

The Critical Application of Internet of Things (IoT) in the Overall Development of Education

Sunil Chahal

Director- Technology Delivery, Concepts IT Inc.

messc0610@gmail.com

Abstract

The advent of internet IoT devices can be used in any kind of industry for its growth. The applications and benefits of IoT in the education industry are diverse. The teachers and the parents can collect the personalized data about students in the classrooms and use them to improve the personalized learning using this will not disturb their learning process. The schools with limited valuable resources can make use of IoT to control the students from overusing activities which will be helpful to other students to utilize the resource. IoT helps the teacher to see the full view of students' mental state, stress level with the help of their heart rate. In this paper the IoT is used as a wearable band. The band will be tied on the hand of the student to monitor the vital readings of heart beat over the time during the school hours. The vital readings are compared with the standards. If the deviation between the actual and the standard found is large scale then it would be informed as alert to the class teacher for further action. Usually this can be used to give counseling to the students having difficulties, stress in different activities as part of the curriculum.

Keywords: IoT devices, Education Industry, Heartbeat, Wearable band.

1. Introduction:

A digital stress monitor is an Internet of Things gadget that uses a person's cardiac reading to gauge how stressed they are. Similar to when someone is experiencing a heart attack, or myocardial infarction as it is termed medically, the student is anxious experience an increase in their heartbeat [1][6]. This gadget records a person's heart rate locally and sends it to a server on Digital Ocean. The server performs all of the calculations, and it is the server that determines whether or not the student is anxious. Which creates a graph using the information from each server-system. The development board is a Node MCU, and the programming language is micro-python [2]. An interpreter called Read Eval Print Loop) used to run the micro-python code. This is a high level scripting programming language shell which accepts a one user inputs, runs it, and then gives the user the results. Additionally, a pulse sensor is used in this study to figure out the pulses from the source of the heart rate was determined. Strong links among the pressure and cancers and cardiovascular diseases, as well as other grave conditions have been observed in the medical community. Additional tension was demonstrated for damage inflammatory response

and decrease performance in all success metrics [3][5]. Stress is extremely difficult to detect and cannot be measured.

Through the association of tension and heart rate, may determine the variety of system, such as may or may not a student is tense, whether they are fearful or apprehensive, whether they are exercising, whether they are over trained, and many other things [4]. [7]. each application has a large user base and is used extensively from healthcare sector. Furthermore, there exist a minimum number of samples that include information on a user's normal heart-beat rate and high heart-beat rate, along with the ones that do provide information on just 200 individuals are insufficient to develop a machine learning method. By using this paper, we may quickly and simply compile accurate information on various students. Additionally, when exercising, our heart rates should be increased, particularly if we are performing any cardio-exercise and it is age-dependent. Given that most individuals now exercise every day, it is important to determine whether they are exercising properly else not exercising properly.

2. Literature of Review:

The variations in heart-beat rate for each heart beats are referred to as heart-beat variability. As per the NIH (National-Institute of Health) adults, children over the age of 10, and infants typically have resting heart rates between 60 and 100 beats per minute. Infants typically has the heart beat that exceeds 100 beats per min. The relationship among heart rate and fitness is linear [8]. The well-experienced sports student may have a heart beat as low as 40 beats per minute, but a student in perfect size may have the heart beat of 50 – 60 beats per minute in idle state. [9]. The average student's heart rate may vary from the base level of 60 and 80 beats per minute. There are a number of factors, such as environmental stressors and physical and mental workload that limit the diagnosticity of heart rate. According to the job strains model of demand control, students are more likely to experience job stress in positions where they have little support from the society and they have no advantage of their daily routine, or When ever if any inequality exists among the work and the employee's capacity cope with the needs [10].

Long-term conditions may result in cardiovascular illnesses. When under stress or anxiety, a person's heart rate clearly increases, but each person's response is unique. A cardiac surgeon claims that due to the nonlinear nature of heart rate, it is challenging to determine age from it. However, if we know a person's age, we can utilize their heart rate to determine if they are healthy, unhealthy, or over trained. According to studies, athletes are over trained if they had the greater heart rate during the idle at seven during early morning for minimum or more days in a row. An athlete's strength and fitness may decline as a result of overtraining. The maximum heart rate that a person can have is $(220 - (\text{his/her age}))$. During cardiac arrest, doctors charge the defibrillator using this as guidance. When exercising or doing daily routine while on gymnasium, a student heart beat must be within the range 50% and 70% of 220 minus his or her age. He needs to work out harder if his heart rate is lower [4][6].

3. Design and the Implementation

a. Method Used

Thus the created model uses a student's heart rate variability to determine whether they are under stress. Additionally, it can assist in identifying patterns of variations in a person's heart rate when they are exercising in a gym. Each device is unique and requires calibration in order to work properly. The individual performing the calibration should be at ease and should be sleeping. This is accomplished establish a fundamental (figure 1), which the systems utilizes after calibration to detect whether the user is under stress or worried, over trained, or currently training (Fig.2). In order to maintain track of readings for a certain student, the server acts as the repository for storing the values of the heart beat rates of different students. and they are segregated with the help of the network ID of the user. They are represented graphically by scattered graph (Fig.5).

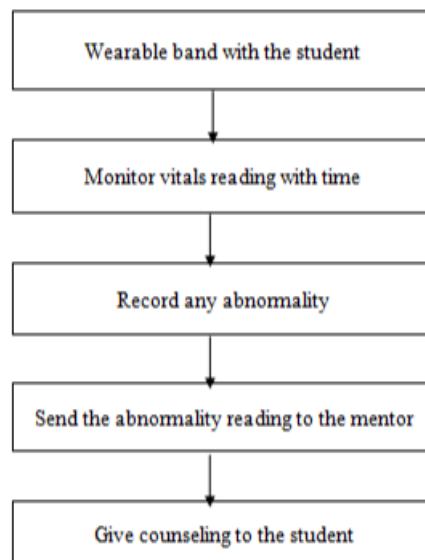


Figure.1. Data Flow Representation

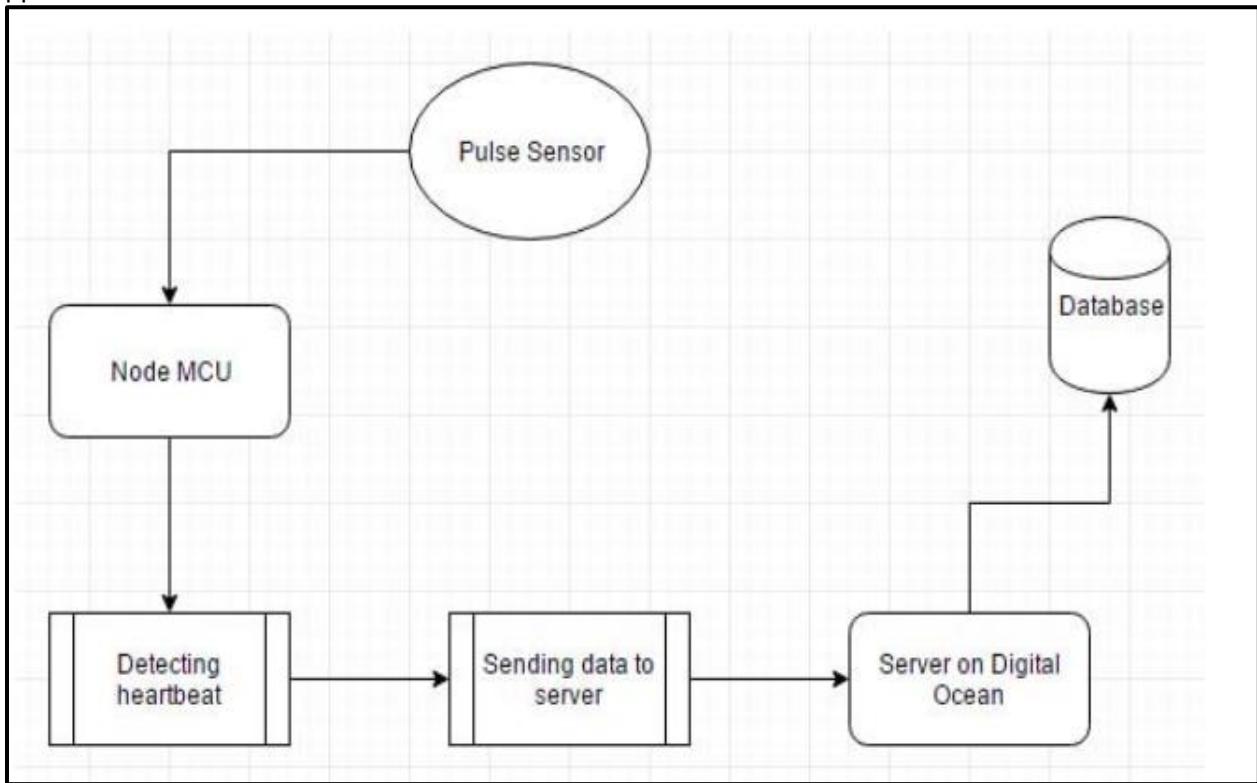


Figure.2. Block Diagram Representation

4. Hardware Requirements for Implementation

- Constituents employ Node MCU. It has an ESP8266 Wi-Fi module and a Tensilica Xtensa LX106 32-bit microprocessor with 160KB RAM, which is substantially superior than the Arduino UNO's 8-bit ATMega328P with 2KB RAM (Fig.3). It connects to Wi-Fi and works with micro python, a stripped-down edition of Python. It is quick and simple to use and offers flexibility.

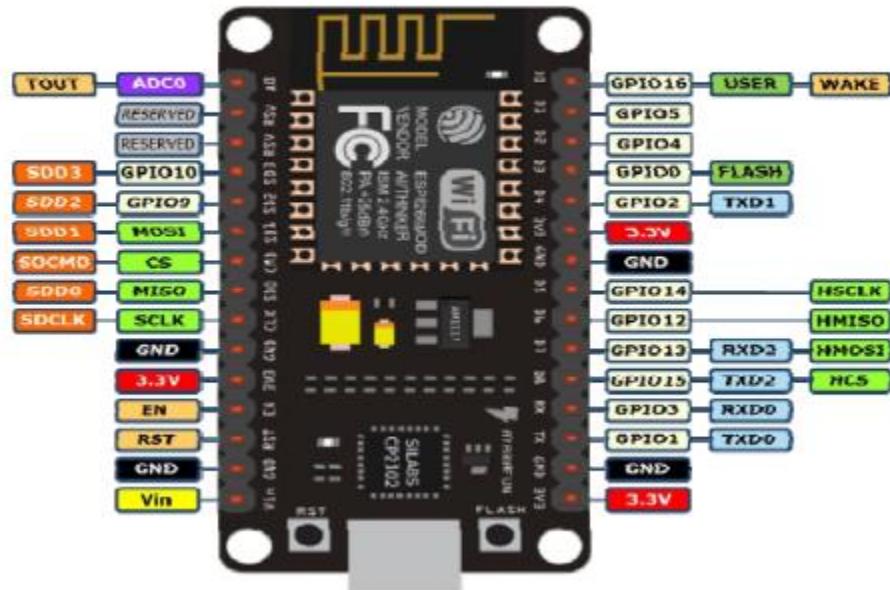


Figure.3. An MCU Node

B. Signal Pulse Detector

This measures body's signal pulse that is summed over the period of time to determine the heart beat. The heart rate information may be applied, with a variety of contexts, including athletics, healthcare, and among mobile app developers, among others. Monitoring our levels of stress and anxiety can be a part of our daily lives and may promote healthier living. By touching the sensor with the tip of a finger or by fastening the sensor to a wrist, it takes a reading. The threshold value of the pulse sensor, the range lies the value of 525 - 610, should be adjusted (Figure-4). One must add the number of pulses in a minute in order to calculate heart rate. Calculating the inter beat interval is used to achieve this.

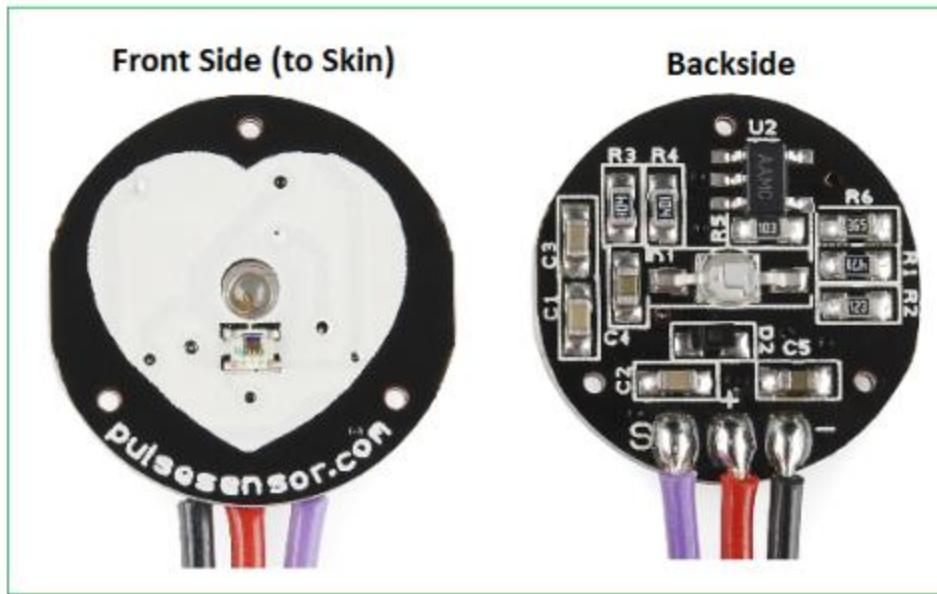


Figure 4. Pulse Signal Sensor

c. Program & Server Process

Regularly, MCU-node measures its pulse and sends the results to our webserver accompanied by a timeframe. Flask has been used to create the server, which has been set up on the cloud it running Ubuntu 16.04 LTS. Due to fact our paper does not require very powerful hardware, humans utilizing the cloud in most of the areas. A Server uses NginX to manage concurrent queries, responses as well as dynamic load-balanced on top of a Gunicorn WSGI Server with a Flask overlay. The server is constructed using the Restful API and MVC Controller model, exposing a number of endpoints to the user. The index parameter enables users to view visualizations of the data uploaded to the server and their current level of stress. The healthtracking portion of our paper is exposed by the / endpoint, which uses the age given in the response to assess Figure 6 as well as figure 7 depicts if a student doing exercise or not. The target is the one of the place the sensing device information forwarded through the MCU-node. A responder builds up the secured file of the student's heart rate throughout the day throughout time. This process can be utilized data base examine of responder to see the different period of a particular day when a student's heart beat is elevated above the benchmark as well as, the result, roughly estimate their anxiety levels. Additionally, utilizing the Application Programming Interface of G-Graph in addition with extra pictorial packages, the website creates representations of this data.

V. Findings and Analysis

We compute the stress labels of the student, identify the stressed median in our data set, and map that to our detector. Furthermore, while there are some relationships between age and resting

heart rate, it is not possible to draw a firm conclusion from them. Because the association between activity detection and 50–80% of maximum heart rate is precisely defined, our paper's exercise detection component performs effectively.

A. Pictures

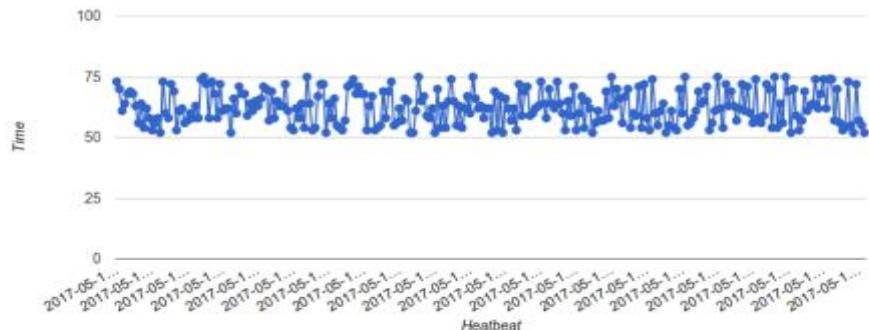


Figure 5: Time-versus-heart rate

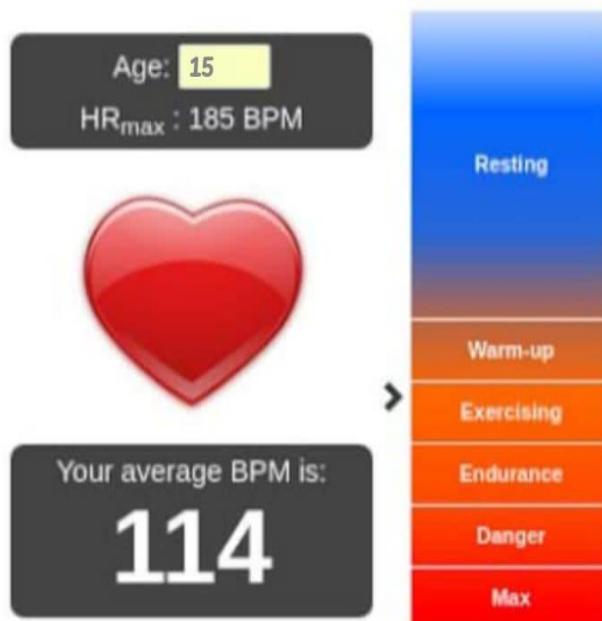


Figure 6: Identifying if student doing Exercise / Playing

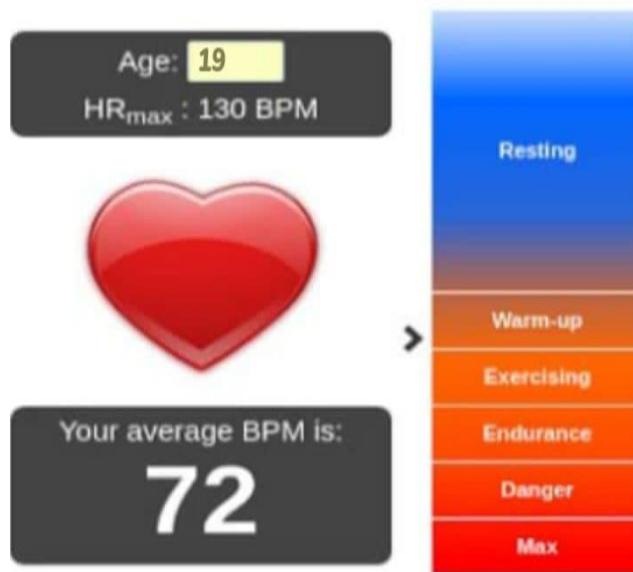


Figure 7: Identifying student's calm or at rest condition

Vi. Classification

A. Logistic Regression

A key component of supervised learning understands the relationship between two datasets: the watched information X and the external variable y that we are trying to predict, which is typically referred to as "target" or "names." The n sampling size of 1dimensional clusters are frequently what y is? Each supervised predictor in the scikit-learn really uses a fitt(a, b) function for fitting the models as well as predict(a) methodology to return the projected grades y given unlabeled perceptions X. The task is referred to as a grouping assignment if it is expected to organise the opinions in a set as far constrained marked and, which the conclusion of day, to "identify" the information observed. If, however, goal is for predicting the constant target variable, the work is referred to as a regression task. When the dependent variable is dichotomous, (LR) Logistic Regression is an appropriate suitablewaning analysis for the use as a guide (binary). The calculated relapse examination is a foresighted inquiry, just like any relapse examinations. In order to represent information and make a relationship among a single ward dual feature as well as minimum with one actual, numerical, intermediate or auto proportional grade factor clear, strategic relapse is used.

Process:

- Learning Volume = 318nos
- No. of parameters = 270 fields
- Using Classifiers
- Constructing Confusion-Matrix
- Estimating Learning as well as Assessment Correctness

B. Support Vector Machine (SVM)

An isolated hyperplane is the basic characteristic of a Support Vector Machine (SVM), which are computational method. In the end, the computation produces an optimal hyper plane that categorizes new situations provided identified preparation information (controlled taking in).

Process:

- Learning Volume = 318nos
- No. of parameters = 270 fields
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7. Evaluating Findings:

A confusion matrix, also defined as an error matrix, is just a particular table design that indicate how well a method of which the results of an algorithm, Figure 8 and 9 shows a supervised machine learning one (in unsupervised machine learning, it is typically referred to as a pairing matrix),, and its validation accuracy is shown in figs. 10 and 11. It is used in the field of machine learning, particularly the issue of statistical classification. The instances in a predicted class are represented in each column of the matrix, while the occurrences in an actual class are represented in each row (or vice versa). The name refers to how simple it is to determine whether the system is conflating two classes (i.e. commonly mislabeling one as another). Estimated tag is on the y-axis and real labelling appears on the x-axis in the confusion matrices below.

(i). Confusion-Matrix for the learned models

Confusion-Matrix of (LR) Logistic-Regression

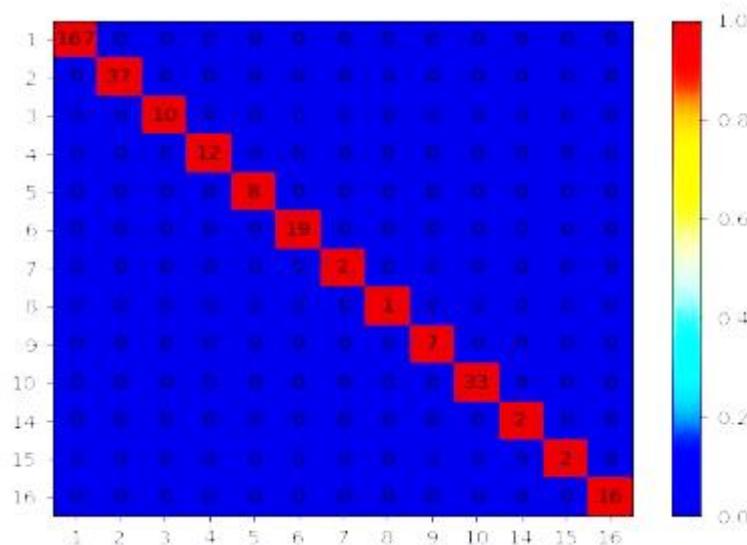


Figure 8: Measurement of Correctness (Accuracy) is 100 percentage

Support Vector Machine (SVM) confusion-matrix for the learned model

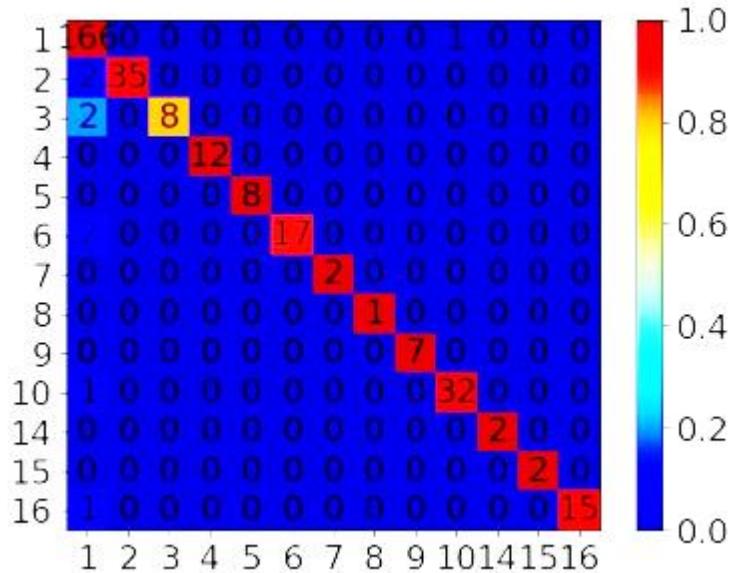


Figure 9: Measurement of Correctness (Accuracy) is 97 percentage

(ii). Validation Accurate Measures

(LR)Logistic Regression:

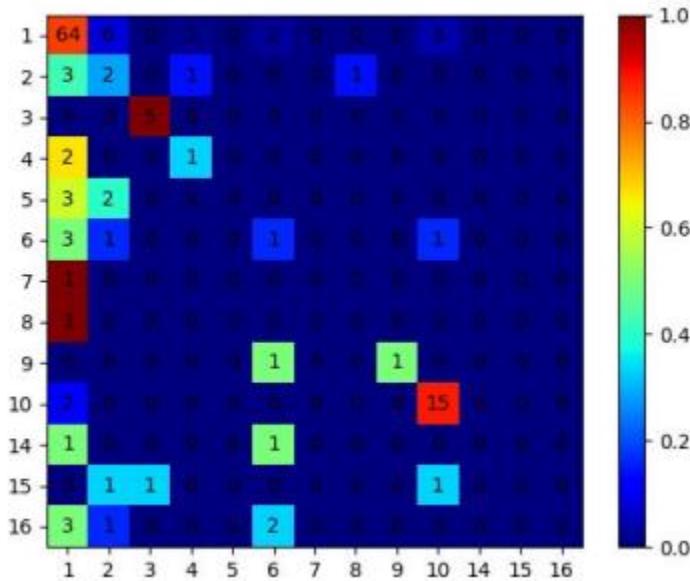


Figure 10: Measurement of Correctness (Accuracy) is 66 percentage

SVM - Support Vector Machine

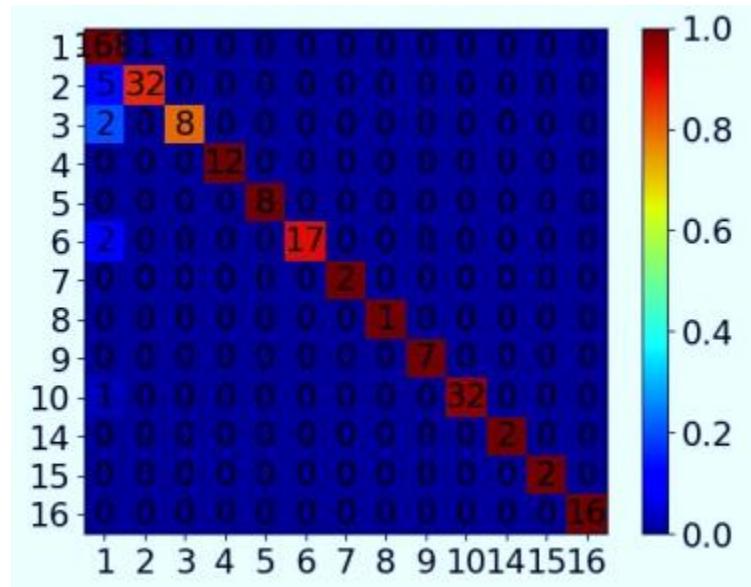


Figure 11: Measurement of Correctness (Accuracy) is 68 percentage

8. Conclusion:

The inaccuracy rate is determined by locating all incorrect estimates within perplexed matrices., which is then subtracted from 1 to determine the precision of the classifier.

Classifier	Train Accuracy	Test Accuracy
Logistic Regression	100 %	66 %
SVM	97 %	68 %

There are two classification techniques being used. The accuracy of the attribute frequency classifiers VF - 15 algorithms, that develops classifying gaps throughout learning then employs these to evaluate its classifiers, is 62%, while the exactness of the Bayesian classification algorithm Naive Bayes approach, which employs the Bayesian methodology, is 50% during testing.

Classifier	Test Accuracy
VF - 15	62 %
Naive Bayes	50 %
VF - 15 with weights to features	68 %

SVM and Logistic Regression were employed by the system, which significantly outperformed VF - 15 as well as Bayesian Network with no exterior biases. The balanced VF - 15's performance was

comparable to that of SVM, despite the fact that SVM did not use exterior weight, unlike the balanced VF - 15, which would have been developed through Genetic Algorithm. Using Logistic Regression and SVM, respectively, we obtain efficiency of 66% & 68%, showing an increase in efficiency after using SVM.

9. Future Scope:

The article offers information on measuring heartbeat applications furthermore acts like a foundation for future studies in the area. The article also encounters the problem of insufficient information, since all ML algorithms can only produce accurate observations or forecasts when this is used on accurate statistics. Therefore, the following stage of the current research might compile heartbeat observations from many people. Any safety and health checking equipment can be integrated with this task. In order to achieve better outcomes, the program analyses the student's heart rate as well as their daily activity pattern to detect when they are exercising and when they are stressed out.

This is because any device has the potential to issue a wrong alarm only when a user is not actually at risk. One among the most exciting potential and prevalent applications of the work is the ability to gauge the student's mood using his or her profile, daily heart rate readings, and galvanic skin response. We require high accuracy for critical analyses like arrhythmia and stress, which calls for additional data that is best obtained from devices like fitness trackers, smartphones, smart watches, and other similar devices. Additionally, brain systems (Neural Network) that perform properly on databases with a large amount of characteristics, can be used for higher precise modeling.

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