# Drug Abuse Detection Framework based on Fuzzy Neural Network and IoT

**Prof. Linda Sara Mathew[1], Prof. Kukoo Anna Mathew[2], Sabarinath M[3], Ananthu S Kumar[4] and Jyothis S[5]**

*[1]Assistant Professor, Dept. of Computer Science and Engineering, Mar Athanasius College of Engineering, Kothamangalam, Kerala, India*
*[2]Assistant Professor, Dept. of Computer Science and Engineering, Mar Athanasius College of Engineering, Kothamangalam, Kerala, India*
*[3,4,5]Dept. of Computer Science and Engineering, Mar Athanasius College of Engineering, Kothamangalam, Kerala, India*

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**Abstract -** *The increasing use of drugs among the youth is a big concern nowadays. The inability to detect drug consumption is a major issue. One of the ways to detect drug consumption is with the use of IoT devices. IoT devices are providing various dimensionalities and online services. These applications have provided a new platform to millions of people for getting benefits in various fields. Ubiquitous physiological sensing has the potential to profoundly improve our understanding of human behavior, leading to more targeted treatments for a variety of disorders. This led to the introduction of IoT technology and related devices to be used in the medical field, strengthening the various features of these drug detection online applications. The huge volume of big data is generated by IoT devices in day to day activities. Cloud computing technology is used to handle the large volume of data and also provide the ease of use. In the present scenario, cloud-based applications are playing a major role in this fast world. The present drug detection applications also use the Cloud Computing technology for secured storage and accessibility. For availing better services to the people over the online drug detection, the proposed project uses a new Cloud and IoT based Mobile drug detection application for monitoring and detection of drug usage among the youth. In this project, a new systematic approach is used for the drug detection and the related medical information is generated by using the UCI Repository dataset. In addition, the proposed project applies SVM(Support Vector Machine) Classifier, Neural Network and Fuzzy Tool Box for diagnosing the drug and its severity. The electrocardiogram sensor unit is used to further improve the accuracy of the result.*

***Key Words***: SVM, AD8232, IoT Sensors, Data Classification.

## 1. INTRODUCTION

In recent years, the government and other organizations have recognized the risk of drug abuse and the importance of detection and prevention. These initiatives that have been implemented include choosing treatment over incarceration, increasing parity for drug abuse treatment[1][5], and improving opportunities for collaboration among different healthcare and drug abuse facilities [6].The main issues for these organisations is the live monitoring of drug abuse.In recent years, the ability to continuously monitor the activities, health, and lifestyle of individuals using sensor technologies has reached unprecedented levels. Wearable "on-body" sensors now enable routine and continuous monitoring of a host of physiological signals including heart rate, blood pressure, respiratory rate, blood glucose and more. In the proposed system machine learning technologies like SVM(Support Vector Machine) Classifier, Neural Network and Fuzzy Tool Box are used. Routine and continuous monitoring of a host of physiological signals including heart rate, blood pressure, respiratory rate, blood glucose and more. In the proposed system machine learning technologies like SVM(Support Vector Machine) Classifier, Neural Network and Fuzzy Tool Box are used.

## 2. Data Collection

### 2.1 E3 Wristband

The E3 is a medical grade wearable device that offers real time physiological data acquisition, enabling researchers to conduct in-depth analysis and visualization [7].E3 band monitors the individuals heartbeat, heat flux, body temperature, EDA (Electrodermal Activity), GSR (Galvanic Skin Response) and so on. The E3 bandis shown in Fig. 1.

**Fig -1**: E3 Wristband

This wristband is then connected to the individual's smart phone by Bluetooth. This data is continuously sent to the E3 band server along with the user credentials using the E3wristband mobile app. The system collects this information from the server continuously by using the E3 band API [17].

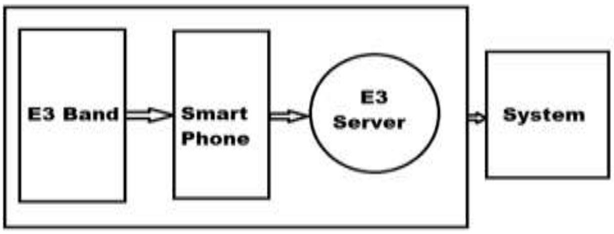


**Fig -2**: Data Collection from E3

### 2.2 ECG Sensor

The system is also monitoring the individual ECG signals. The components used for this section are:

- Arduino UNO: This is the important part of data collec-tion. Arduino Uno is a microcontroller based on the ATmega328P. It has 14 digital input/output pins, 6 analog inputs, a 16 MHz ceramic resonator (CSTCE16M0V53-R0), a Universal Serial Bus connection, a power jack. It consisted of everything that needed to support the micro-controller. Connect it to a computer with a USB cable or power it with a Alternate Current to Direct Current adapter or battery to get started. The image of an Arduino UNO microcontroller is shown in Fig. 3.

**Fig -3**: Arduino UNO

- ECG Sensor(AD8232): Wearable ECG Sensor is used as a monitoring device. A substantial body of work has explored the use of ECG using wearable bands, primarily in the context of understanding physiological stress [16]. The work on physiological stress focuses primarily on the use of heart rate-based features to determine an individual's stress level. The usage of drugs will significantly change heart rate levels. The output of the ECG sensor is analog, the trained SVM model takes only digital input for the classification. Because of that we need to use an Analog to Digital converter.

**Fig -4**: ECG sensor

- ECG Electrodes : An electrode is a conductive pad which is attached to the skin and recording of electrical currents from a human body. An ECG lead is a graphical description of the electrical activity of the heart and it is created by analysing several electrodes [18].It is shown in Fig. 4. There are basically three electrodes that need to stick to the skin in two ways. One way is on the two wrists and on the thigh. The other way is to stick the electrodes on two chest and on the right waist.

**Fig -5**: ECG Electrodes

- Analog to Digital Converter(ADS115): The ADS1115 is a 16bit ADC with four multiplexed inputs. It has an internal calibrated reference for high accuracy. ADCs follow a sequence when converting analog signals to digital. They first sample the signal, then quantify it to determine the resolution of the signal, and finally set binary values and send it to the system to read the digital signal. Two important aspects of the ADC are its sampling rate and resolution. The images of ADS115 are given in Fig. 6.

**Fig -6**: Analog to Digital Converter

The AD8232 breaks out nine connections from the IC that one can solder pins, wires, or other connectors to. SDN, LO-plus, LO-minus, OUTPUT, 3.3V, GND provide essential pins for operation. This monitor with Arduino or other development environments. This board also consists of RA (Right Arm), Left Arm, and Right Leg pins to attach and use your own customised sensors. Moreover, there is an LED indicator light that will pulsate to the rhythm of a heart beat. The output from the AD8232 module can be collected either in two ways. First we can collect the data as analog data from the Arduino UNO. Then we can process the data using a software model to convert analog data to digital data.

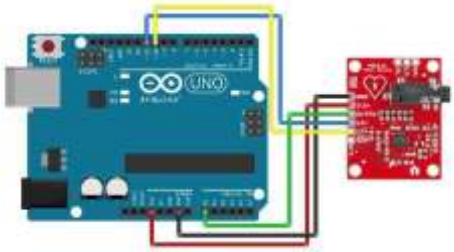


**Fig -7**: Arduino UNO - AD8232 Connection

Secondly we could use an ADC. The ADS1115 is a digital to analog converter (ADC) that we can connect to a processor to measure analog signals. On the Arduino Uno, Mini or Nano models, we have 6 ADC of 10 bits. The ADS1115 provides four 16-bit ADCs, 15 for the measurement and one for the sign. The ADS1115 is connected by I2C, so that is easy to read. It has 4 addresses, which is selected by connecting the ADDRESS pin. The significance of using ADS1115 is to obtain greater precision and accuracy, in addition to freeing the processor from this burden. In certain configurations, it is possible to measure negative voltages

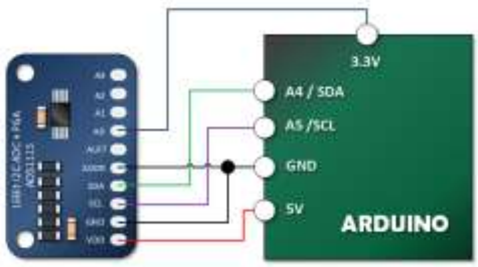


**Fig -8**: Interfacing of ADS1115 with Arduino UNO.

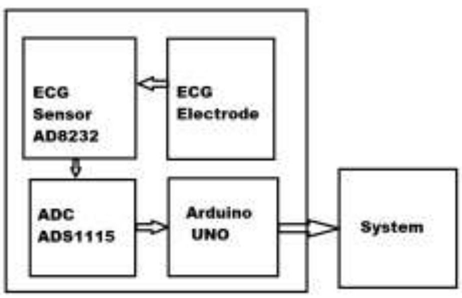


**Fig -9**: ECG Sensor Data Collection Chart

## 3. DATA PROCESSING

### 3.1 Data Preprocessing

Pre-processing of data refers to the transformations applied to our data objects before feeding it to the algorithm. Data Preprocessing is a technique that is used for converting the raw data into a clean one. That means, whenever the data is collected from different sources it is collected in raw form which is not feasible for the analysis. The dependencies among the different features are identified and eliminated. Also we apply normalization methods to the data during data preprocessing. Normalization is a technique that is applied as a part of data preparation for machine learning [21].

| hr | gsr | calories | temp | heat flux | eeg |
|---|---|---|---|---|---|
| 116 | 0.0000493 | 1.4 | 73.4 | 190.8000493 | 80.81839482 |
| 106 | 0.0000491 | 1.5 | 73.4 | 180.9000491 | 76.10974897 |
| 99 | 0.0000491 | 1.5 | 73.4 | 173.9000491 | 72.86812646 |
| 109 | 0.0000504 | 1.4 | 73.4 | 183.8000504 | 77.50324462 |
| 129 | 0.0000504 | 1.5 | 74.3 | 204.8000504 | 87.39615571 |
| 149 | 0.0000499 | 1.5 | 74.3 | 224.8000499 | 97.25064587 |
| 163 | 0.0000502 | 1.4 | 74.3 | 238.7000502 | 104.2676757 |
| 130 | 0.0000502 | 1.5 | 74.3 | 205.8000502 | 87.88269473 |
| 92 | 0.0000507 | 1.5 | 74.3 | 167.8000507 | 70.03233433 |
| 91 | 0.0000502 | 1.4 | 74.3 | 166.7000502 | 69.57232091 |
| 85 | 0.0000502 | 1.5 | 74.3 | 160.8000502 | 66.93106757 |
| 85 | 0.0000504 | 1.5 | 74.3 | 160.8000504 | 66.93106761 |
| 83 | 0.0000521 | 1.4 | 74.3 | 158.7000521 | 66.04655803 |
| 111 | 0.0000524 | 1.5 | 75.2 | 187.7000524 | 79.095752 |
| 112 | 0.0000536 | 1.5 | 75.2 | 188.7000536 | 79.56574647 |
| 118 | 0.0000536 | 1.4 | 75.2 | 194.6000536 | 82.39362259 |
| 115 | 0.0000551 | 1.5 | 75.2 | 191.7000551 | 80.98159085 |
| 128 | 0.0000548 | 1.5 | 75.2 | 204.7000548 | 87.20910573 |
| 131 | 0.0000551 | 1.4 | 76.1 | 208.5000551 | 88.95030157 |
| 129 | 0.0000548 | 1.5 | 76.1 | 206.6000548 | 87.99314821 |
| 136 | 0.0000554 | 1.5 | 76.1 | 213.6000554 | 91.39810821 |
| 130 | 0.0000557 | 1.4 | 76.1 | 207.5000557 | 88.46528221 |
| 123 | 0.0000554 | 1.5 | 76.1 | 200.6000554 | 85.10366685 |

**Fig -10**: E3 Band Data

The goal of normalization is to change the values of numeric columns in the dataset to a scale that is in between 0-1 or -1 to +1, without distorting differences in the ranges of values. The normalization i s applied to the feature vector to reduce or equalize the priority among the features. So that the values that generated for a particular feature have no effect because of the variation in the value range compared to other features. We apply min-max methods to the dataset that gathered from the E3 band(shown in figure 10) and AD8232 data(shown in figure 11).

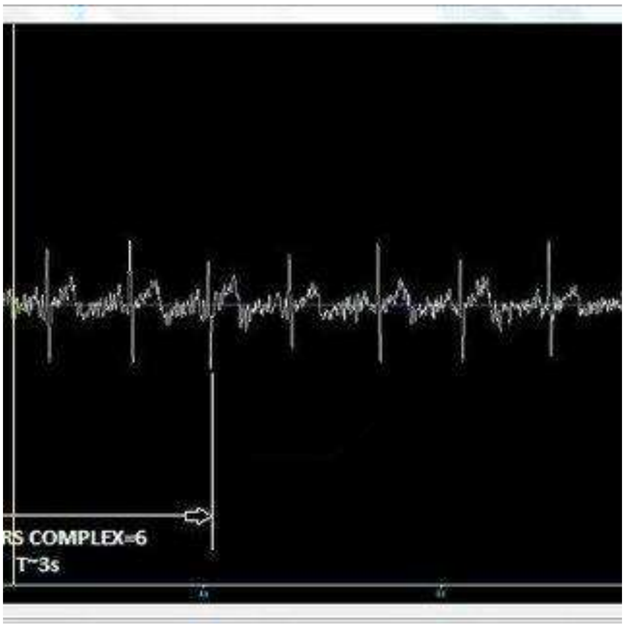


**Fig -11**: ECG sensor data

## 3.2 Training Phase

The basic idea behind the system is to detect the changes and its after effects in our body due to the consumption of drugs in an excess manner. This changes in our body can be detected using various methods. Here we are actually combining two different ways to detect these changes to further improve the accuracy of the system [19].The methods combined are wrist band based monitoring and prediction and ECG Based prediction.

### 3.2.1.Training of Multi Layer Perceptron

As shown in Fig. 2, we collect the data from the wrist band in a continuous manner. Based on a particular interval the data is collected from the server. This is then fed to the Multi Layer Perceptron network. A multilayer perceptron (MLP) is a class of feed forward artificial neural networks (ANN). The term multilayer perceptron is used ambiguously, sometimes loosely to refer to any feed forward ANN, sometimes strictly to refer to networks composed of multiple layers of perceptrons .The system implemented consist of a MLP with 5 hidden layers and activation function used is logistic function. The output of MLP is a floating point number that ranges between 0 to 4. This value is based on the severity of the drug usage. The previously collected band data are labeled with this floating point value between 0-4. During the training phase our model tries to learn the target value for the training data set [21]. A hidden layer "hides" its desired output. Neurons in the hidden layer cannot be observed through the input/output behaviour of the network. There is no actual way to know what the desired output of the hidden layer should be. Commercial ANNs incorporate three and sometimes four layers, including one or two hidden layers. Each layer can contain from 10 to 1000 neurons. Experimental neural networks may have six or even seven layers, including 4 or 5 hidden layers, and utilise millions of neurons. With a single neuron, it is not too hard to see how to adjust the weights based upon the error values. With a multi-layer network, it is less obvious. For one thing, what is the "error" for the neurons in non final layers? Without these, we don't know how to adjust. A training set of input patterns is presented to the network. The network computes its output pattern, and if there is a visible error or a difference between predicted and actual output patterns, the weights are adjusted to reduce this error. The previously collected data set from the E3 band is used for training and about 70 percentage of the collected data is used for training and 30 percentage of data is used for validation. The activation function used in this network is sigmoid function. In a back propagation neural network, the learning algorithm has 2 phases. First, a training input is presented to the network input layer. The network of the perceptron propagates the input pattern from layer to next layer until the output is generated by the output layer. If this pattern is different from the desired output value, an error value is calculated and then propagated backwards through the hidden layer from the output layer to the input layer. The weights are modified as the error is propagated.

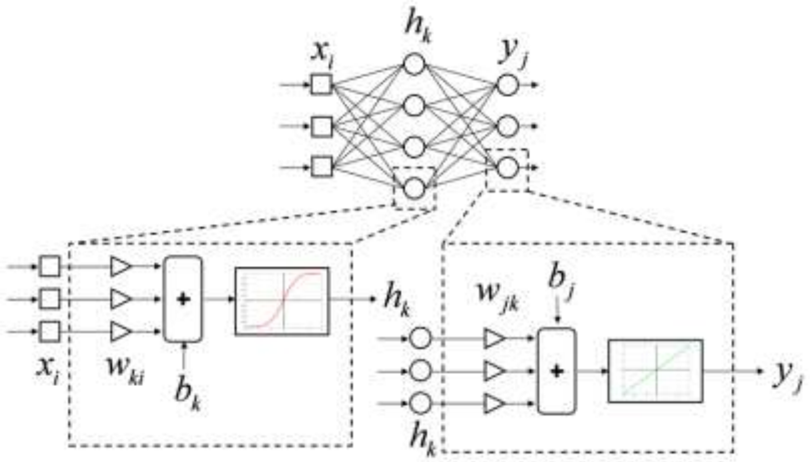


**Fig -12**: Training of Multi Layer Perceptron having one hidden layer

### 3.2.2.Validation of Multi Layer Perceptron

Successively, the fitted model is used for the prediction of the observations in a second dataset that is called the validation dataset. The validation dataset provides an unbiased evaluation of a model that is fit on the training dataset. 30 percentages of the E3 band data is used for validation. The model will give a good prediction if it is correctly fitted.

### 3.2.3. Training of Support Vector Machine (SVM)

The data collected from the ECG sensor is a graph that continuously varies according to the combined electrode state. The usage of ADS1115 will help to find the digital data that is supported by the SVM classifier [20]. When we convert the analog data to digital form, we can have N numbers of distinct numbers at a given time interval. Each of those numbers is considered as a feature value. In total we have N features. 75 percent of the data points are used for training and the rest 25 percent are used for validation. A support vector machine (SVM) is a supervised machine learning model that tries to use classification algorithms for 2-group classification problems. SVM tries to find a hyperplane that classifies our data in N dimensional space. The result generated by a SVM model is a binary result, either yes or no.

But our number of output labels are 5. That means we require 5 numbers of SVM models for each class. Then we combine the results of all the SVM models using the one vs all method to find the most suited label for that particular data object. In order to separate two classes of data points, there are many possible numbers of hyperplanes that could be chosen. Our objective is to find a plane that is having maximum margin.

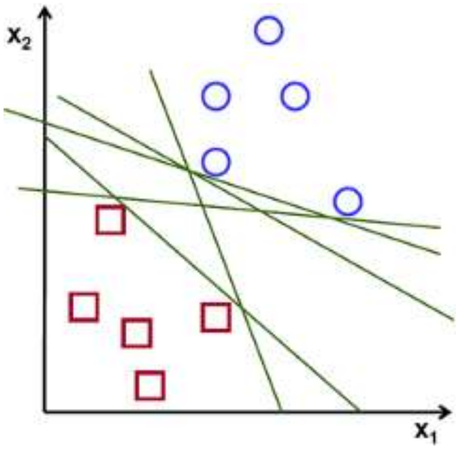


**Fig -13**: Different hyperplanes that classifies data points

That means the maximum distance between data points of both classes. Maximizing the margin distance provides some reinforcement so that the future data points can be classified with more confidence and accuracy. Figure 13 shows the different possible hyper planes that correctly classify the data points and figure 14 shows the one hyperplane that is having maximum margin. Each data object from the ECG sensor belongs to either of the label integer numbers between 0 and 4. Previously collected labeled data are used for training the different SVM models. The first model is used to classify whether the data belongs to class label 0 or not. Second model used to classify whether the data belong to class label 1 or not, likewise for remaining models. Each model comes up with a hyperplane that has a maximum margin with the data points of the two classes.

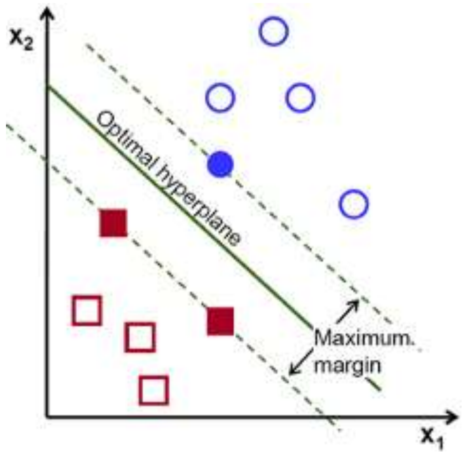


**Fig -14**: Hyperplane having maximum margin

### 3.2.4. Validation of Support Vector Machine (SVM)

After the training phase we need to check the performance of each model (5 SVM trained models) by giving new unknown data points. 25 percent of the dataset is used for validation. Present each data object to each one of SVM that is specifically used for one of the 5 output labels and find the cumulative result using one against all methods [22]. By this method we predict the label of all 25 percent of data objects that were reserved for validation. Finally we compare the result obtained with the corresponding actual label of data point. A model is considered as a good one if it rightly fist with the training samples. Overfitting and underfitting are needed to be avoided. The validation phase will give an exact idea of the trained model performance [23].

### 3.3. Overall System Design

The final output of the proposed system is whether the monitoring person is using drugs, particularly cocaine or not, if yes what is the severity of usage. At this point of time we have trained MLP models ready to accept input, five trained SVMs and ready to accept input from ECG. The person is allowed to wear both E3 band and ECG electrodes and the server is programmed to accept the data coming from both sources. The server consists of two buffers that can hold up to 60 data objects. In each second the buffer receives a data object and when it reaches 60.we block receiving data and find the aggregate of data values in each buffer. Then the aggregated data object of E3 band is presented to the trained MLP. The other object that is the aggregated object of ECG is passed to each of the SVM classifiers. Exactly one model predicts a particular class and the rest of models will predict negative results. The positive result that is predicted will be assigned to the data object.

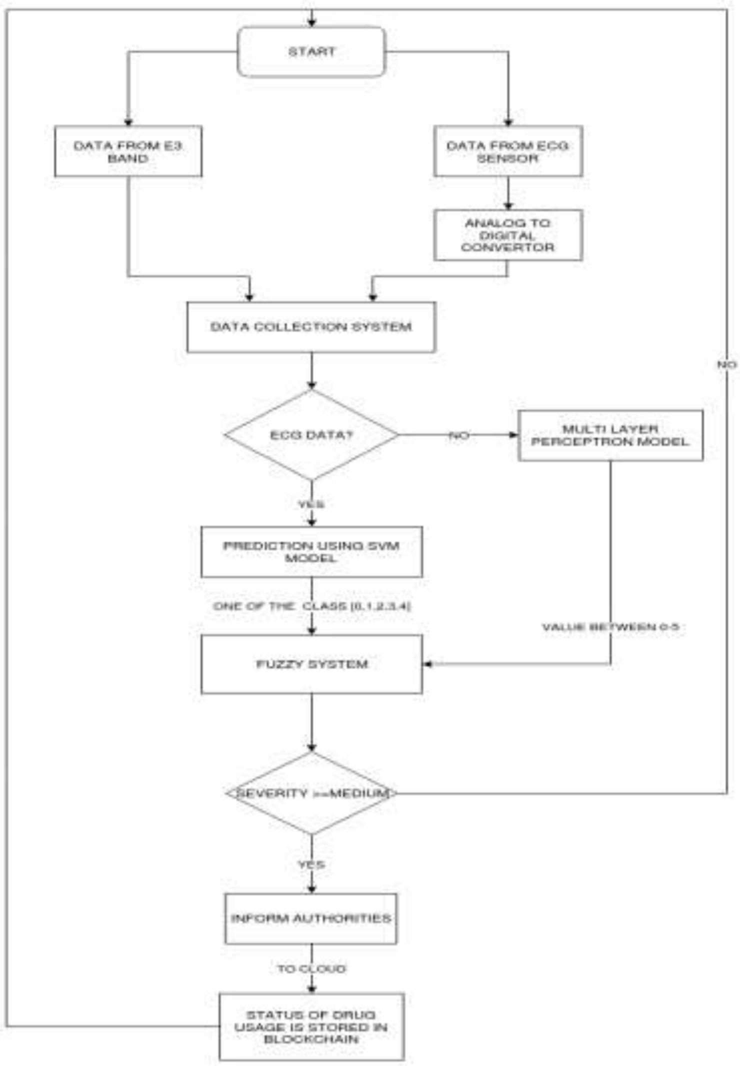


**Fig -15**: Overall system.

For example SVM 1 predicted the class label 1 for data objects and the rest of the SVMs classifies data to negative class (eg: data not belonging to class 3). Then the data object is assigned with class label 1. Now both buffer data have an output value. In the case of E3 band, it is a value between 0 and 5. In the case of ECG data the output is a class label. These two results are passed to a fuzzy system to check the severity of the person who is currently monitored.

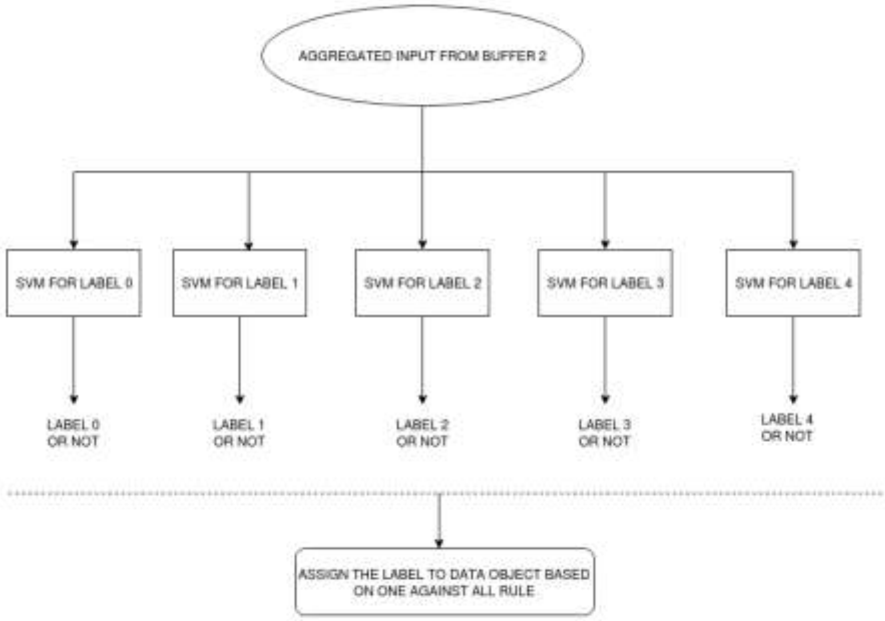


**Fig -16**: SVM sub system

The significance of fuzzy logic is used to map an input space to an output, and the primary mechanism for doing this mapping is a collection of if then statements called rules. Every rule is evaluated in parallel, and the order of the rules are not important. The rules are useful because all the rules refer to variables and the adjectives that describe the variables. Before we can build a system that interprets rules, we need to define all the terms that the system plans on using and the adjectives that describe them. To say that the car is far, we need to define the range that the car's distance can be expected to vary as well as what we mean by the word far. The following diagram provides a road map for the fuzzy inference process.

- Fuzzify inputs: Resolve all the fuzzy statements in antecedent to a degree of membership between zero and one. If there is one part to the antecedent, then this is the degree of support for the rule.
- Apply fuzzy operator to multiple parts of antecedents: If there are more than one parts to the antecedent, apply fuzzy logic operators and resolve the antecedent part to a single real number between 0 and 1. This is the degree of support for that particular rule.
- Application of implication method: Use the degree of support for the entire rule to shape the output of the fuzzy set. The consequences of a fuzzy rule assigns an entire fuzzy set to the output. This fuzzy set is represented by a membership function. If the antecedent is only partially true, (that is, it assigns a value less than 1), then the o/p fuzzy set is truncated according to the implication method that we have.

Fuzzy Logic Toolbox provided MATLAB functionalities, methods, apps, and a Simulink block for analyzing, designing, and simulating systems based on fuzzy logic. Functions are provided for many common methods, including fuzzy clustering and adaptive neuro fuzzy learning. The toolbox lets you model complex system behaviors using simple logic rules, and afterwards implement these rules in a fuzzy inference system. You can use it as a stand-alone fuzzy inference engine. Alternatively, you can use fuzzy inference blocks from Simulink and simulate the fuzzy system within a comprehensive model of the entire dynamic system.Output of fuzzy system is either of the following:

1. Normal
2. Medium
3. High
4. Severe

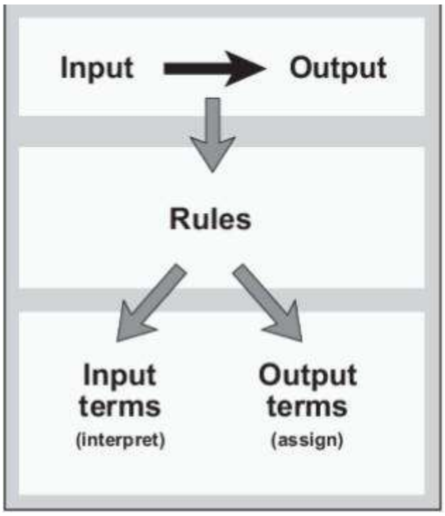


**Fig -17**: Fuzzy inference process.

If the usage is above normal then the message regarding the usage of cocaine is sent to the concerned authorities including police, parents, school authority etc. We all know that usage of any kind of drugs is a punishable offence. It is also important to know whether a person has a history of drug usage. For that the information that is sent to the authorities is also stored and can be retrieved by the concerned departments for further reference. The emerging technology such as Blockchain is really suited for data security [12] [13].

Blockchain ID is a digital form of ID that is engineered to replace all forms of physical identification. Data about drug usage of a person can be stored using blockchain ID and that can be accessed by the concerned authorities for the identification and personality assessment of that person [14]. The speciality of data stored in block chain is that it is distributed. Blockchain technology enables the distributed public ledgers that hold immutable data in a secure and encrypted way and that ensure transactions can never be altered [26]. Thereby we can ensure that the personal data such as Drug usage history cannot be altered.

## 4. RESULT

Drug abuse detection platform is a framework that is used to detect drug usage among people by continuously monitoring a person and collecting the required feature values without making any uneasiness to the body of that person. For that the modern technologies like E3 band and ECG sensors are efficiently used. The experiment shows that the data from both devices are accessed in a timely manner and data accuracy is also helped to generate correct prediction. Here we use two machine learning techniques, one is Multi Layer Perceptron- that gives 81 present prediction accuracy to the validation set and other one is Support Vector Machine- we validated all the five SVM models and each has a prediction accuracy of above 75 percentage. For the prediction of "drug usage" using an ECG sensor we trained different classifiers and evaluated the performance of all of these classifiers. The different classifiers are SVM, Decision Tree, Naive Bayes, K-Nearest Neighbour [24].

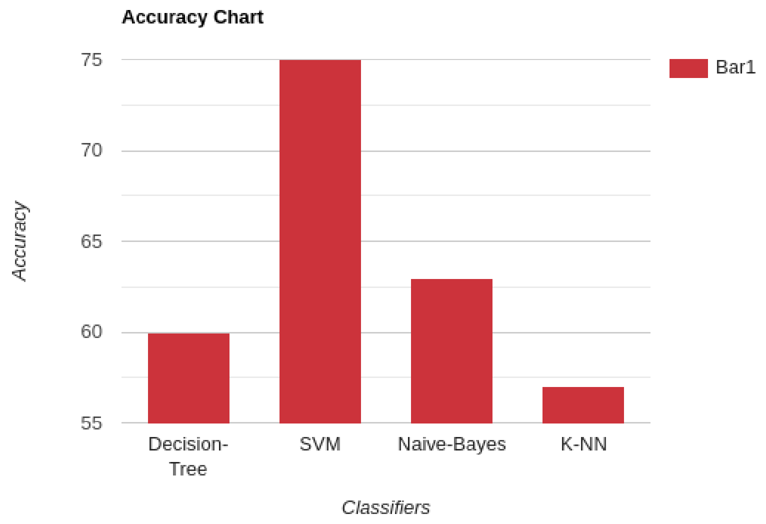


**Fig -18**: Comparison between different classifiers

Among all these trained models Support Vector Machine has the highest accuracy on unseen data set, that is the reason behind the adoption of SVM model for ECG data [28]. Next aspect before implementing a model to the system is the optimum number of training sets that are required for each chosen machine learning model. Required condition is that the model would not suffer from overfitting. Overfitting is a modeling error that may occur when a function is too closely fit to a set of data points, so that the model may not work well for unseen data points as it works for a training set. From figure 19, it is evident that accuracy of both models(SVM and MLP) increases initially and comes to a peak then it falls on an increasing number of training sets [21]. The usage of Blockchain technology is an added benefit in a way that the distributed public ledger ensures the immutability of stored drug usage information of a person.

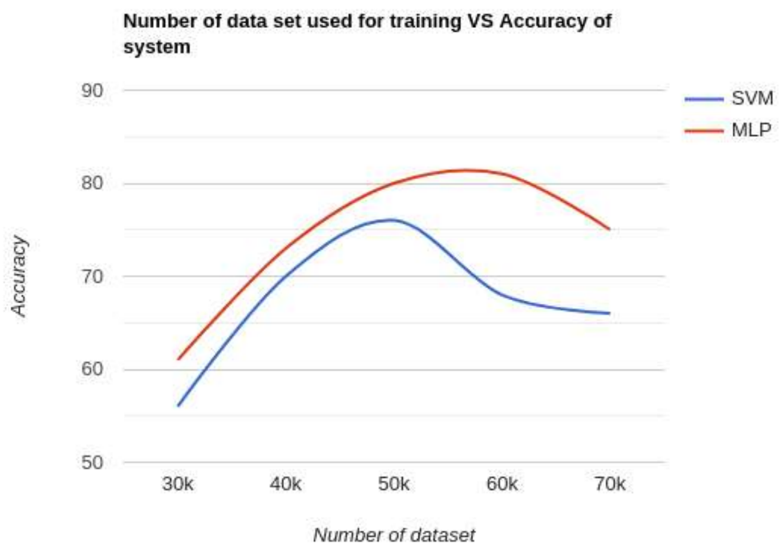


**Fig -19**: Performance with different number of datasets

## 5. CONCLUSIONS

The proposed system is implemented as a way to continuously monitor drug consumption among the youth, in particular cocaine usage. The existing drug detection methods like blood test, urine test, hair test, sweat test etc, all of these lack live monitoring [30]. Another major issue is that all these tests require large processing time. So, our system is designed to overcome these challenges. The proposed system consists of basically two parts which are E3 wristband and ECG sensor for continuous and efficient data monitoring. E3 band monitors the individual's heart beat, heat flux, body temperature, EDA(Electrodermal Activity), GSR(Galvanic Skin Response) and so on. This data is then fed to a previously trained MLP regressor. The ECG sensor is used connected with Arduino UNO to collect the ECG signal for further processing. This collected data is then fed to a previously trained SVM classifier. The results obtained from both of these are then combined using Fuzzy Logic Toolbox. The generated result is then used to estimate the severity of drug consumption in a more accurate manner.

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