Black Sea Journal of Engineering and Science
doi: 10.34248/bsengineering.1603745

Open Access Journal
e-ISSN: 2619 – 8991

Research Article
Volume 8 - Issue 4: 1121-1126 / July 2025

ARTIFICIAL NEURAL NETWORKS IN DRUG ADDICTION DIAGNOSIS

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Abstract: This study aims to find a simple mechanism to help researchers and families identify addicts. In this paper, the Artificial Neural Network (ANN) method has been examined to determine whether a person is an addict. In this study, the dataset obtained from students from different countries and published as open source by Atif Masih was used. This dataset contains 50343 samples with 11 features. The study involved testing and comparing multiple neural network architectures based on their average classification accuracy. When the correlation matrix is examined, it is seen that the relationships between the variables are almost negligible. This can be attributed to the fact that the variables are categorical. Each architecture was trained using 10 different seed numbers, and the mean accuracy was calculated accordingly. The experiment results have obtained 75.53% classification accuracy for correct diagnosis in our system. Our model could significantly expedite the diagnosis and treatment of addiction, providing a valuable tool for families, physicians, and investigators. The paper proposes a Decision Support System (DSS) for diagnosing addiction, leveraging one of the most widely-used machine learning techniques: Artificial Neural Networks (ANN).

Keywords: Drug addiction, Artificial neural network, Decision support system

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Received: December 18, 2024
Accepted: June 03, 2025
Published: July 15, 2025
Cite as: Karaman E. 2025. Artificial neural networks in drug addiction diagnosis. BSJ Eng Sci, 8(4): 1121-1126.

1. Introduction

Addictions (alcohol, drug et al.) can affect people regardless of their social orfinancial status or age. Many factors of psychological, biological or socio-economic nature are responsible for these addictions. Everything together makes determining its causes (Lewenstein et al, 2020). Drugs have been the core reason for the various crimes occurring in the society and also the root cause for the devastation of many youngsters. Drug habits are addictive and have also led to the death occurrence of thousands of addicts (Junghare et al, 2019). As a result of the complexity and overlapping symptoms, it becomes intrinsically difficult to differentiate addiction from various other diseases. This inherent ambiguity demands greater level of efforts and vigilance from part of the investigators and family members. They have, therefore to embrace a complex model that fuses deeply the observational data with more valid diagnostic tools. They, in so doing, assume a better position to address an individual's needs and offer suitable interventions. This process therefore evidences the fact that full-fledged diagnostic techniques and support need to come up for not only the diagnostic tools but also the persons involved in the process of identification and treatment of the addiction.

Machine learning techniques have been the main area of interest for researchers in the computer science field over the past few years. The main reason for interest in machine learning techniques is due to their apparent relation with the essential skills associated with intelligence. Machine learning literature is very rich in learning theory, and these techniques have normally improved the speed and accuracy of the learning mechanism for a number of concepts significantly (Bottou, 2014). Today, technology in machine learning has been of immense help in processing medical data. Many research works have been carried on diagnosis in medicine, and the outcome of the research is excellent. Certain big hospitals maintain the data of correct diagnosis in the form of case histories. This information can be fed into the computer and, after running the learning program, excellent results can be obtained. In theory, this would be feasible from the descriptions of cases solved in the past: the automatic derivation of medical diagnostic knowledge with the view to improve diagnosis speed and accuracy, hence reliability. Also, this can be used to teach nonspecialist students or doctors how to diagnose patients in some specific diagnostic problems (Fausett, 2006; Michalski et al, 1983).

This study aims to find a simple mechanism to help researchers and families identify addicts. In this paper, the Artificial Neural Network (ANN) method has been examined to determine whether a person is an addict. This method was implemented by analyzing several cases of addiction from different countries (Pakistan, Afghanistan etc.). In this context, the potential of ANN for analyzing addiction cases and making accurate diagnoses has been evaluated. In conclusion, machine learning techniques play a significant role in medical diagnostic processes and can be an effective tool in solving complex issues like addiction. This study highlights the practical applications of ANN, shedding light on potential research and development opportunities in this field.

2. Materials and Methods

There are many studies in the literature using machine learning techniques on drug addiction. Islam Arif et al, (2021) made a prediction using machine learning algorithms on addiction, which has become a significant problem in Bangladesh. For this purpose, they applied nine machine learning algorithms (namely k-nearest neighbors, logistic regression, SVM, naïve bayes, classification, and regression trees, random forest, multilayer perception, adaptive boosting, and gradient boosting machine). Among these algorithms, the Logistic regression algorithm stood out with 97% accurate prediction. Kumari et al, (2018) presented a model of addict abuse prediction with the help of machine learning techniques. Their model was flexible enough to include several features such as age, gender, country, ethnicity, education level, neuroticism, openness to experience, extraversion, agreeableness, conscientiousness, impulsivity and sensation seeking. Other temporal features used were day, week, month, year, and decade. All of the above-mentioned features were combined by the authors within their Artificial Neural Network for Demographics and Artificial Neural Network for Chronological data models, ANN-D, and ANN-C respectively. The authors combined demographic and time series features in their model to gain better predictive accuracy and, more importantly, to shed more light on the correlates of addict abuse. Afzali et al, (2019) compared the performance of seven machine learning algorithms to predict drug-alcohol use among adolescents in Australia and Canada and interpreted the difference between them. As a result, the elastic network machine learning algorithm showed the best predictive performance in both the Canadian and Australian samples. (Shahriar et al, 2019) were to aim to find out the important social, familial and health factors related to drug abuse of the age group of 15-40. they used three algorithms (ANN, Random Forest and SVM) for this. Consequently, among these three models, ANN performed the highest accuracy rate (%93).

2.1. Artificial Neural Network

The term "Artificial Neural Network" is derived from Biological neural networks developing the structure of a human brain. Much similar to a human brain, artificial neural networks also have neurons which are interconnected to one another in different layers of the networks. These neurons are known as nodes.

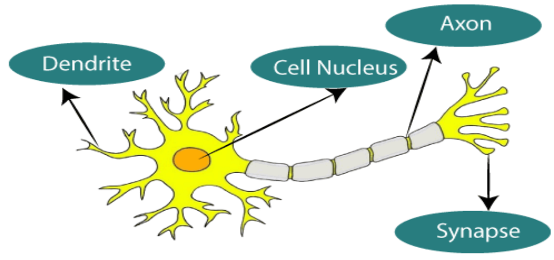

Figure 1. Structure of biological neural network.

An artificial neural network in the realm of Artificial Intelligence is so that computers may have the opportunity to understand things and make decisions in a manner somewhat human, trying to emulate the network of neurons that make up a human brain. An artificial neural network is created through the programming of computers to act simply like the interconnected cells of the brain. There are about 1000 billion neurons in the human brain. Each neuron has a connection point somewhere between 1,000 and 100,000. The information is stored in such a way that it is distributed, and we can draw out more than one unit of this information while needed from our memory parallelly in the human brain. We can say the human brain is composed of unbelievably great parallel processors (Araghinejad, 2014).

Artificial Neural Networks (ANNs) are composed of an input layer, a number of hidden layers, and an output layer (Bottou, 2014). The input layer comprises several neurons, each representing a system input, with each neuron assigned a weight that adaptively changes during the training phase. The hidden layers are particularly useful for handling data that are not linearly separable, allowing the network to capture more complex patterns. The final layer, the output layer, represents the ultimate output of the network. The learning process of ANNs involves the user collecting representative datasets and applying training algorithms to enable the network to automatically discern and learn the underlying patterns in the data. Through this training process, the ANN adjusts its weights and biases to minimize errors and improve its predictive accuracy (Vaswani et al, 2017).

There are various types of Artificial Neural Network (ANN) models, with the Multilayer Perceptron (MLP) being the most prevalent. An MLP consists of three or more layers, including an input layer, an output layer, and one or more hidden layers. The primary objective of the MLP is to establish a mapping function $F{:}X \rightarrow Y$ that correlates the input X with the output Y, leveraging the historical data collected during training. Consequently, the MLP can be employed to predict outputs for new, unseen inputs based on the learned relationship (Poulton, 2001).

Figure 2 shows a simple Multilayer Perceptron neural network in which, in most cases, a bias is added to the input layer with weight value one so that neural network may not get saturated. The inputs provided are fed into the input layer and then multiplied by the weights as they pass from the input layer to the first hidden layer. These weighted inputs are summed in each neuron inside the hidden layer and processed by a transfer function.

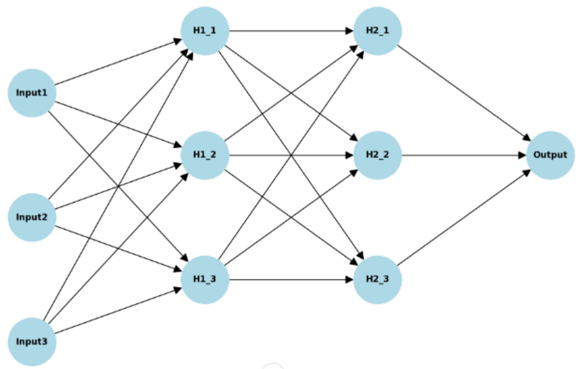

Figure 2. Artificial Neural Network (ANN) structure.

Neural networks utilize transfer functions to transition from one layer to the next. These functions incorporate mathematical formulas to generalize the desired output. There are several types of transfer functions commonly used in ANNs, among which the most prevalent are:

- Linear Transfer Function (LF): This function is computed simply as a=n, where n represents the sum of the weighted inputs.
- Log-Sigmoid Transfer Function: This function has a range between 0 and 1, and its formula (equation 1) is given by:

$$1a = \frac{1}{1+e^{-n}} \quad (1)$$

This description highlights the basic operation and common transfer functions within a simple MLP neural network, illustrating how inputs are processed through weighted connections and transfer functions to produce the network's output (Araghinejad, 2014).

There are numerous algorithms that can be utilized during the training phase of a Multilayer Perceptron (MLP). In this study, we employ one of the most widely recognized neural network algorithms known as the Feed Forward Back Propagation learning algorithm. With this algorithm, the input is repeatedly fed into the neural network, and for each output, the corresponding typical output and error are calculated. This error is then backpropagated through the neural network and used to adjust the weight values, thereby reducing the error with each iteration and enabling the neural network to approximate the typical output more closely.

Artificial Neural Networks (ANNs) possess the remarkable ability to classify new or noisy data, a feature known as generalization. Generalization is one of the primary advantages of ANNs. Optimal generalization is achieved when the dataset is divided into two distinct parts:

- *Training Set:* Used to train the neural network.
- *Testing Set:* Employed for the final evaluation of the neural network's overall performance.

By partitioning the dataset in this manner, the neural network can be effectively trained, validated, and tested, ensuring robust generalization capabilities and reliable performance on new and unseen data.

2.2. Data Preparation

In this study, the dataset obtained from students from different countries and published as open source by Atif Masih (Kaggle, 2024), an academician at Govt Islamia Graduate College Kasur University-Pakistan, will be used. This dataset provides in-depth information about variables related to drug addiction among university students. The dataset contains features from experimentation to denial of treatment that would be very insightful related to the study of addictive behavior dynamics. It includes a target variable classifying students addicted or non-addicted based on these features. This dataset contains 50343 samples with 11 features (Table 1).

Table 1 illustrates the name, description and category of the features. Also, We have checked if there is a null value in the data set. The last column defines the number of missing values for the relevant attribute. All variables were encoded into numerical inputs to be used in the neural network, which receives numerical inputs values as variables with two independent attributes, such as: Social Isolation item is encoded into binary values of 0,1; for instance, the answer to the attribute could be 1, which means "Yes," and 0, which means "NO".

First, we evaluated how we would develop a policy regarding missing values. There are many methods for this (such as assigning mode, median or mean). However, these preferences can lead to data manipulation. İn conclusion, it was deemed appropriate to remove null examples from the data set, both because the data set was large and because it included clarity. As a result of this arrangement, the number of examples were decreased from 50.342 to 30.073. Of the students in this dataset, 9.120 declared that they were drug addicts and 20.953 declared that they were not addicts. In binary classification problems, with data samples coming from two groups-as in the study at hand-the problem of class imbalance occurs when one class contains significantly fewer samples compared to the other class, representing the majority. In many cases, the minority group is of interest, that is, the positive class (Johnson and Khoshgoftaar, 2019). One famous example of class imbalance in machine learning relates to the medical diagnostic task of disease detection-the majority of patients do not have a disease and the interest lies in detecting it. In that case, the majority group may be a group of healthy patients who fall into the negative class. It becomes very hard to learn from such imbalanced datasets. First of all, one should comprehensively understand the class imbalance problem and the existing methods to address it, as this kind of skewed data is present in many real-world applications. Unfortunately, this was also a characteristic of our dataset, which had a negative impact on the prediction.

Table 1. List of features

Features	Abbreviations	Description	Category	Missing Value
Addiction Class	AC	Classifies students as addicted or non-addicted	1:Yes 0: No	0
Experimentation	Exp	Whether the student has experimented with drugs	1:Yes 0: No	2562
Academic Performance Decline	APD	Indicates if there's a decline in academic performance due to drug use	1:Yes 0: No	2498
Social Isolation	SI	Whether drug use leads to social isolation	1:Yes 0: No	2550
Financial Issues	FI	Indicates if the student faces financial difficulties due to drug use	1:Yes 0: No	2537
Physical Mental Health Problems	PMHP	Presence of physical or mental health issues related to drug use	1:Yes 0: No	2454
Legal Consequences	LC	Whether there are legal consequences associated with drug use	1:Yes 0: No	2576
Relationship Strain	RS	Indicates if drug use strains relationships with others	1:Yes 0: No	2543
Risk Taking Behavior	RTB	Engagement in risky behavior under the influence of drugs	1:Yes 0: No	2577
Withdrawal Symptoms	WS	Presence of withdrawal symptoms when trying to quit drug use	1:Yes 0: No	2612
Denial and Resistance to Treatment	DRT	Indicates denial or resistance to seeking treatment for drug addiction	1:Yes 0: No	2453

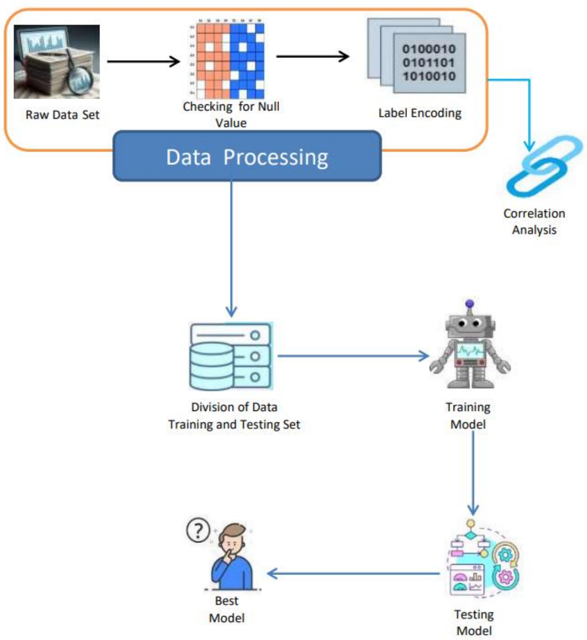

Figure 3. Research process steps.

3. Results

Before moving on to the classification model with ANN, it will be important to analyze the relationship between 11 variables. For this, the most useful method, the correlation matrix, will be examined. A correlation matrix is a table showing correlation coefficients between sets of variable (Gupta, 2019). The correlation coefficients between the variables are shown in Table 2.

When the correlation matrix (Table 2) is examined carefully, it is seen that the relationships between the variables are almost negligible. This can be attributed to the fact that the variables are categorical.At this stage the model was created. Initially, the dataset was partitioned into two mutually exclusive subsets: a training set and a test set. A proportion of 80% of the total data instances was allocated to the training set, while the remaining 20% was designated as the test set. This division was performed prior to model training and evaluation to ensure the model's performance could be assessed on unseen data. Afterwards, a model was created with the training data and this model was validated with the test data. The study involved testing and comparing multiple neural network architectures based on their average classification accuracy. Each architecture was trained using 10 different starting numbers and the average accuracy was calculated accordingly. Since the model consisted of 10 independent and 1 dependent variables, the input layer consisted of 10 neurons and the output layer contained a single neuron that would produce binary classification (0 or 1). The Log-Sigmoid function was used as the transfer function for all architectures. The learning rate was set to 0.3 and the momentum parameter was fixed at 0.2. Models were created with one, two and three hidden layers and their average classification accuracies were compared. The architecture that provided the highest accuracy with the lowest error rate was determined as the optimum model.

Table 2. Correlation matrix

Features	AC	Exp	APD	SI	FI	PMHP	LC	RS	RTB	WS	DRT
AC	1	0.002	0.000	-0.008	0.001	-0.009	0.004	-0.002	0.003	0.009	-0.002
Exp		1	0.006	0.007	-0.001	-0.002	-0.003	0.002	-0.005	0.003	0.002
APD			1	0.001	-0.006	-0.008	0.001	-0.003	0.004	-0.002	-0.002
SI				1	-0.003	-0.001	-0.002	-0.009	0.004	-0.002	0.003
FI					1	-0.006	-0.008	-0.002	-0.003	0.002	-0.005
PMHP						1	0.004	-0.008	0.001	-0.003	0.004
LC							1	0.002	0.007	-0.001	-0.002
RS								1	0.004	-0.006	-0.008
RTB									1	0.002	0.004
WS										1	-0.003
DRT											1

Table 3. Summary of result

Network Architecture	Classification Accuracy %	Classification error percentage %
10 > 50 > 1	65.33	61.12
10 > 60 > 1	65.02	62.31
10 > 80 > 1	66.71	60.19
10 > 100 > 50 > 1	72.44	59.56
10 > 80 > 50 > 1	75.53	57.82
10 > 80 > 40 > 1	74.25	58.12
10 > 70 > 50 > 1	72.47	60.31
10 > 70 > 35 > 1	73.56	59.02
10 > 50 > 25 > 1	72.87	60.01

>represents the transition between layers.

Table 3 summarizes the results obtained using different hidden layers for building the ANN. Various architectures were used; the best of them was obtained by using two hidden layers: 10-80-50-1 architecture with 75.53% average classification accuracy.

Table 4 presents the Confusion Matrix showing the predictive performance of our model. In machine learning, a confusion matrix is a performance evaluation tool that projects the accuracy of a certain classification model. It reflects the number of true positives, true negatives, false positives, and false negatives. This would help in the analysis of model performance, detection of mis-classifications, and further improvement of predictive accuracy. Table 4 shows the model's classification performance across two classes: Class 0: Correctly predicted 3489 instances as 0, but misclassified 696 instances as 1. Class 1: Correctly predicted 1025 instances as 1, but misclassified 805 instances as 0.

Table 4. The confusion matrix of the model

	True Label		
Predicted Label	3489	805	0
	696	1025	1
	0	1	Class

4. Discussion

In this paper, we aimed to achieve an accurate diagnosis to identify addiction in youth, facilitating timely treatment and ultimately preserving lives. Addressing addiction plays a critical role in supporting families, physicians, and investigators in managing and mitigating the impacts of substance abuse. To this end, the paper proposes a Decision Support System (DSS) for diagnosing addiction, leveraging one of the most widely-used machine learning techniques: Artificial Neural Networks (ANN).

The proposed system comprises an input layer with ten neurons, each representing symptoms of addiction as input variables. The model architecture includes two hidden layers and an output layer that classifies individuals as either "Addict" or "Non-Addict." The model achieved a classification accuracy of 75.53%, which, while sufficient, suggests room for improvement. The binary nature of all variables in the dataset likely contributed to the lower-than-expected accuracy. Incorporating numerical variables into the model could enhance its predictive performance. Additionally, applying other machine learning techniques (ensemble learning methods, SVM, etc) could yield higher accuracy scores.

The findings suggest that this model could significantly expedite the diagnosis and treatment of addiction, providing a valuable tool for families, physicians, and investigators. Furthermore, expanding the dataset used for training the proposed system would likely improve its accuracy, thereby increasing its reliability and effectiveness in real-world applications. Potential difficulties in integrating the model into existing healthcare systems, data privacy issues, or steps required to make it user-friendly for healthcare professionals can be coordinated by an expert software and clinical team.

Author Contributions

The percentages of the author's contributions are presented below. The author reviewed and approved the final version of the manuscript.

	E.K.
C	100
D	100
S	100
DCP	100
DAI	100
L	100
W	100
SR	100

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The author declared that there is no conflict of interest.

Ethical Consideration

The author confirms that the ethical policies of the journal, as noted on the journal's author guidelines page, have been adhered to. All participants filled out informed consent forms in the study

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