugs again are still common, yet this is not a treatment failure signal. This indicates, however, that an adjustment in treatment is needed to help a person regain control and recover.

II. RELATED WORK

Several researches on drug addiction have been conducted by researchers and governments. Such studies suggested that health care providers use computer systems that can save a soft copy of medical information, and prescriptions. These studies are aimed at managing and reducing the exchange of illegal recipes that save money and effort. In addition, the system databases have privilege of supporting research and relevant studies to develop a system for recognizing addicted individuals. The National Institute for Drug Abuse (NIDA) encourages investigators to be interested in neuroscience research related to the development of connections between technology use and addictive behavior for the identification of addicts. It also supports the use of programs to further develop the understanding of brain processes that lead to drug abuse to reduce the prevention and treatment[5].

In [6], the authors suggested the use of a mobile application and wearable sensors in the Cognitive Behavioral Therapy of addiction of drugs. This study shows one of the benefits of clinically using mobile applications and wearable sensors in avoiding medical shocks that may occasionally lead to suicide. In [7], the authors recommended to promote the use of information technology (IT) to produce better results in drug addiction identification and / or increase public awareness rather than traditional methods. They also provided a solution for drug addicts and their families through social media and simplifying the usage reduction of drugs that could offer other benefits including identifying other illnesses such as AIDS and possible crimes that help creating a database that contains information for researchers using DSS to identify addicts of drugs.

Machine Learning is becoming more popular in health care services, if not very important, and several factors encouraged the use of machine learning techniques in health care services, such as fraud and abuse identification, data exchange, and benefits of health care providers.[8]. ML applications can assist all parties involved in the health sector. For example, ML can help health insurance coverage to investigate fraud and abuse, health care organizations to make customer management decisions, doctors to identify the best treatment and best practices, and patients access better health and affordable services[9]. A large amount of data produced by health care activities is very complicated to be analyzed by traditional methods. ML provides techniques and technologies to convert these large amounts of data into valuable information for making decisions [8], [9].

In this paper, we study the causes of drug addiction in Egypt in order to obtain adequate information on the symptoms experienced by drug addicts by specialist doctors and the families of addicts. We then used this information to predict if the person is an addict or not by using ANNs in order to detect early cases of abuse to reduce the spread of addiction.

One of the most recent developments is the Drug Clust tool. It is a package of R which uses the machine learning to predict side effects. There are two main steps in the analysis of pipeline; cluster analysis followed by the analysis of enrichment. The data analysis pipeline first comprises drugs on the basis of similar components. Bayesian recommendations assume when making this cluster analysis. The second step is the enrichment analysis stage made to get more biological interpretations of the created clusters. The enrichment analysis helps in detecting interactions between drug clusters and complementary profiles. Complementary profiles mean the drugs that interact with the same drugs and interact with same biological pathways and cause similar effects. Index is a metaphor that is used to discover the statistical significance of clusters. The prediction performance was presented in several datasets that were publicly available;[10] these drugs were passed by Niu et al. After producing randomly in the experiments of simulation average scores were used to measure drugs. Three different sources of data were collected together for the study i-e, drug targets, chemical descriptors and drug treatment symptoms[11]. Methods of machine learning combinations were used to allocate different weights for drugs on the basis of various side effects associated with drugs, their targets and treatment indicators. Awarding scores is a concept correlated with the gaming industry, which is used in this project to define a major combination between drug

associations, drugs and drug side effects and can help researchers in pharmaceutical companies to produce hypotheses for the discovery of medicine.

III. Evaluation methods

Precision and recall

First, Precision and recall which are considered common metrics used for evaluating classifier performance. Precision can be defined as the percentage the model predicts correctly positive when a decision is made. It can be calculated by dividing the number of correctly identified positive examples and the total number of examples positively classified. On the other hand, Recall is defined as the percentage of the correctly identified positives out of the existing positives. It can be calculated by dividing the number of correctly classified positive examples and the total number of positively true examples in the test set.

Both of high recall and high precision have to be in a ideal model. The F-measure in Equation 4 presents the harmonic measure and recall in single measurement. The range of F-measure is 0 to 1, in which 1 measure is a perfectly capturing precision and recall classifier.

$$\boldsymbol{Precision} = \frac{TP}{TP+FP} \quad (1)$$

$$\boldsymbol{Sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

$$\boldsymbol{Specificinty} = \frac{TN}{TN+FP} \quad (3)$$

$$\boldsymbol{F-measure} = \frac{2(Precision)(Sensitivity)}{(Precision)+Sensitivity} \quad (4)$$

Where,
TN is True Negative: case was negative and predicted negative,
TP is True Positive: case was positive and predicted positive,
FN is False Negative: case was positive but predicted negative,
FP is False Positive: case was negative but predicted positive.

Kappa coefficient,

The second approach is Cohn's kappa statistic which is used to compare datasets. It takes 1 as value for a perfect classifier that always classifies correctly whereas the 0 value is for a random classifier.
The kappa coefficient value can be calculated using the following equation:

$$k = \frac{p_0 - p_e}{1 - p_e} \text{……..(5)}$$

where p_0 is the classification accuracy and pe is the hypothetical accuracy of a random classifier on the same data.[12]

III. THE PROPOSED MODEL

A. Dataset

No single factor can predict whether a person will become addicted to drugs or not. Risk for addiction is influenced by a set of factors that include individual biology, social environment, age, educational problems and stage of development. The more important factors an individual has, the greater the chance that taking drugs can lead to addiction. For this reason we used the principle component analysis algorithm to calculate the correlation between the attributes and the class label for all samples. The study included 320 persons (160 Egyptian addicts and160 Egyptian non-addicts). Age of Egyptian addicts range from 30 to 45 years with 33.88 years in average, and a standard deviation of 6.960. Whereas age average for non-addict Egyptians is 35.75 with a standard deviation of 4.689. All attributes are shown in table (1) for each sample.

TABLE I. DATA SET ATTRIBUTES

Attributes Names	Attributes Names	Attributes Names
Age	Father's education	Type of drug
Educational level	Mother's education	way of taking the drug
Place of residence	Mother's working condition	Number of abuse
Marital status	Availability of household	Duration of drug use
Job	House hold information sets	Prescription drugs abused
Sex	Persons living at house	Stopping using drugs when want to
Average monthly income	Relationship between parents	Lost friends
Age at the beginning of treatment	Relationship with mother	Experienced withdrawal symptoms
Drug Knowledge	Relationship with father	treatment program
causes of drug use	medical problems	trouble at work

TABLE II. NUMBER AND PERCENTAGE OF SAMPLES ACCORDING TO AGE

Age	Number	Percentage	Number	Percentage
	Egyptian addicts		Egyptian Non-addicts	
30-35	62	38.75%	62	38.75%
35-40	34	21.25%	70	43.75%
40-45	64	40%	28	17.5%
Mean	33.88		35.75	
Standard Deviation	6.960		4.689	

As shown in table (2) we can see that 40% of Egyptian addicts from above 40 years, while 38.75% from 30 to 35 year and 21.25 % from 30 to 40 years. For the non- addicts Egyptian the table show that nearly 44% from 35 to 40 years, while 38.75% from 30 to 35 years and 17.5% from 40 to 45 years.

TABLE III. NUMBER AND PERCENTAGE OF SAMPLES ACCORDING TO EDUCATIONAL LEVEL

Education Level	Number	Percentage	Number	Percentage
	Egyptian addicts		Egyptian Non-addicts	
Secondary education	116	72.5%	69	60%
University education	44	27.5%	64	40%

Table (3) illustrates that, the education level for the samples, we can see that of the Egyptian addicts were 72.5% finished secondary education and 27.5% finished university; while for the non-addicts 60 % were in secondary and 40% were in university level.

TABLE IV. NUMBER AND PERCENTAGE OF SAMPLES ACCORDING TO MARITAL STATUS

Marital status	Number	Percentage	Number	Percentage
	Egyptian addicts		Egyptian Non-addicts	
Single	68	42.5%	12	7.5%
Married	58	36.25%	146	91.25%
Divorced	34	21.25%	2	1.25%

Table (4) Show that, the marital status is an important factor for addiction because the percentage for addicts exceed in the divorced status.

TABLE V. START OF ADDICTION

The age at Start of Addiction	Mean	Standard Deviation
	30.24	4.025

Table (5) Show that the mean years for the age at start addiction were 30.24 year with standard deviation 4.025 year.

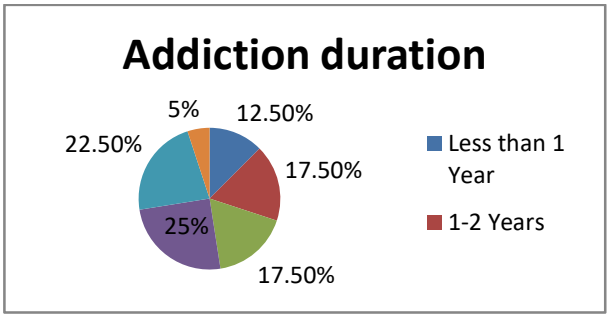

Figure 2: Addiction duration

Figure (2) show that the addiction duration is exceeds from 4 to 8 years.

B. The proposed system

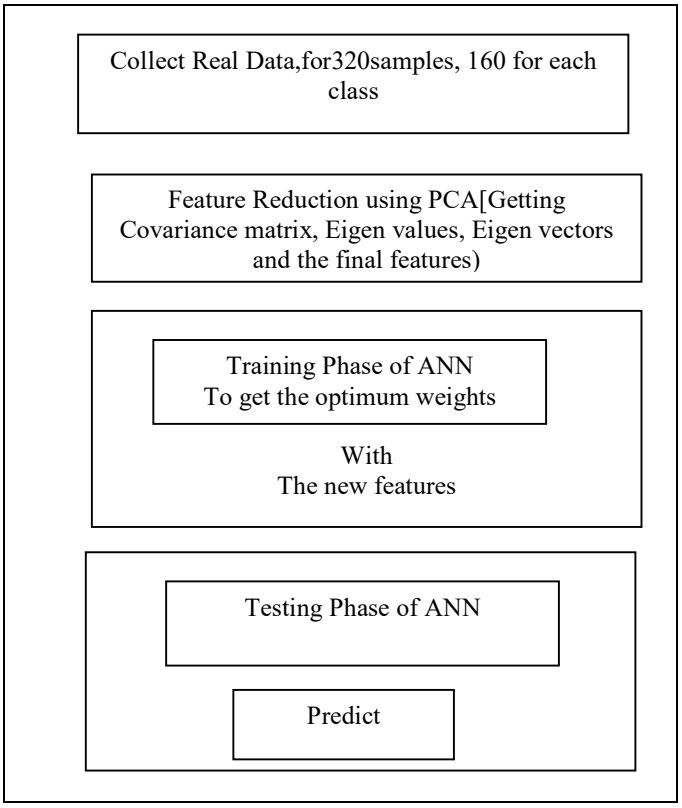

Figure 2: Proposed Model

As shown in figure 3, we have 31 attributes for each sample; one of them is the class label; there are two classes' class 1 that is the presence of the disease and class 0 that is the absence of the disease. There are 320 samples in the data set; 160 samples for class 1 and 160 sample for class 0. There are two steps in the proposed model; the first step is the

preprocessing phase by using principle component analysis algorithm to reduce the redundant attributes; the second step is the classification phase; in this step we used the back propagation neural network for classification; We used PCA algorithm can use number of correlated variables to transform it to uncorrelated ones which is called principle components. PCA firstly uses the given dataset but after ignoring the class labels if found. A mean vector is then calculated from the dataset. Covariance matrix is computed using the dataset. Eigen vectors and Eigen values are then computed. By using the Eigen values obtained Eigen vectors are sorted in decreasing order. Finally, number of Eigen vectors is used to transform the samples to the new reduced subspace.[13]

Algorithm 1 " PCA"

Given: Data set with N samples $x_1, x_2, \dots . x_N$ each example $x_n \in R^D$

Goal: Reduce the data from D dimensions to K dimensions (K<=D)

Want to capture the maximum possible variance in the projected data

Let $u_1, \dots, u_D$ *be the principle components(Eigen vectors), assumed to be orthognal such that*:

$u_i^T u_j = 0$ *if* $\neq j$ *and should be orthonormal such that* $u_i^T u_i = 1$

the Eigen vector of size $D \times 1$

We sort the vectors Ascending according to the Eign value

We will pick only the frirst K principal components

1: *Compute the mean of the data*

$$\bar{X} = \frac{1}{N}\sum_{n=1}^{N} X_n$$

2: *Compute the Covariance matrix*

$$C = \frac{1}{N}\sum_{n=1}^{N}(x_n - \bar{x})(x_n - \bar{x})^T$$

3: *Find the eign values*(λ)

$|\lambda I - C| = 0$

4. Find the Eigen vector for each Eigen value from step 3

5: *Sort The Eign vectors Ascending*

$Q = \begin{pmatrix} corresponding\ to\ the\ top\ k \\ eign\ values \end{pmatrix}$

5: *Call these vectors as* $u_1, u_2, \dots u_k$

(*such that* $\lambda_1 \geq \lambda_2 \dots \dots \geq \lambda_{k-1} \geq \lambda_k$

6: *The Final feature vectors* (*with K diemention*)

$New = (Q \times Old\_Feature) + Mean$

We use Artificial Neural Network (ANN) technique in classification step as a result of it uses to resolve complexness issues. Artificial network adapts itself by ordered training algorithmic rule and its design and connected weights. This paper uses feed forward neural network with multi-layers with back propagation learning algorithm. Operations of the human neural system are used to design artificial neural networks. Since then, a very large variety of networks have been constructed. All are composed of units (neurons),and connections between them with weights, which together determine the behavior of the network. The choice of the network type depends on the problem to be solved.[14]

Algorithm: Artificial Neural Network (ANN) algorithm

Given the inputs (attributes values) and MSE(Mean squared error)

1: Start with the first sample with initial weights (set to small random value).

while stopping condition is false do steps 2-9

2: for each sample in the training set, do steps 3-8

Feed forward Phase :-

3: Each input unit (Xi) receives signal Xi & broad casts this output for each input to all units in the layer above (the hidden layer)

4: Each hidden unit (Zj) sums its weighted input values,

$$Z - i_{nj} = V_{aj} + \sum_{i=1}^{n} x_i v_{ij}\ , Where\ V_{aj}\ is\ a\ bias$$

then applies its sigmoid function to compute its output value

$$Z_j = 1/(1 + e^{-(Z - inj)})$$

Then sends this values to all units in the layer above

5: Calculate the output:

$$Y - i_{nk} = W_{ok} + \sum_{i=1}^{n} Z_j w_{jk}\ , Where\ W_{ok}\ is\ a\ bias$$

$$Y_k = 1/(1 + e^{-(Y - i_{nk})})$$

Back propagation of error:-

6: Computes the error in the output layer

$$\delta_{2k} = Y_k(1 - Y_k) * (T_k - Y_k), T_k\ is\ the\ target$$

7: computes its error information in hidden layers

$$\delta_{1j} = Z_j(1 - Z_j) * \sum_{k=1}^{m} \delta_{2k}\, w_{lk},$$

8: if the Error > MSE(Mean squared error) then Update weights and bias :-

$$W_{jk}(new) = \eta * \delta_{2k} * Z_j + \alpha * W_{jk}(old)$$

$$V_{ij}(new) = \eta * \delta_{1j} * x_i + \alpha * V_{ij} old$$

9: Test stopping condition.(Number of iteration)

EXPERIMENTAL RESULTS:

To evaluate the planned system, we've used Matlab R2016b program to implement, test and evaluate our system.

Variety experiments are conducted exploitation lapto p computer with subsequent specifications:

Eight GB of RAM, Intel® Core™ i7-4210U mainframe running at two. 40 gig cycle per second and under Windows® 64-bit software system. The database used in the experiments is collected from real different with 320 samples (160Addicts and 160 non-addicts). Each case in this database has 30 parameters as shown in table1.

TABLE VI. MODEL ACCURACY

Method	Accuracy 8-fold	Accuracy 10-fold	Accuracy 15-fold
MLP, (13,7,1)	91.2%	90.2%	85.2%
MLP(15,10,1)	90.2%	89.2%	87.2%
MLP, (10,7,1)	94.7 %	91.2%	88.6%

TABLE VII. EVAULATION PARAMETERS FOR THE MODEL

Measure	Value	Derivations
Accuracy	0.9469	(TP + TN) / (P + N)
Precision	0.9375	TP / (TP + FP)
Sensitivity	0.9554	TP / (TP + FN)
Specificinty	0.9387	TN / (FP + TN)
F1 Score	0.9464	2TP / (2TP + FP + FN)
Kappa coefficient	0.895	$k = \frac{p_0 - p_e}{1 - p_e}$

As shown in table 6 we pick different values of k in k-fold cross validation to split the data to training and testing and then we choose variety of layers and nodes in every layer to train the samples and obtain the final weights of the network, wecheck the data in numerous cases just in case of using 3 layers, the initial layer we choose ten nodes, seven nodes within the second layer and one nodes in the output layer we got94.7% accuracy in 8-fold cross validation.
Table7 show the evaluation parameters for 8-fold cross validation for MLP with 10 layers in the input layer, 7 nodes in the hidden layer and one node in the output layer.

ACKNOWLEDGMENT

We would also like to thank DrAyman Ahmed Abdel Hady from the department of Anthropology, Cairo University, Egypt for providing us with the data set.

CONCLUSIONS

In this paper, we aimed to identify people with addiction correctly and also to put the treatment line for saving their life that will be supportive for families and investigators. The scheduled system called back propagation neural network which uses one of the leading widespread machine learning techniques. The composition of this system is two layers one of them is input layer with ten neutrons of addictive symptoms, the other layer is hidden (an output layer) that represents the possibility of being an addict or not. As well as, eight fold cross validation was used to entree the generalization of the planned system in which 320 cases were collected from Addiction Treatment Hospital specializing within the treatment of addiction settled in Egypt , from that one hundred sixty cases were addicted to medicine and 160 cases as non- addict, giving an accuracy of 94.7%. According to these results, it will be easy for families, physicians and investigators to hurry up the addiction treatment.

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