



IJIRCCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 9, Issue 6, June 2021

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 7.542



9940 572 462



6381 907 438



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Implementation of Stress Level Detection using Machine Learning

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ABSTRACT: Psychological stress affects physiological parameters of a person. Prolonged exposure to stress can have detrimental effects which might require expensive treatments. Acute levels of stress in people who are already diagnosed with borderline personality disorder or schizophrenia, can cost them their lives. To self-manage this important health problem in the framework of smart healthcare, a Machine Learning based system (StressLysis) is proposed in this article. The learning system is trained such that it monitors stress levels in a person through human body temperature, rate of motion and sweat during physical activity. The proposed Machine Learning system has been trained with a total of 26,000 samples per dataset and demonstrates accuracy as high as 99.7 percent. The collected data are transmitted and stored in the cloud which can help in real time monitoring of a person's stress levels, thereby reducing the risk of death and expensive treatments. The proposed system has the ability to produce results with an overall accuracy of 98.3 percent to 99.7percent, is simple to implement and its cost is moderate. Stress-Lysis can not only help in keeping an individual self-aware by providing immediate feedback to change the lifestyle of the person in order to lead a healthier life but also plays a significant role in the state-of-the-art by allowing computing on the edge devices.

KEYWORDS: Smart Healthcare, Ambient Intelligence, Internet of Medical Things (IoMT), Stress Level Detection, Deep Neural Network (DNN).

I. INTRODUCTION

Image Stress in humans can be classified into eustress, neustress and distress. Eustress is considered to be “good” stress and can motivate a person to elevated performance . Neutral stress is called neustress. As it does not cause any harm to the well-being of a person, it can be ignored. Stress with negative effects on the human body is called distress and is an important type of stress to focus on. Depending on its time characteristics, distress is classified into acute and chronic stress. Acute stress are short but intense levels of stress, while long term intense levels are considered as chronic stress. Chronic stress has very serious consequences on the healthy living of humans . Stress increases muscle tension and causes impairment in daily physical activity. Increase in stress levels can push a person to complex mental illnesses such as borderline personality disorder (BPD) which causes dangerous mood swings, change in behavioural patterns, eating disorders and provoke the stressed person to take unhealthy decisions. The Internet of Things (IoT) helps in creating seamless wireless health monitoring systems. Some significant IoT applications include secure surveillance systems , the smart grid, smart parking systems, smart healthcare and numerous other applications in smart cities . The “edge” IoT includes a wide range of sensors and actuators (“things”) wherein edge computations are performed. Edge computing involves intelligent processing closer to the things in order to reduce communication traffic and improve IoT response , . The edge also includes devices which collect and transmit real time data . The Internet of Medical Things (IoMT) is a particular application of the IoT consisting of primarily medical-related devices and services, such as on body sensors, smart gadgets, smart infrastructure, smart homes, emergency response, and smart hospitals, all connected through the IoT. One of the primary applications of the IoMT is real time monitoring, which leads to better emergency response, provides easy but controlled access to patient data, remote access to healthcare and connectivity among stake holders in the smart healthcare framework .

II. RELATED WORK

Though consumer electronics for smart healthcare has a great potential to improve the quality of our lives, its usage is limited based on its accuracy and reliability. Research in consumer electronics for smart healthcare has been focused on assisting visually impaired individuals [2], [3], monitoring physiological signals such as Electrocardiography (ECG) [4], heart rate [5], and wearables such as wrist gadgets, rings, patches, badges, glasses, and bracelets [1]. In [5], the researchers have proposed a wrist gadget for monitoring stress level using the heart rate, which has the limitation of detecting stress level during a high intensity workout. In such scenarios, though the increase in heart rate might help in burning more calories, it cannot identify the stress level of the individual. Other stress monitoring consumer electronic wearables include the Inner Balance by Heartmath, the Spire, the WellBe, Zensorium's Being, and Tinke. They use IR blood flow sensors with breathing as a parameter, patented respiration sensors, vibration motors, optical sensors, and three-axis accelerometers with small meditation sessions and breathing exercises as remedies. However, the complexity of the design increases the overall cost of these available systems. For monitoring stress level using different types of stressors, researchers have proposed biofeedback processes integrated with gaming [6], usage of mobile phones [7], monitoring linguistic outputs of an individual [8] etc. Biomarkers for stress level detection have been identified through ECG, respiration, skin conductance, and surface electrocardiography in [9], heart rate variability in [10], continuous monitoring of ECG, impedance and acceleration of the head in [11], and functional Magnetic Resonance Imaging (fMRI) in [12]. In [13] and [14] stress level prediction is performed with a fuzzy logic controller using sweat rate, step count and temperature as the stressors. However, this proposed system had only 150 samples of data thus affecting the accuracy and increasing its complexity, as the samples have to be entered manually in the system.

III. METHODOLOGY

A) Proposed Work :

In system , sensor system is used to monitor three parameters: humanbody temperature, sweat reduction rate and motion detection.

- The sensor inputs from the human body are received and stress analysis done using Machine Learning and the stress detection unit.
- The stress level is classified as low, normal, and high

B) System Architecture

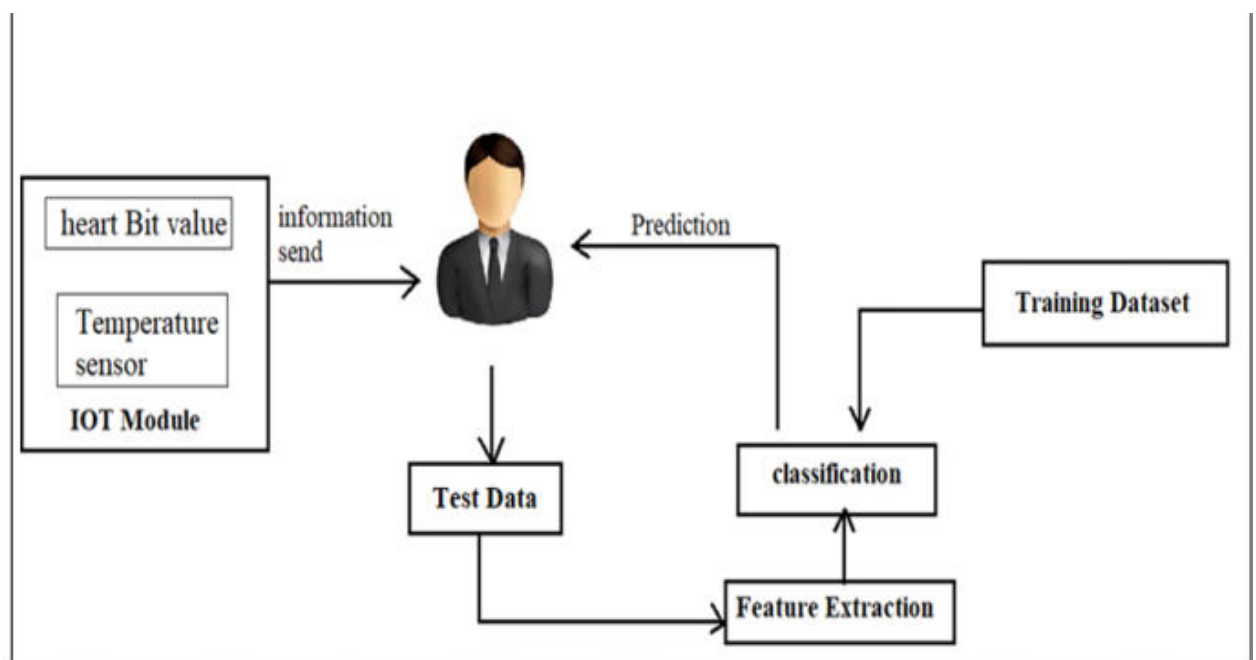


Fig: System Architecture

C) Modules :

1. Machine Learning:
The Inputs from sensors are analyzed through earlier results to give results for stress level
2. IOMT:
Sensors are used to detect three parameters human body temperature, sweat and motion detection

D) Algorithms

1) SVM

```

Input: D dataset, on-demand features, aggregation-based features,
Output: Classification of Application
for each application App-id in D do
  Get on-demand features and stored on vector x for App-id
  x.add ( Get-Features(app-id));
end for
for each application in x vector do
  Fetch first feature and stored in b, and other features in w.
  hw,b (x) = g (z) here z= ( wT x + b)
  if (z > 0)
    assign g(z)=1;
  else g(z)=-1;
  end if
end
end
    
```

2) Decision Tree

1. Check if algorithm satisfies termination criteria
2. Computer information-theoretic criteria for all attributes
3. Choose best attribute according to the information-theoretic criteria
4. Create a decision node based on the best attribute in step
5. Induce (i.e. split) the dataset based on newly created decision node in step 4
6. For all sub-dataset in step 5, call C4.5 algorithm to get a sub-tree (recursive call)
7. Attach the tree obtained in step 6 to the decision node in step 4
8. Return tree

3) KNN

K-nearest neighbors (KNN) algorithm is a type of supervised ML algorithm which can be used for both classification as well as regression predictive problems. However, it is mainly used for classification predictive problems in industry.

Step-1: Select the number K of the neighbours–

Step-2: Calculate the Euclidean distance of K number of neighbours–

Step-3: Take the K nearest neighbours as per the calculated Euclidean distance.–

Step-4: Among these k neighbours, count the number of the Data points in each category.

4) Naïve Bayes:

Input:	Training dataset T, $F = (f_1, f_2, f_3, \dots, f_n)$ // value of the predictor variable in testing dataset.
Output:	A class of testing dataset.
Step:	<ol style="list-style-type: none"> 1. Read the training dataset T; 2. Calculate the mean and standard deviation of the predictor variables in each class; 3. Repeat Calculate the probability of f_i using the gauss density equation in each class; Until the probability of all predictor variables ($f_1, f_2, f_3, \dots, f_n$) has been calculated.
	<ol style="list-style-type: none"> 4. Calculate the likelihood for each class; 5. Get the greatest likelihood;

IV. EXPERIMENTAL RESULTS

- A) Experimental Setup:
The sensors are used to examine the stress level.

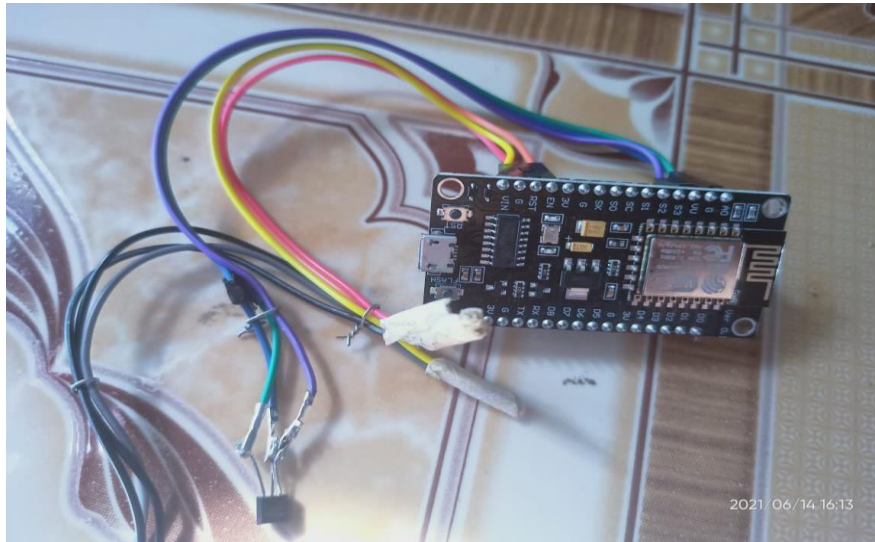


Fig: Experimental Setup

- B) Application Results

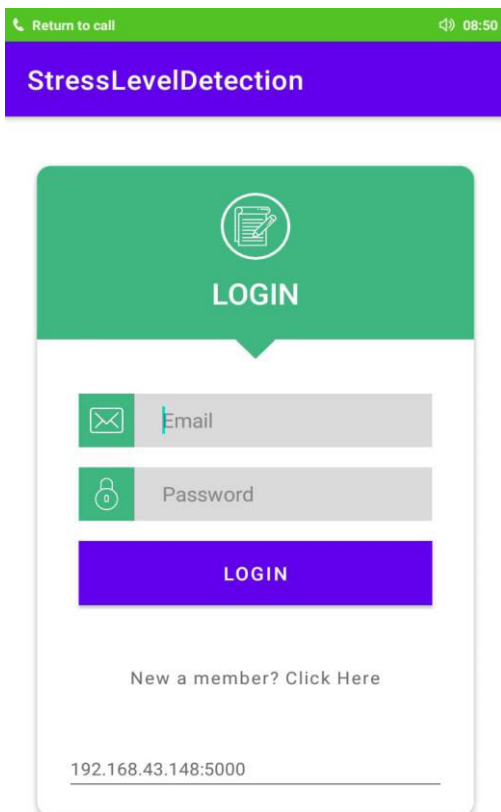


Fig: Login Screen

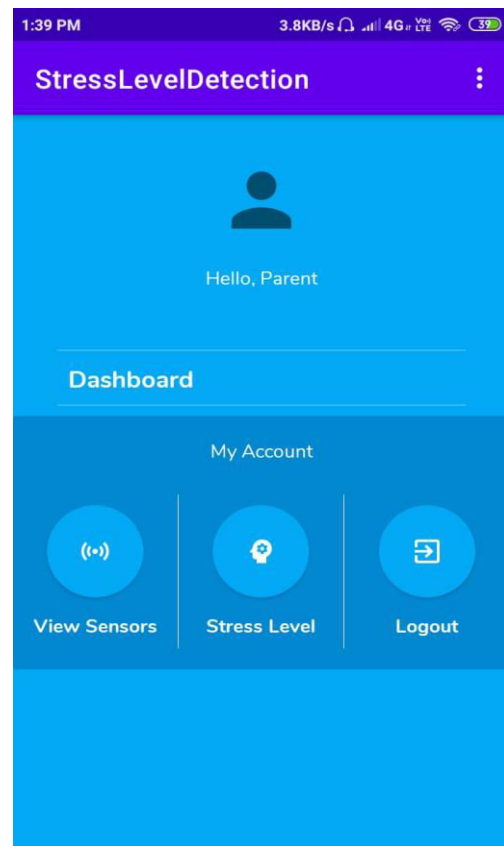


Fig: Dashboard

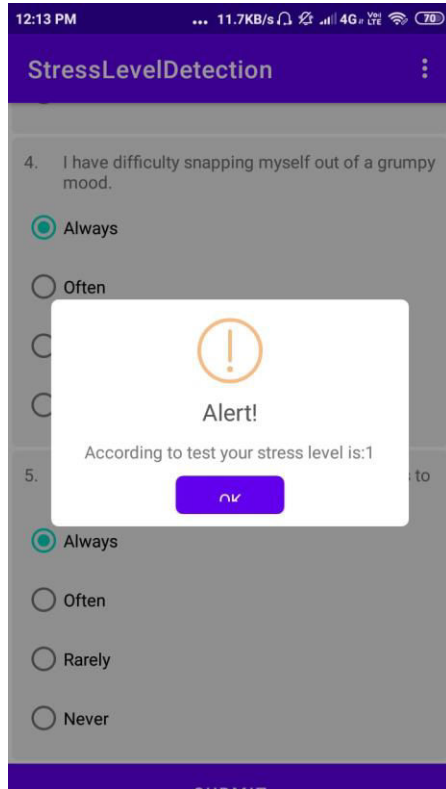


Fig : Alert for Stress level

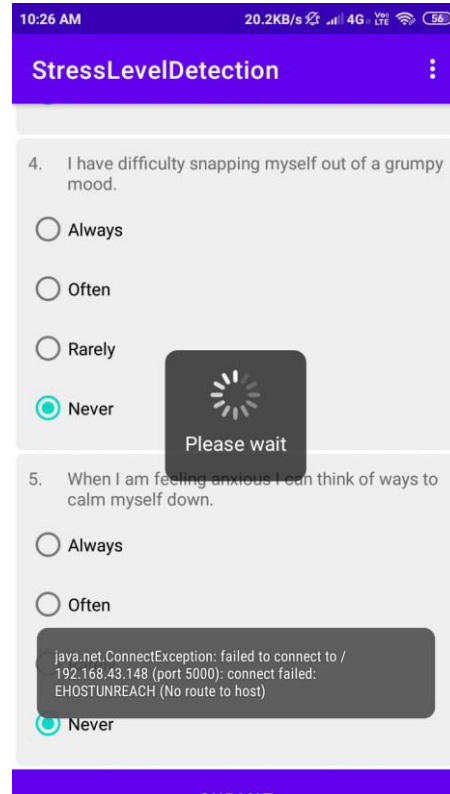


Fig: Quiz for Detection

C) Analysis Results:

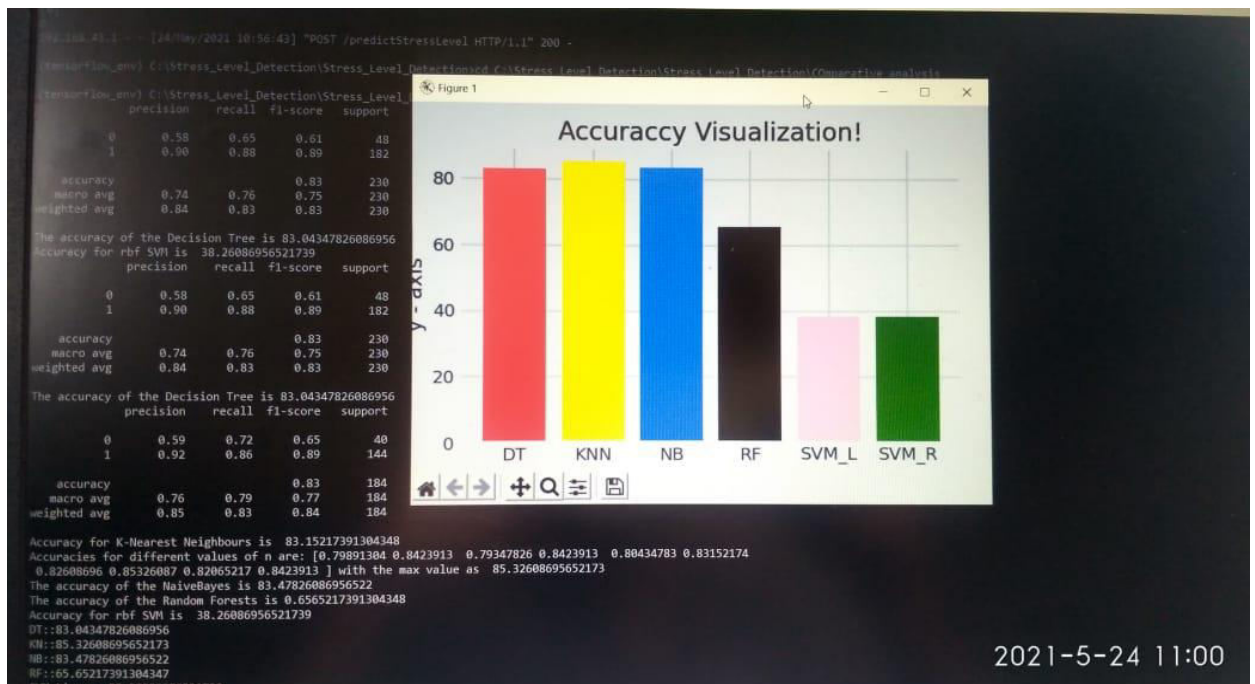


Fig: Accuracy Model for Machine Learning Algorithm

V. CONCLUSION

A system for stress detection has been developed. In addition to helping the user in achieving emotional balance, the system helps in monitoring chronic stress from early stages. A deep learning system will be developed and tested with three different datasets with sample sizes of 2000, 4000 and 20,000. The training of the system is done with 6733 framework is done in real-time with the help of available frameworks. The results when the system is tested with the training set were accuracy is calculated. The accuracy and loss plots confirm that as the sample size increases accuracy. A GUI implementation of the concept is used to represent the ease of use the system which can later be developed as a mobile application. This GUI is displayed and connected to an IoT cloud for data access and storage. The different combinations of the stress, namely low, medium and high are displayed. Low level signifies no stress. Medium level signifies presence of stress while high level signifies stress on high level and medical steps should be taken to take care of same.

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