Stress-Lysis: An IoMT-Enabled Device for Automatic Stress Level Detection from Physical Activities

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***Abstract*—This is an extended abstract for a Research Demo Session based on our published article [1]. Physiological signals inside the human body depend on various factors. One of those important factors is psychological stress. Long term exposure to stress has many negative effects which may lead to major health issues such as cancer. Monitoring such long term, high impact stress is very important to maintain a healthy emotional balance. Keeping this in mind, Stress-Lysis, a smart healthcare framework is proposed. Through Stress-Lysis, an approach is proposed to not just monitor stress but also allow the user to live a happy, stress-free life. This is achieved with a wearable, edge level processing device.**

***Index Terms*—Smart Healthcare, Internet of Medical Things (IoMT), Stress Level Detection, Machine Learning**

I. Introduction

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 [2]. Neutral stress is called neustress. Distress can have negative impact on the human body. Depending on its duration, it can be classified as acute or chronic stress. Acute stress lasts for short periods of time with low intensity, while chronic stress is experienced for longer intervals of time with more intensity. Prolonged chronic stress can cause many disorders including insomnia [3] and overeating [4]. Stress has a significant impact on the quality of life [5].

Using the concepts of Internet-of-Medical-Things (IoMT), Stress-Lysis, a stress detection device is introduced in this work. Stress-Lysis has the potential of extending its applications by being able to integrate with other real-time devices existing in the market. Though there are a good number of marketable devices in the literature, the relationships between chronic stress and methods to monitor stress are not utilized.

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II. The Proposed IoMT-based Stress Detection System - Stress-Lysis

A. Proposed Novel IoMT Based Architecture

Fig. 1 represents the architectural description of the proposed model. The input sensors take the signal data which is transferred to the unit where the stress state classification to low , medium and high states is performed. The previously analyzed data along with the present data is stored in the cloud, using the Internet. Fig. 2 shows the flow of training and testing the machine learning models.

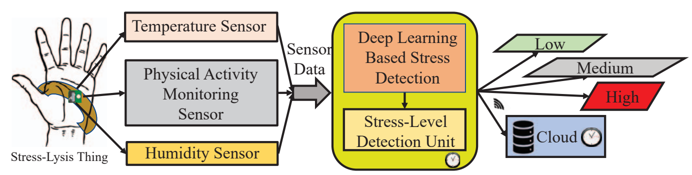


Fig. 1. The proposed architecture of the Stress-Lysis system [1].

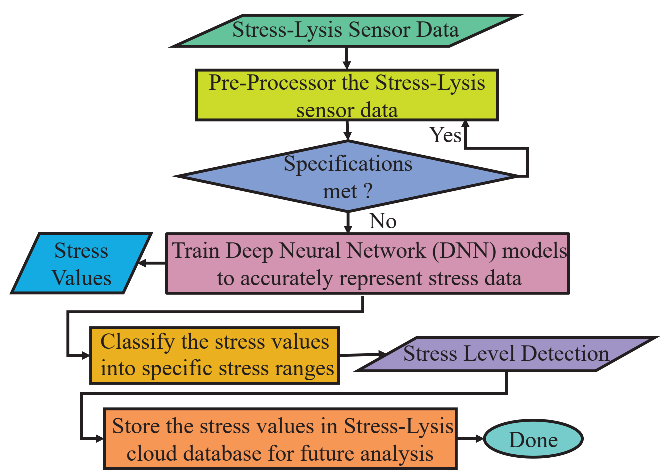
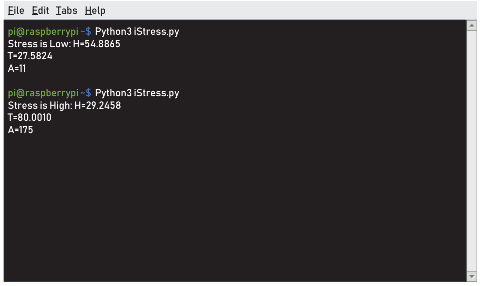


Fig. 2. The proposed algorithm for stress detection in Stress-Lysis [1].

B. Design of Stress-Lysis Sensing Wrist Band

1) Sensor for measuring Body Temperature Variability: The mental state along with the physical condition of a human body can be analyzed by observing the body temperature variations. The fluctuations in temperature for a specific period of time are known as its rate. A contact sensor to monitor this rate is used in Stress-Lysis.



(a) Serial Monitor Window

(b) CE Cloud Server Connectivity.

Fig. 3. Stress data analysis using the developed Stress-Lysis prototype [1].

TABLE I
RANGE OF SENSOR VALUES [1].

Sensor	Low Stress	Normal Stress	High Stress
Accelerometer (steps/min)	0-91	92-129	130-200
Humidity (mg/min)	10.00-15.00	15.01-20.00	20.01-30.00
Temperature (°F)	79.01-84.00	84.01-95.00	95.01-99.00

2) Sensor for Sweat Analysis: A physical component which is released from the skin of a human body is sweat. Reasons for the secretion of sweat include physical exercise, stress, exposure to heat, etc. A humidity sensor is used to detect the moisture released in the palm area in Stress-Lysis.

3) Sensor for Activity Monitoring: The rate of change in velocity under certain forces is defined as acceleration. The causing forces for the velocity change could be static or dynamic. Here, the steps taken by the person along with the other body movements like sitting, standing, walking, running etc. are considered.

C. Deep Learning Modeling of Physical Activity Monitoring

A Deep Neural Network (DNN) model is trained and tested with a total of 26,000 samples which are acquired from three different data sources. The data samples are of size 2,000, 4,000 and 20,000 taken from [6], [7], [8]. The machine learning model uses the stress ranges with appropriate sensors. as shown in Table I.

III. CONSUMER ELECTRONIC PROOF-OF-CONCEPT USING OFF-THE-SHELF COMPONENTS

In order to not overwhelm the performance of the single board computer (SBC) used, 2,000 data samples have been used for testing and training the DNN model. The outcome from the SBC analysis along with the IoT storage can be observed in Fig. 3. A minimum accuracy of 98.3% and maximum accuracy of 99.7% are observed. The cost of implementation, easiness in design, no human entry methodology and low power usage are advantages of this implementation.

IV. CONCLUSIONS

A new methodology to monitor the stress level fluctuations is presented through Stress-Lysis which has the potential of controlling and monitoring chronic stress from an early stage. A total of 16,000 data samples have been used to train and test the model with an accuracy approximately in the range of 98.3% to 99.7% and a loss of less than 1%.

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