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Application for Drug addicts using Artificial Neural Networks

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Abstract

This is an application build with the aim to implement a proper advisory system for drug addicts. Drugs are the prime cause for the devastation of personal as well as social life of youngsters. Application uses Artificial neural networks to map the input provided by the users on the basis of questionnaire asked by the application. Artificial Neural networks are being used widely for the applications related to prediction and classification. The accuracy achieved in above mentioned tasks has made neural networks a reliable technique to generate results by using data gathered from different sources as training set. This application takes input from the user as the duration and type of drug intake and provides scores related to addict's conscientiousness, sensation, openness, etc. as output in detailed report format. This helps user or rehab medics to decide preliminary actions to be taken to recover the addiction and to identify the problems being faced by the addict. Application also provides information regarding High risk of drug use, anti-social behavior and negative urgency in the report generated.

Keywords: Artificial Neural Networks, A-score, O-score, E-score

1. Introduction

Technological Advancement has provided pace in various fields like medical, military, business, etc. Most of the applications are related to using the data generated in respective fields and using that data to generate effective observations and results. For doing this task of deriving useful patterns from data, Machine learning is used. Machine learning comprises of various techniques like Linear regression, SVM (support vector machine), Decision Tree and ANN (artificial neural networks), etc., which are categorized into supervised, unsupervised and Semi-supervised learning algorithms. This algorithm uses the provided training data to learn and do the task like prediction and classification on unseen data.

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. According to the world drug report

(Vishwas Ransing) there were 25,71,52582 alcohol users, 8,22,88826 alcohol dependents, 82,28,883 cannabis users in India [1]. Considering this figure, one can figure out the scale up to which drug addic- tion has its effects on population. This consists of users from every age group. In past some years various attempts have been made to create the system helpful for detection of drug addiction and its effects, to help addict overcome the addiction. This application is also an attempt to provide primary observations on effects of drugs being consumed by drug addicts.

2. Conceptual Model

The Application's motive is to provide results which will help user or rehabilitation doctors to understand the effects of drugs being taken by the drug addict. It takes input data from the user which is related to the types of drugs and amount of duration in which they had consumed those drugs. It also takes the input from user related to the addict's personal information such as Name, Gender, Age. Inputs taken related to the drugs are firstly converted into suitable numerical format and then passed to the Artificial Neural Network. Artificial Neural Networks then generate the output and passes that output to the report generator where all the conclusions are made on the basis of results provided by Artificial Neural Network. Report generator uses personal data related to the user which is taken as input from the user to generate a proper report format. The detailed flow of execution is shown in figure 1 . The report format consists of list of drugs being taken by user and generated scores related to their conscientiousness, agreeableness, openness, etc. It also explains what does this score implies in general terms. Application also provides the probable addiction level and risk of drug usage (High, low, medium). Application also provides primary steps to be taken to counter the addiction.

3. Literature Survey

[1] Expert system for identification of drug addiction: This paper describes about how an expert system could be built to analyze the addiction level of drug addict and how a questionnaire for the addict should be created. It Also, provides insights on how drugs consumption is curbing the society with the help of facts and figures.

[2] Five factor model of personality: This paper provides the information about the parameters that need to be considered while describing about addiction level and its effects on addict. Five factor model describes how conscientiousness, openness, agreeableness varies for a drug addict and how this parameter could be used to create a proper advisory report.

[3] ANN based credit risk identification and control for commercial banks: This paper describes about how ANN are helpful in prediction task and the kind of data in terms of volume and variety they need to perform the particular task.

[4] Flood loss prediction of coastal city based on ANN: This paper describes about another application of ANN in terms of prediction. It also provide information on weight correction and input values for ANN.

[5] Analysis of feed forward and recurrent neural networks in predicting the significant wave height at the moored buoys in Bay of Bengal: This paper provides information regarding use of recurrent neural networks for predictive tasks.

[6] Automatic Personality Recognition from reading text speech: In this paper, author has used 5 factor personality concepts for distinguishing personalities on the basis of text speech.
[7] Comparing performances of logistic regression, decision trees, and neural networks for classifying heart disease patients: In this paper, author has described the behavior of different machine learning classifiers and their advantages/disadvantages.
[8] Automatic personality recognition of authors using big five factor model: In this paper, Five Factor Model is used for classifying author's personality by analyzing text written by author.
[9] Using Big Five Personality Model to Detect Cultural Aspects in Crowd: In this paper, author tried to identify the cultural aspects of crowd by monitoring the video sequences of crowd. To find out the cultural differences between different crowd based on the Big-five factor personality model.

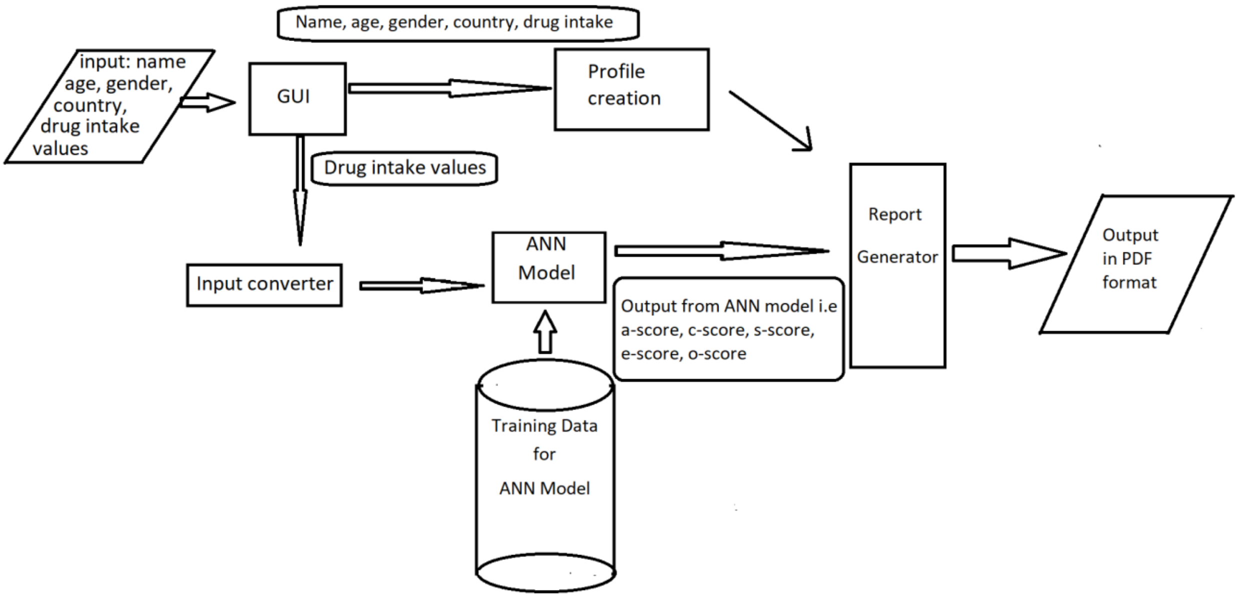


Figure 1: System Architecture

4. Our Approach

4.1.1. A. Theoretical approach

According to five factor model of personality, if we know the extent of person's conscientiousness, agreeableness, openness, extraversion, sensation, neuroticism then we can find out the nature of person's anti-social behavior, negative urgency and risk of drug usage. Here much of antisocial behavior in normal persons is unpinned by high N(neuroticism) and Low C(conscientiousness) and the 'negative urgency' which is ability to act harshly when distressed is associated with high N, low C and low A(agreeableness). It has been found that drug users scored higher on neuroticism and openness and lower on agreeableness and conscientiousness as compared to non-drug users. High risk of drug use is associated with high N and low O and high risk of drug use is also correlated with low A and C. In order to gain values of Conscientiousness(C-score), agreeableness(A-score), Openness(O-score), Extraversion(E-score), Sensation(S-score), Neuroticism(N-score) as output, its corresponding inputs are associated with the intake duration of various drugs [2]. We have divided intake duration of various drugs in categories such as never used, used in a decade ago, used in last decade, used in last month, used in last week, used in last day. These durations are taken as input for wide range of variety of drugs such as alcohol, amphet, amyl, caff, cannabis, cocaine, caffeine, nicotine, ketamine, Ecstasy, etc.

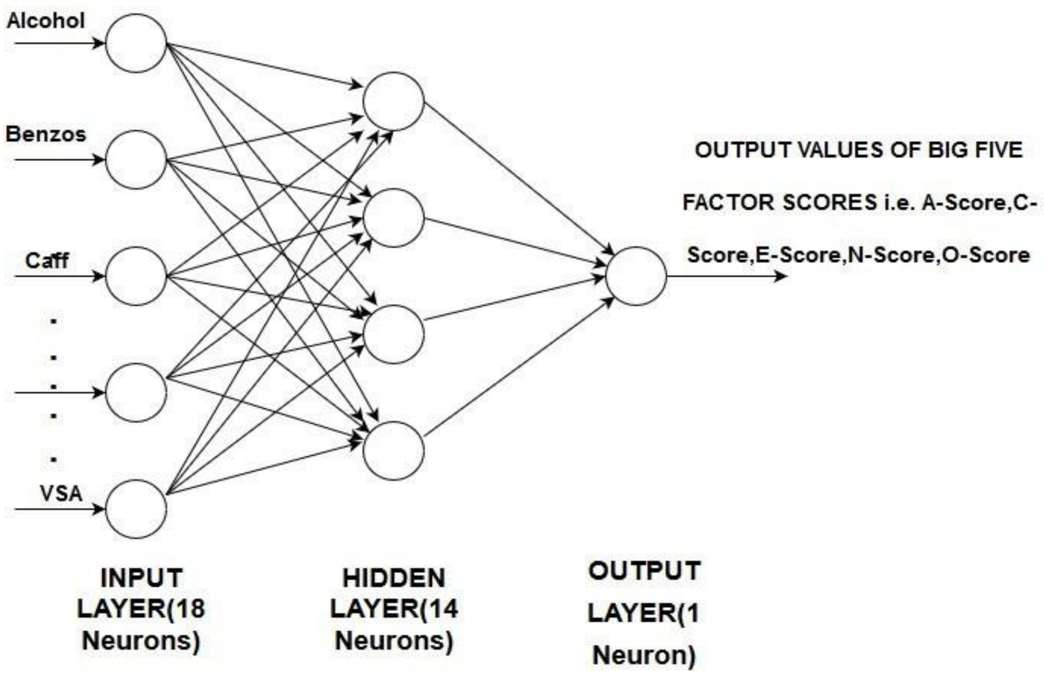
The 5 main factors we will be focusing in output are N, E, O, A, C summarized as below:

1. Neuroticism(N) is a long-term tendency to experience negative emotions. 2. Extraversion(E) is manifested in outgoing, warm, active, assertive, talkative, cheerful and in search of stimulation characteristics. 3. Openness(O) is a general appreciation for art, unusual ideas and imaginative, creative and wide interests. 4. Agreeableness(A) is a dimension of inter personal relations, characterized by altruism, trust, kindness, modesty, compassion and cooperativeness. 5. Conscientiousness(C) is a tendency to be organized and dependable, strong willed, persistent, reliable, and efficient [2].

4.1.1. B. Technical approach

To provide the correct output for the input provided we are using Artificial Neural Networks. Artificial neural network model is using drug consumption data set as training data set. Why ANN? ANN models are nonlinear and require less statistical background other than models such as Decision tree or K-mean algorithm. It also provides invariable results in prediction tasks where as models such as Decision tree or K mean are mainly preferred in classification problems. Figure 2 shows the neural network architecture:

Figure 2: Artificial neural network



In neural networks input is provided through input layer along with the weights and biases, the hidden layer performs addition of products input and weights through every node and passes them through the activation function. The output layer provides the corresponding result of prediction through its nodes. Every node in neural network is called as perceptron.
1) Activation Function: Use of activation functions is the tricky part in neural networking. Activation function of neural network completely depends upon the range of output required. As an activation function , we are using NN Relu function whose output ranges from 0 to + infinity. Why NN ReLu?
The reason behind using NN ReLu as activation function is the range of output parameters. The range of output parameters(c-score,a-score,e-score,n-score,o-score) varies between 0 to +5.5. It has the capability to generate output in the range of required output values (i.e.c-score,a-score,e-score,n-score,o-score) ranging from 0 to +5.5. Other activation functions such as Sigmoid, SoftMax could not be used as their range of values lies between 0 to +1 and these activation functions are mostly used for probabilistic models. Below is the graph representing Relu function[10] in figure 3:

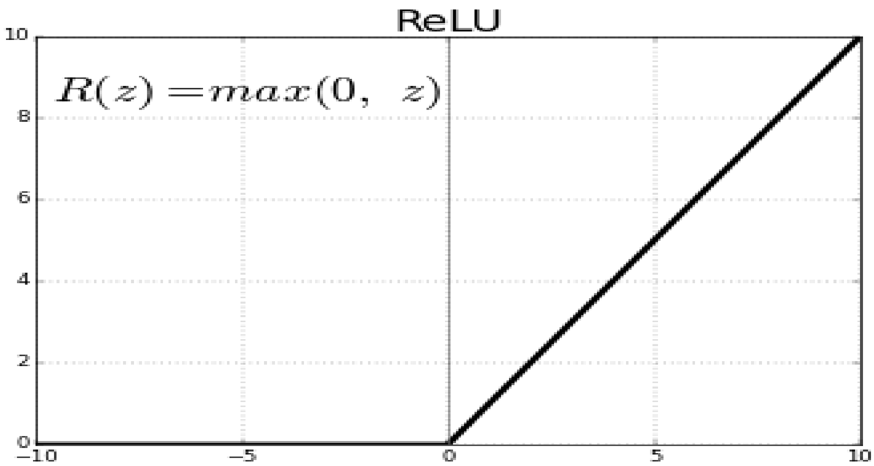


Figure 3: Activation function

Using NNRelu as an activation function desired outputs can be generated for all output parameters. Layers: In the ANN, number of nodes in input layer are 18 which is equivalent to number of inputs. In the output layer there is only 1 node which fires value of particular score for which NN is designed. In the hidden layer number of nodes are 14 (2/3*(number of nodes in input layer+number of nodes in output layer)). TensorFlow: we have used tensor flow libraries named keras and layers for the implementation of neural network model. 2) Dataset: Dataset for training neural network has been taken from UCI repository, named as Drug consumption Data set. It consists of 1885 instances. 3) Optimizer: As an optimizer we have used RMS Optimizer as learning algorithm for finding out correct weights in each layer. 4) Inputs: Input accepted from the user will be in classes such as, class0(CL0) - never used, class1(CL1) - used a decade ago, class2(CL2) - used in last decade, class3(CL3) - used in last year, class4(CL4) - used in last month, class5(CL5) - used in last week, class6(CL6) - used in last day. But as given inputs are in character format one cannot use them directly as input for the ANN so we assign each class with a numerical token such as for CL6 class token assigned is 6 , for CL5 class token assigned is 5 and so on. In such way the input data is converted so that it is according to the data set and suitable for ANN. Above input values from users are taken for set of drugs namely alcohol,amphet,amyl,benzos,caff,cannabis,choc,coke,crack,ecstacy,heroin,ketamin,leath,lsd,meth,mushroom,nicotin,vsa. 5) Outputs: Output of different parameters such as A-score, C-score, O-score, N-score varies from 0 to + 5.5. When input data is passed through ANN with above configurations , desired output can be obtained.

5. Results and Discussion

To check out model's accuracy we took a single case of inputs and created an array of those input values as shown in figure 5.

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	o_score	alcohol	amphet	amyl	benzos	caff	cannabis	choc	coke	crack	ecstacy	heroin	ketamin	leath	lsd	meth
1880	4.88511	5	0	0	0	4	5	4	0	0	0	0	0	3	3	0
1881	3.58331	5	0	0	0	5	3	4	0	0	2	0	0	3	5	4
1882	1.72447	4	6	5	5	6	6	6	4	0	4	0	2	0	2	0

Figure 4: Dataset

From the dataset shown in figure 4, the input case having index number 1800, we converted it into an array to specifically check the model's output for the particular given instance. As per data, model should provide output somewhere around 4.86

```
In [90]: dataset.isna().sum()
         import numpy as np
         inp=[5,0,0,0,4,5,4,0,0,0,0,0,3,3,0,0,0,5]
```

Figure 5: Input array

Figure 5 shows conversion of inputs into an array. Then we normalized all the inputs in the array. We normalize data in order to transform values from different scale to a common scale. Figure 6 shows normalization of array:

```
In [97]: def norm(x):
           return (x - train_stats['mean']) / train_stats['std']
         normed_train_data = norm(train_dataset)
         normed_test_data = norm(test_dataset)
         normed_inp=norm(inp)

In [98]: n_inpt=np.array([normed_inp])
```

Figure 6: Normalization

Then we converted normalized input array into an array of shape having 18 values as input layer of neural network consisting of 18 neurons. This conversion can be seen on console line no.98 of Figure 6. Figure 7 shows model code of neural network.

```
In [99]: def build_model():
           model = keras.Sequential([
             layers.Dense(14, activation=tf.nn.relu, input_shape=[len(train_dataset.keys()
             layers.Dense(1)
           ])
         optimizer = tf.train.RMSPropOptimizer(0.001)
         model.compile(loss='mse',
                       optimizer=optimizer,
                       metrics=['mae', 'mse'])
         return model
         model = build_model()
```

Figure 7: Model code

Above Neural network model is trained for 2000 iterations on the test dataset. The implementation of training is shown in figure 8:

```
In [102]: class PrintDot(keras.callbacks.Callback):
            def on_epoch_end(self, epoch, logs):
              if epoch % 100 == 0: print('')
              print('.', end='')

          EPOCHS = 2000

          history = model.fit(
            normed_train_data, train_labels,
            epochs=EPOCHS, validation_split = 0.2, verbose=0,
            callbacks=[PrintDot()])

          .......................................................
          .......................................................
```

Figure 8: Model training

We calculated the mean square error and mean absolute error : Figure 9 shows mean absolute error of ANN model for generation of O score.

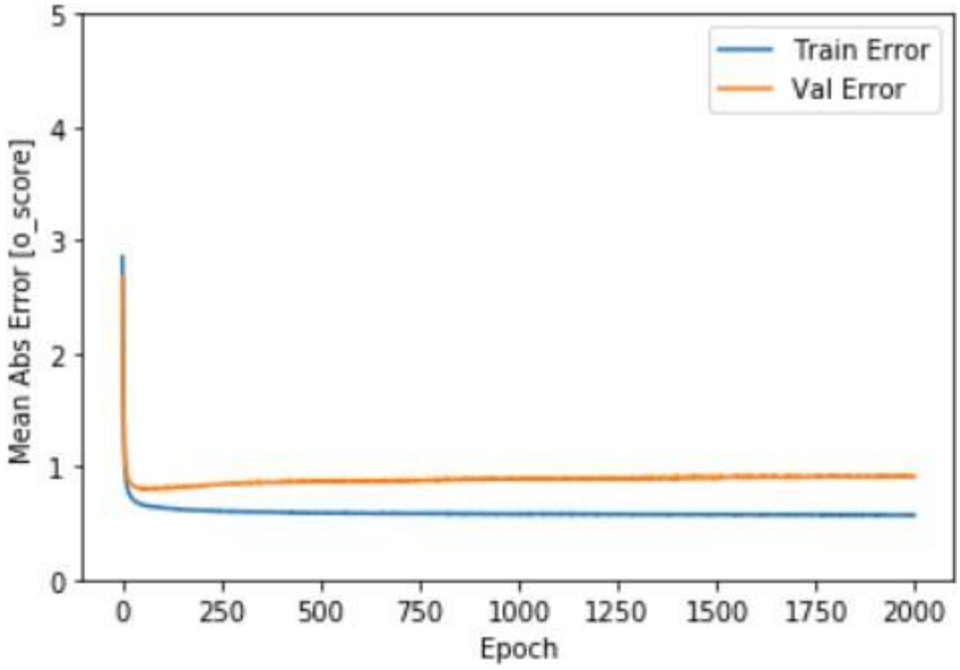

Figure 9: Mean absolute error

Figure 10 shows mean square error of ANN model for generation of O score.

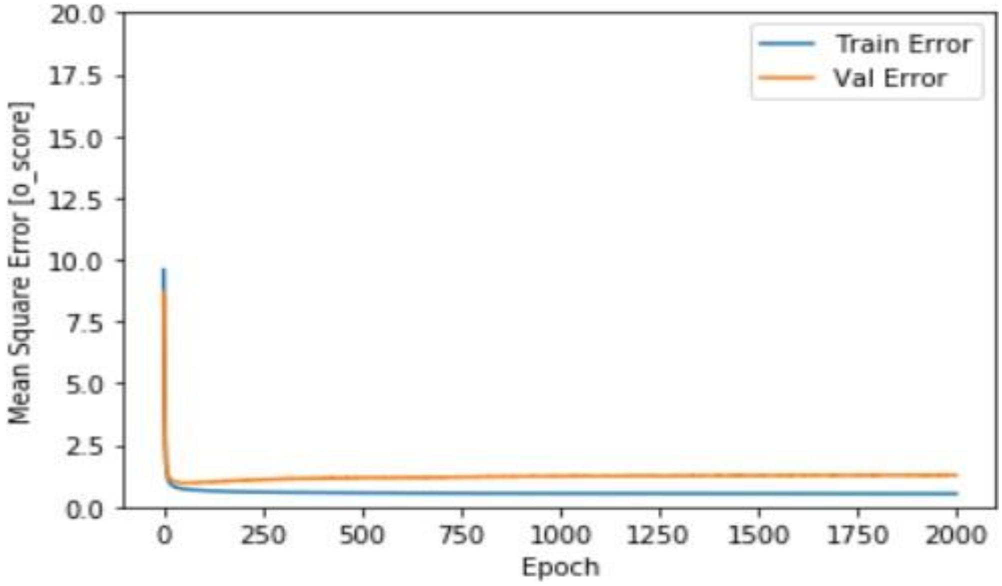

Figure 10: Mean square error

Mean absolute error stopped declining further after 0.56 and mean squared error stopped declining after achieving value of 0.53. It is shown in figure 11 given below.

	val_loss	val_mean_absolute_error	val_mean_squared_error	loss	mean_absolute_error	mean_squared_error	epoch
1995	1.277813	0.906910	1.277813	0.534488	0.568682	0.534488	1995
1996	1.284548	0.905663	1.284548	0.533752	0.569068	0.533752	1996
1997	1.273761	0.904609	1.273761	0.535845	0.570581	0.535845	1997
1998	1.284262	0.912878	1.284262	0.535492	0.571768	0.535492	1998
1999	1.283374	0.908926	1.283374	0.533313	0.569404	0.533313	1999

Figure 11: Mean error table

After passing test dataset to trained model it generates values in the range of expected outputs as shown in figure 12.

```
In [107]: test_predictions = model.predict(normed_test_data
                                           ).flatten()

          test_predictions

Out[107]: array([3.1869316, 2.839435 , 2.413225 , 2.7614698, 2.633223 , 2.802991 ,
                 2.6098535, 2.6768677, 2.098331 , 3.0641098, 2.0310807, 2.788467 ,
                 3.0135689, 2.700347 , 2.4966075, 2.8523607, 2.2608836, 2.5667973,
                 2.719799 , 2.1709194, 2.656981 , 2.7025094, 2.5677452, 2.2486796,
                 3.4288511, 3.2340279, 2.0809846, 2.6762266, 2.0775669, 2.6768677,
                 2.5881233, 2.6537237, 2.228218 , 2.8643036, 2.3031502, 2.5258493,
                 2.1974   , 3.3721404, 2.3315911, 3.1185179, 2.4919372, 2.332913 ,
                 2.296937 , 2.1277843, 2.2939062, 2.424282 , 2.4020314, 3.905047 ,
                 2.9395075, 2.0224724, 3.2891173, 2.1055963, 2.6644845, 2.5397613,
                 1.9962723, 2.3702455, 2.4061902, 2.5224981, 2.5904067, 3.0743847,
                 2.801763 , 3.4098616, 2.3685238, 2.9153237, 2.456502 , 2.5344205,
```

Figure 12: Train data results

To see the precise outcome, we passed the earlier created normalized array of a single input case to the model. Expected result was somewhere near to 4.8 and ANN model predicted it as 4.43 as shown in figure 13. As margin of error is considerably smaller, it can be concluded that model can provide efficient output values.

```
In [109]: test_predictions = model.predict(n_inpt
                                           ).flatten()

          test_predictions

Out[109]: array([4.431794], dtype=float32)
```

Figure 13: Output

As model has predicted o score value around 4.43, the openness score of particular addict's case can be considered above normal.

In such a way through values generated on different personality traits such as s score(sensation), a-score(agreeableness), e-score(extraversion) by their respective ANN models, main five personality traits of a drug addict can be identified on a scale and can be helpful for rehabilitation centers in deciding further treatment for different cases. Based on scores(A-score,C-score,E-score,O-score) generated by ANN, we can comment on patient's personality traits. High risk of drug use in future is correlated with high N and O. High risk of drug use in future is correlated with low A and C. Antisocial behaviour in normal person appears underpinned by high N and low C[2].

S.kaur et.al[1] have developed an approach on identifying drug addict's addiction level. But the approach does not provide more information other than addiction level and fails to comment on effects of drug intake on addict's personality. The difference between results and approaches have been compared in Table 1.

parameters	S.kaur et.al	Proposed
Algorithm	Decision Tree ID3	Artificial Neural networks
Input values	Response to questionnaire about addict's frequency and duration of drugs.	Input regarding type of drugs addict consumed and duration of intake.
output	Level of addiction Low, Moderate, Severe	Scores of five personality traits(a-score,c-score,e-score,o-score,n-score) and level of addiction High,Low,Medium
Generate Results regarding impact on personality traits due to drugs?	No	Yes
Generate results regarding addiction level	Yes	Yes
Provides result in scalable numerical format	NO, Final output is addiction level(Low,high,moderate)	Yes, It provides final output in numerical values of five personality traits, which helps in measuring impact of drugs in quantitative manner.

Table 1:Comparison between approach and results.

Knowing about patient's scores in different personality traits doctors can identify the specific areas of behavior of addict where they need to work. Cases having low score on agreeableness will have to be treated for betterment of their interpersonal relationships. cases having high N i.e. Negative urgency would be required to give treatment for reducing their experience on negative emotions. Cases scoring low openness score will require treatment for enhancing their appreciation towards imaginative and creative interests. In such a way every addict could be analyzed on an individual level and can be treated accordingly.

6. Future Scope

Application can be further developed for regular disease detection by using symptoms as an input for ANN. Though the availability of the data related to the disease and its symptoms could be a barrier for it. Application can also be further developed to create similar report format for the normal diseases, which will be helpful in general hospitals and rehabilitation centers.

7. Conclusions

The focus was to create a model which can provide information regarding impact of drugs on addict's Conscientiousness, agreeableness, Openness, Extraversion, Sensation, Neuroticism. On the basis of scores generated by ANN for each personality trait based on five factor model of personality, rehabilitation centers or individual can understand the impact of drug intake on addicts personality traits(i.e. agreeableness, consciousness, extraversion, neuroticism, openness). Generated scores will help to identify that on which personality traits does individual needs an improvement and rehabilitation centers doctors can plan treatment for patient accordingly. The focus was to create a model which can provide information regarding impact of drugs on addict's Conscientiousness, agreeableness, Openness, Extraversion, Sensation, Neuroticism.

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