Stress-Lysis: A DNN-Integrated Edge Device for Stress Level Detection in the IoMT

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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 deep learning based novel system (Stress-Lysis) 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 deep learning system has been trained with a total of 26,000 samples per dataset and demonstrates accuracy as high as 99.7%. 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% to 99.7%, 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.**

***Index Terms*—Smart Healthcare, Ambient Intelligence, Internet of Medical Things (IoMT), Stress Level Detection, Deep Neural Network (DNN)**

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 [1]. 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 [2], [3]. 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 behavioral patterns, eating disorders and provoke the stressed person to take unhealthy decisions [4], [5].

The Internet of Things (IoT) helps in creating seamless wireless health monitoring systems. Some significant IoT applications include secure surveillance systems [6], [7], the smart grid, smart parking systems, smart healthcare and numerous other applications in smart cities [8]. 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 [9], [10]. The edge also includes devices which collect and transmit real time data [11].

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 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 [12].

Through this research we have developed an accurate, rapid stress level detection IoMT system, called "Stress-Lysis", that can detect stress level at the user end (at the edge) while storing the data in the cloud. The proposed Stress-Lysis sensor system can be easily integrated in a glove or a palm-band to monitor stress levels in real-time. The overall objective is to provide a solution to the monitoring of the stress levels of a person by developing an intelligent system which helps in maintaining the emotional balance of the users, as shown in Fig. 1.

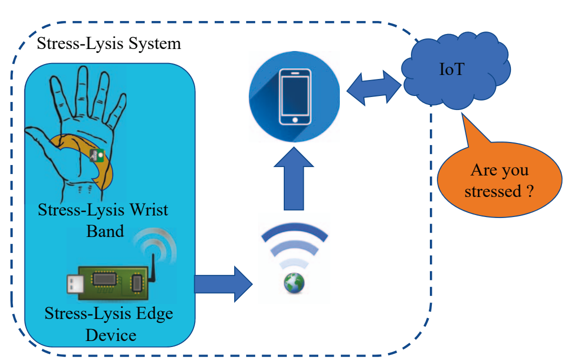

Fig. 1. Conceptual overview of the proposed stress-level detection system.

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This paper is organized as follows: Section II highlights the novel contributions of this paper. Section III presents existing related research. A detailed presentation of our research is given in Section IV. Section V discusses the proposed novel approach for accurate analysis of stress level. Section VI validates the model with implementation results of the proposed system. Section VII presents the proposed solution within a Consumer Electronics (CE) framework, and section VIII concludes the paper.

II. Novel Contributions

The proposed Stress-Lysis system, when developed into a wearable can allow individuals to monitor the naturally occurring parameters, and track their estimated stress levels without any manual interaction. When deployed, this system will be of benefit in the fields of smart healthcare. A cloth band across the palm can be the final fabricated device with sensors incorporated. The network connectivity can be made using Wi-Fi with which the measured data can be stored in the cloud allowing for easy, controlled access. The display unit of the device lets the user know the status of stress allowing for immediate relief measures.

The **novel contributions of the current paper** can be summarized as follows:

- A novel, accurate, and rapid stress level detection system that acquires and models sensor data, and detects stress level at the user end (at the edge) and stores the data in the cloud.
- A novel real-time deep learning system for accurate stress detection from physiological activity.
- A novel consumer electronic proof of concept with Deep Neural Networks (DNN) deployed on edge devices, thus contributing to the advancement of the state-of-the-art.
- A novel approach that combines human body temperature, rate of motion, and body sweat to accurately detect stress rapidly, in contrast to existing approaches which use only a single parameter.
- A novel smart sensor device that uniquely quantifies the body temperature, rate of motion, and body sweat for fast and accurate stress level detection.
- A hypothesis to monitor stress level in real-time based on daily activities is proposed.

III. Stress Detection Approaches: State-of-the-Art

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 [13], [14], monitoring physiological signals such as Electrocardiography (ECG) [15], heart rate [16], and wearables such as wrist gadgets, rings, patches, badges, glasses, and bracelets [1].

In [16], 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.

A taxonomic representation of various stress detection systems is represented in Fig. 2. The classification is done based on the type of sensing device, the cause of stress, and the type of computing. In this figure, "things" refers to any physical device such as sensors, actuators etc., that has its own IP address and can connect to a network to send/receive data [9]. "Stressors" are the behaviors that stimulate the signals detected by the sensors used. Computing in the data preprocessing stage can be done at the edge, the fog, or the cloud. Computational facilities near the sensor are called edge, while computations between the sensors and the cloud are called fog.

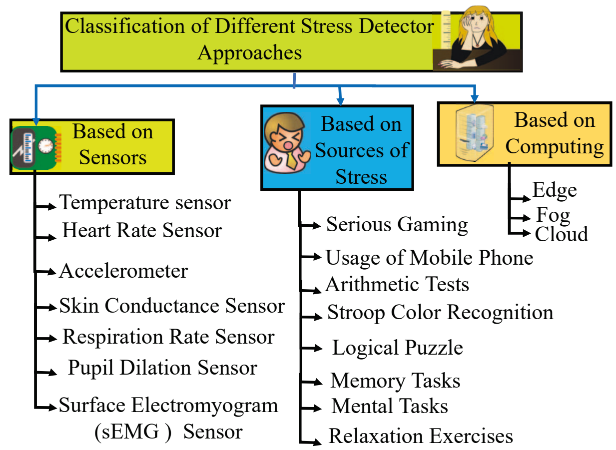


Fig. 2. Taxonomy of different stress detection approaches.

For monitoring stress level using different types of stressors, researchers have proposed biofeedback processes integrated with gaming [17], usage of mobile phones [18], monitoring linguistic outputs of an individual [19] etc. Biomarkers for stress level detection have been identified through ECG, respiration, skin conductance, and surface electrocardiography in [20], heart rate variability in [21], continuous monitoring of ECG, impedance and acceleration of the head in [22], and functional Magnetic Resonance Imaging (fMRI) in [23].

In [24] and [25] 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.

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

The proposed IoMT-based stress detection system is developed based on a hypothesis which can help in monitoring acute and chronic stress. The proposed hypotheses and architecture along with the sensor design are explained in the following subsections.

A. Proposed Hypothesis for stress level detection

The main contribution of this research includes developing a real-time stress detection system, Stress-Lysis, with physical activity as the stressor. Through the Stress-Lysis system, we propose a hypothesis as follows:

Hypothesis: *By monitoring acute stress levels through variation in temperature and sweat during different physical activities, biomarkers for chronic stress can be detected.*

Background: This is based on the fact that physical activity produces endorphin, which is the "feel good" hormone produced by the human brain. Increase in stress levels, can limit the production of endorphin, therefore limiting the benefits of physical activities [3]. With the increase in the number of steps taken per minute, the number of breaths per minute also increases along with the heartbeat and stress of the human body [26], [27]. When the sweat content on the basic parts like palms and face increases, the stress levels of a human being also increase linearly [28], [29]. The temperature of the human body changes with the blood flow in the body. When the hands or feet are cold, the stress levels are high. Warmer hands or feet indicate that the stress levels are normal [30]. The following subsections define the proposed design at the architecture-level and sensor-level.

B. Proposed Novel IoMT Based Architecture

To support our hypothesis, we designed the Stress-Lysis sensor system to monitor three parameters: human body temperature, sweat reduction rate and motion detection. The overall architecture of the Stress-Lysis system is represented in Fig. 3. The sensor inputs from the human body are received and stress analysis is done using deep learning and the stress detection unit. The stress level is classified as low, normal, and high. With the help of Wi-Fi, cloud connectivity is available which helps for storing present and previous stress levels at certain intervals.

C. Design of Stress-Lysis Sensing Wrist Band

1) Sensor for measuring Body Temperature Variability: Body temperature is a primary symptom for any major or minor health issues. By searching for patterns in the temperature variation, the physical and mental condition of a person can be analyzed. Temperature rate is the rate of variation of body temperature within a given amount of time. Generally, temperature sensors can be classified in 2 types: Contact temperature sensors that measure temperature when placed on the body and non-contact sensors that measure infrared or optical radiation received from any area of the body. In this work we modeled a contact temperature sensor that can monitor the rate of variation in body temperature.

2) Sensor for Sweat Analysis: Sweat is defined as the physical quantity which is released through the pores of the skin in certain quantities as a reaction to heat, physical exercise and emotional changes. As the sweat of the body increases, the current flow between two electrodes increases making the human body effectively a variable resistor [31]. Sensors that detect humidity can be used to monitor sweat secretion levels, which are controlled by the human central nervous system. Monitoring the amount of sweat generated can help in finding the stress and arousal levels of the subject monitored. Sweat gland activity as a variable is used in many biofeedback applications such as lie detection, and emotion recognition [32]. The process of normal sweating is called perspiration while an excess sweating disorder is known as hyperhidrosis and is associated with emotional, occupational and social stress. In this work a humidity sensor is used to detect sweat secretion on the palms.

3) Sensor for Activity Monitoring: Accelerometer sensors measure the rate of change in velocity of an object. They typically consist of three separate accelerometers mounted orthogonally on a 3-physical axis system (x, y, and z). The forces causing acceleration can be static or dynamic. The sensed voltage is generated when microscopic crystal structures get stressed by these forces [33]. In this work an accelerometer sensor is used to measure the step count of a person.

V. The Proposed Machine Learning based Novel Approach for Precise Detection of Stress-Level

The design methodologies used for developing Stress-Lysis are explained by a system-level flow chart while the machine learning modeling techniques for stress-level detection are discussed in the following subsections. Fig. 4 presents the proposed DNN based novel stress-level detection algorithm. The operational flow of the Stress-Lysis is also represented in pseudocode form with 3 straight forward combinations of sensor levels in order to determine stress level of a person in Algorithm 1.

A. Deep Neural Network (DNN) Theory

Deep Neural Networks (DNN) or Deep Learning Models are used in pattern recognition applications with very large larger datasets. An identification of the input patterns is done by the network in order to find out the associated output pattern. In other words, a model determines the relationship between features and the label. A standard neural network consists of many simple connected processors called neurons. Input neurons get activated from the sensors perceiving the environment and other neurons gets activated by their weighted connections from the previously activated neurons as follows:

$$z(X) = \sum_{i=1}^{N} (\omega_i x_i + \omega_o), \quad (1)$$

where $X = x_1, x_2, \cdots, x_n$ is the n-dimensional input, z is the response of the neuron, ω_i are the weights for each input and ω_o is a constant bias. A neural network with more than

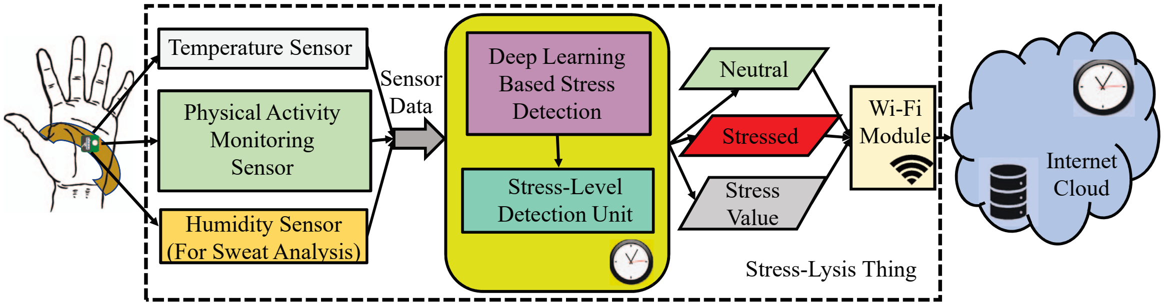


Fig. 3. The proposed architecture of the Stress-Lysis system.

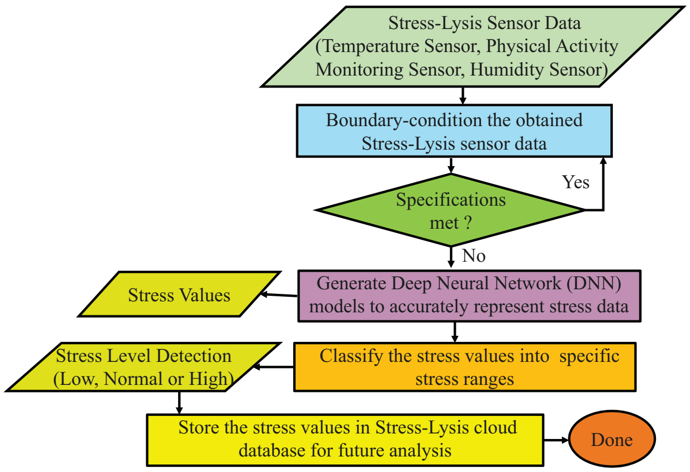


Fig. 4. The proposed algorithm for stress detection in Stress-Lysis.

three hidden layers can be considered a deep neural network layer. There are a number of neural networks such as feed-forward neural network or fully connected neural network, convolutional neural network, reverse neural network, etc. There are different types of activation functions such as sigmoid or logistic, Re-Lu (Rectified Linear Unit), soft-max, tanh, leaky Re-Lu, etc. The number of hidden layers and the neurons associated with each of the hidden layers are free parameters and can be considered at random. The output layer is where the network ends and the predictions are given.

Algorithm 1 Pseudocode for Stress-Lysis

1: Initialize the accelerometer sensor variable (acc) to zero.
2: Initialize the Humidity sensor variable (hum) to zero.
3: Initialize the temperature sensor variable (tem) to zero.
4: Get in and store the actual sensor data values to the assigned variables.
5: Feed the data to the DNN model.
6: Using tf.Transform remove the garbage values from the obtained sensor data.
7: **if** acc $<$ 91 and 10<hum>15 and 79.01<tem> 84 **then**
8:     assign stresslevel variable to low
9: **else**
10:     **if** 92<acc<129 and 15.01<hum>20.00 and 84.01<tem>95.00 **then**
11:         assign stresslevel variable to normal
12:     **else**
13:         **if** 130<acc<200 and 20.01<hum>30.00 and 95.01<tem>99.00 **then**
14:             assign stresslevel variable to high
15:         **end if**
16:     **end if**
17: **end if**
18: Repeat the steps from 7 though 17 for all the possible combinations in the epoch.
19: Classify the Stress Range by using the stresslevel variable.
20: To determine the efficiency of the system, calculate loss, accuracy of the model with the functions in the model.

B. Deep Neural Network Model for Stress-Lysis

As the Stress-Lysis system monitors stress data on a daily basis, a large amount of data will be generated. Hence, DNNs are used. In this work, a supervised learning mechanism is deployed, where the system will be trained with known outputs. In this work a fully connected neural network was used in which the neurons in one layer receive input connections from the previous layer. The number of neurons in the input layer corresponds exactly to the number of input features considered, here 3.

The detailed structural organization of the network is given in Fig. 5. This organization can be divided into three different stages: stage one has sensor inputs from the Stress-Lysis wrist band , stage two consists of a series of hidden layers which can help in analyzing the sensor inputs, and the third stage has the output as detected stress. With help of logistic regression, Stress-Lysis is designed as a classification model to predict one of n categories from m inputs. The series of hidden layers are represented as L1, L2, L3. In Stress-Lysis, the neurons at the three hidden layers are 10, 20 and 10, respectively. The number of neurons in the output layer corresponds exactly to the number of stress range classifications. After the boundary-conditioned sensor values (explained in Section VI) is fed to the network, the data goes through all the hidden layers where the weighed inputs to that layer are calculated using Eqn. (1). This produces a net input, as given in Eqn. (2) which is then applied to the activation functions to produce the output. The predictions at the output layer are produced as given in Eqn. (2). Given a layer i and its values $(x)_i$, the next layer j with values $(h)_j$ can be derived by:

$$h_j = f((W)_j, i \cdot (x)_i + (b)_j, i), \tag{2}$$

where $(W)_j, i$ is the weight matrix, $(b)_j, i$ the bias, and f is the Rectified Linear Unit (ReLU) activation function:

$$f(x) = \begin{cases} 1 & x > 1 \\ x & x = 1 \quad \text{and} \quad 0 \\ 0 & x < 0 \end{cases} \tag{3}$$

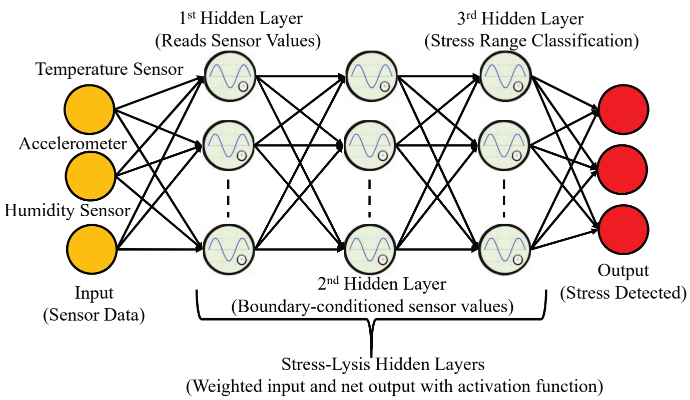


Fig. 5. Hierarchical learning used in Stress-Lysis.

The output layer does the classification and prediction of the input sensor data to a stress range using the soft-max function:

$$p = \text{softmax}(\omega \cdot x + b), \tag{4}$$

where ω, p, and b denote weight, predictor function and bias, respectively.

C. Proposed Methodology for training the Stress-Lysis DNN model

The process of helping the algorithm learn in order to make better predictions is known as training. The training loop feeds the datasets to the model in epochs. The Stress-level training epoch denotes the count at which the model should learn from the training set of the Stress-Lysis dataset. The steps involved in training the Stress-Lysis model are presented in Algorithm 2.

The predicted stress values must be compared to the real stress values in order to estimate the cost or the loss function, accuracy and confidence of the Stress- Lysis system [34]. In Stress-Lysis, the gradient descent algorithm is used in order to optimize the training algorithm. The Stress Prediction Accuracy (SPA), which can be defined as the skill of the Stress-lysis learning algorithm to predict stress levels accurately, is given as:

$$SPA = \left(\frac{TAS}{TSP} \cdot 100 \right), \tag{5}$$

where TAS and TSP denote the Total Accurate Stress Predictions and Total Stress Predictions made, respectively. The confidence of the Stress-lysis system defines the probability of the detected event to fall in different stress-level classifications. Instead of presenting a single error or accuracy value, a Stress Confidence Interval (SCI) is calculated by analyzing the stress interval radius (SIR) of each SCI as follows:

Algorithm 2 Proposed methodology for training of Stress-Lysis DNN models

1: Iterate each stress epoch.
2: Iterate over each variable of the Stress-Lysis dataset by considering the Stress-Lysis sensor inputs and output factor.
3: Predict stress ranges by using the boundary-conditioned Stress-Lysis sensor inputs.
4: Compare the detected stress outputs with the stress predictions from the previous step.
5: Calculate the Stress-Lysis training algorithm's inaccuracy.
6: Calculate the stress data loss and stress level detection accuracy in order to determine the overall efficiency.
7: Update the variables to predict stress levels with the help of optimized algorithm using the *Gradient Descent* algorithm.
8: *Repeat the above steps for the stress epoch count.*

$$SIR = z\sqrt{\left(\frac{(SPA \cdot (1 - SPA))}{n} \right)}, \tag{6}$$

where SPA is the detected stress accuracy defined from Equation (5), n is the Stress-lysis sample size and z is a critical value from the normal distribution [34]. The training and testing of the network are done using a dataset of 26,000 samples based on sensor ranges from Table I which tabulates the range of sensor values classified into 3 levels of stress: low, normal and high.

TABLE I
RANGE OF SENSOR VALUES.

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

VI. DNN MODELS OF STRESS FROM REAL-LIFE DATASETS

This Section presents DNN models which are derived from datasets to be integrated in the sensor for edge computing.

A. Deep Learning System Based Validation

The collected data from Sec. V-A are analyzed using Python and TensorFlow. TensorFlow is a framework which is designed to define and run computations with tensors. Tensors are vector generalizations to higher dimensions. The main objective of writing the program is to manipulate and pass around in the program a `tf.Tensor` object which will eventually produce a value. To address out-of-range, invalid and missing values from the datasets, data pre-processing is done with the `tf.Transform` library in TensorFlow which allows instance and full-pass data transformations through pipelines.

In the DNN, the activation functions are Re-Lu for the 3 hidden layers and soft-max for the final layer as it is useful for classification. The training dataset consists of 2000 samples with 1334 samples used for training while the remaining 667 are used for testing. The accuracy obtained is approx. 99% with 1500 training epochs. The confidence interval of the system using Eqn. (6) is 0.007. Thus the classification accuracy of the model is 99% ± 0.7%. This implies that the true classification accuracy of this model with 2000 samples lies between 99.7% to 98.3%.

Fig. 6 presents a graphical representation of the DNN. All connections can be checked and changes can be made in the program through TensorBoard. The training and testing for TensorFlow here is done with the ranges presented in Table I. Fig. 7(a) shows the accuracy plot with the number of iterations on the x-axis and the accuracy ranging from 0 to 1 on the y-axis. Fig. 7(b) presents the loss function plot. The loss function is the function which is meant to minimize the error in the network over a certain number of iterations.

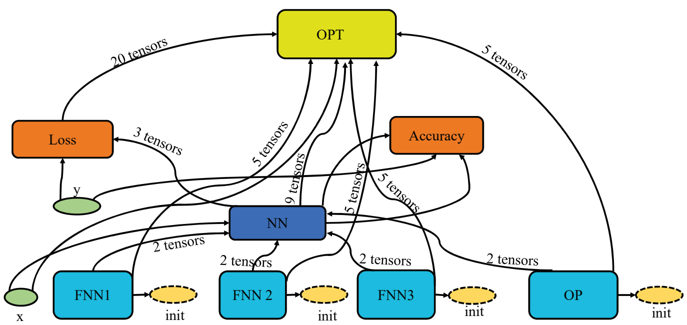
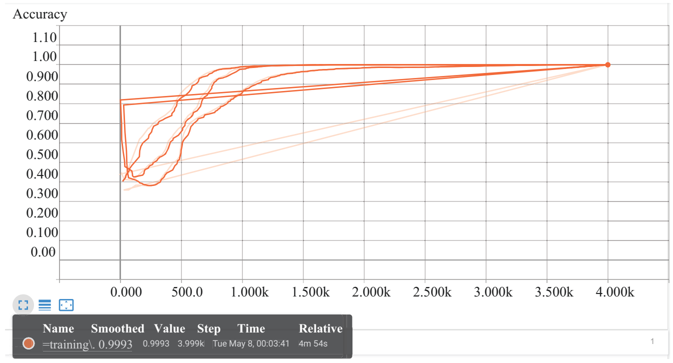
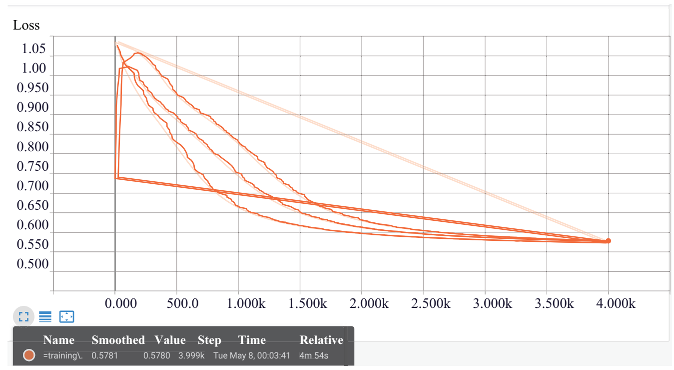


Fig. 6. Graphical representation of the DNN.



(a) Accuracy



(b) Loss

Fig. 7. Accuracy and loss in the deep learning system validation.

TABLE II
BASIC CHARACTERISTICS OF THE VOLUNTEERS

Gender Male : Female	Age Min — Max — Avg	Weight Min — Max — Avg
11 : 5	19 — 81 — 57.4	56 — 85 — 72.7

B. DL Modeling of Human Motion Primitives (HMP)

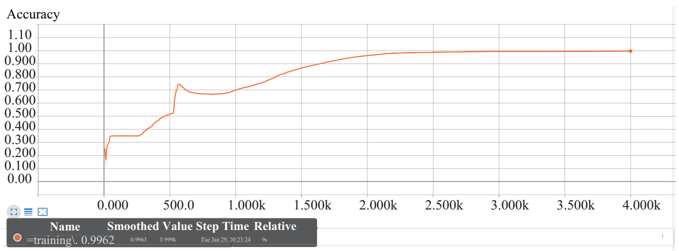
The DNN is again implemented using the Human Motion Primitives (HMP) by using a dataset for activities of daily living (ADL) recognition with wrist-worn accelerometer data [35], [36], [37]. This dataset provides accelerometer data readings of the x, y and z axes of labeled recorded executions of a number of simple human activities which are called Human Motion Primitives. There are fourteen activities that are recorded: brushing teeth, climbing stairs, combing hair, descending stairs, drinking glass, eating meat, eating soup, getting up from bed, laying down on bed, pouring water, sitting, standing, walking and using a telephone. The activities are represented in 979 elements with each element having an average of 300 sample sensor data. The temperature data is considered from [38] and sweat count for training is taken from the existing literature, as shown in Table I. The dataset is composed of the recordings of selected Human Motion Primitives performed by a total of 16 volunteers. The basic characteristics of the volunteers are presented in Table II.

The accelerometer specifications are: Type: tri-axial; Sensitivity: 6 bits per axis; Output data rate: 32 Hz; Location: attached to the right wrist of the user with the x axis pointing toward the hand, the y axis pointing towards the left, and the z axis perpendicular to the plane of the hand. The measurement range is $\pm$14.709g.

The DNN is trained with 4000 samples, out of which 2667 samples are used for training and 1333 samples are used for testing. The accuracy is as high of 99% with a loss of 1%, with 1500 training epochs as shown in Fig. 8(a) and Fig. 8(b), respectively. The confidence interval of the system using Eqn. (6) is 0.005. Thus the classification accuracy of the model is 99% ± 0.5%. This implies that the true classification accuracy of this model with 4000 samples lies between 99.5% to 98.5%.

C. DL Modeling of Physical Activity Monitoring

The DNN presented above is tested with another dataset, the PAMAP2 Physical Activity Monitoring dataset which contains data of 18 different physical activities, performed by 9 subjects wearing 3 inertial measurement units and a heart rate monitor [38], [39], [40]. The data is gathered by using three Colibri wireless inertial measurement units with sampling frequency of 100 Hz. The activity data along with the optional data consist of 18 sample datasets with each dataset comprising of an average of 400,000 sensor data readings. The location



(a) Accuracy

(b) Loss

Fig. 8. Accuracy and loss in the deep learning system validation.

of the sensors is at the wrist, ankle and chest of the person. The heart rate is also listed in this dataset but not used for the training purpose of the system. The sensor units at the ankle, wrist and chest also contain the temperature unit which helps in monitoring the temperature as defined in the protocol. The sweat count is again considered from the literature, as shown in Table I. The activities that are considered are laying, sitting, standing, ironing, vacuuming, ascending and descending stairs, normal and Nordic walk. The protocol of the dataset is described in Table III.

TABLE III
DATASET PROTOCOL

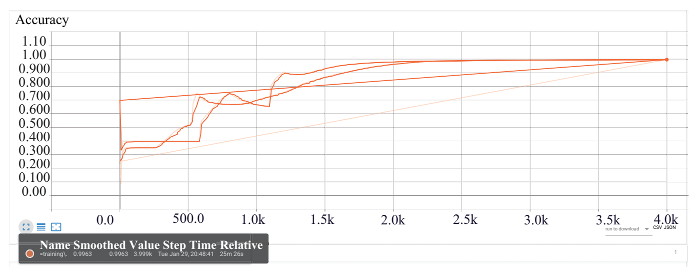
Activity	Metabolic Equivalent (MET)	Time-stamp (min)
laying	1.0	3
sit	1.8	3
stand	1.8	3
iron	2.3	3
break	0	1
vacuum	3.5	3
break	0	1
ascend stairs	8	1
break	0	1
descend stairs	3	1
break	0	1
ascend stairs	8	1
descend stairs	3	1
break	0	1
normal walk	3.3-3.8	3
break	0	1
Nordic walk	5.0-6.0	3
break	0	1

The IMU sensory data contains the following columns: 1 temperature; 2-4 3D-acceleration data; 5-7 3D-acceleration data; 8-10 3D-gyroscope data; 11-13 3D-magnetometer data; 14-17 orientation. Volunteer information is presented in Table IV. The measurement range of the sensor is ± 16g.

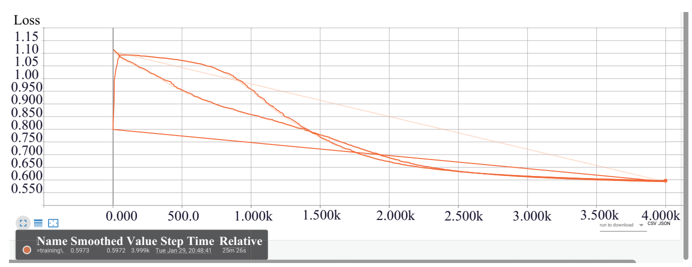
TABLE IV
CHARACTERISTICS OF VOLUNTEERS FOR EXPERIMENTAL ANALYSIS USING STRESS-LYSIS PROTOTYPE

Gender Male : Female	Age Min — Max — Avg	BMI (kg) Min — Max — Avg
8 : 1	23 — 30 — 27.22	22.49 — 27 — 25.11

The deep learning system is trained with 20,000 samples, out of which 13,340 samples are used for training the system and 6660 samples are used for testing. TensorBoard is used to calculate the accuracy which is as high as 99% with a loss of 1%, with 1500 training epochs, as shown in Fig. 9(a) and Fig. 9(b), respectively. The confidence interval of the system using Eqn. (6) is 0.002. Thus the classification accuracy of the model is 99% ± 0.2%. This implies that the true classification accuracy of this model with 4000 samples lies between 99.2% and 98.8%.



(a) Accuracy



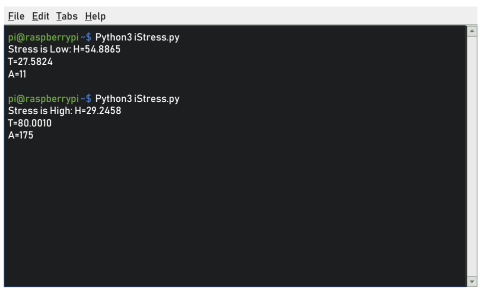
(b) Loss

Fig. 9. Accuracy and Loss in the deep learning system validation.

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

A. *Consumer Electronic Validation of Stress-Lysis*

A single-board computer is used in order to connect the hardware to the cloud server. An accelerometer sensor along with temperature and humidity sensors are used to measure the step-count, humidity and temperature of a person respectively. Here, the sensor used digitally measures relative humidity with a range of 0-80%RH with a 3% accuracy. The maximum value of humidity that can be sensed is 107. The temperature range for this sensor is within the range of -10 to +85°C. The DNN model described above is executed on this device with the real time dataset therefore satisfying the requirements of edge level detection. Fig. 10 shows the complete flow of the data collected from the setup and the collected data given in Fig. 10(a) is sent to the IoT cloud as shown in Fig. 10(b) where it is stored for future analysis. The average time for evaluating stress level in the proposed framework is 2-4 minutes. The purpose of presenting a consumer electronic implementation is to provide a proof of concept for monitoring stress levels using a wearable. However, various factors including proper usage and placement affect the accuracy of the system.



(a) Serial Monitor Window

(b) CE Cloud Server Connectivity.

Fig. 10. Stress data analysis using the developed Stress-Lysis prototype.

The quality of resources that are used to validate the efficiency of the system depends on the computational complexity of the model. The most important characteristics that are considered to evaluate the efficiency of the model are time complexity and space complexity. With an approximate accuracy of 99% and SCI of 0.007, the time required to complete the operation in the model is approximately 3 minutes. In terms of computational time complexity, the neural network used is $O(n^4)$, where n is the total number of neurons in the model and the space complexity is $O(n)$.

B. Comparative Analysis with Existing Literature

The main factors compared are sample size and accuracy. The training dataset or the sample size for the deep learning system based implementation has 26,000 samples. The predictions lead to an accuracy level of approximately 99%. The three different datasets with samples of 2,000, 4,000 and 20,000 produced an accuracy as low as 98.3% and as high as 99.7%, with SCI of 0.007, 0.005, and 0.0072 respectively. This shows that the system that is proposed is trustworthy and the results are produced with minimal loss. Stress-Lysis is being compared with already proposed stress related studies. Table V presents a comparative perspective of Stress-Lysis with other systems presented in the literature.

VIII. Conclusions and Future Research

A novel system for stress detection has been presented. In addition to helping the user in achieving emotional balance, the proposed Stress-Lysis system helps in monitoring chronic stress from early stages. A deep learning system is developed and tested with three different datasets with sample sizes of 2000, 4000 and 20,000. The training of the system is done with 67% of the sample size while the testing is done with 33% of the sample size. Validation and testing of the proposed framework is done in real-time with the help of available frameworks. The results when the system is tested with the training set were accurate in a range of 98.3% to 99.7% with a loss of 1% or less. 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 also displayed. Finally, a consumer electronics implementation of this approach has been performed using a dataset of 2,000 samples on a single-board computer running the DNN, thus proving the system can be implemented at the edge. The ease of accessing the data off-line is provided by the IoT cloud implementation. Cloud access is provided and is verified by using online cloud software. The results of the proposed system, Stress-Lysis show an accuracy in the range of 98.3% to 99.7% in determining the stress range of a person. Advantages of the developed prototype include low-cost, minimal complexity in the design, low power consumption and attendance-free operation.

Our future directions in this area of research include deploying the developed prototype as wearables for veterans and women to analyze the stress values during post-traumatic stress disorder (PTSD).

Acknowledgment

The authors would like acknowledge the help of Dr. Madhavi Ganapathiraju during the initial phases of this research.

This material is based upon work supported by the National Science Foundation under Grant Nos. OAC-1924112 and OAC-1924117. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

TABLE V
COMPARATIVE PERSPECTIVE WITH OTHER STRESS DETECTION SYSTEMS.

Research	Stressors	Sensors/Things	Accuracy %	Cost $	Energy Consumed	System Complexity
Wijsman, et al. [20]	Puzzels, Calculations, Memory Tasks	ECG, Respiration, ESR	74.5	High-211	Moderate	Moderate
Zhang, et al. [41]	Daily Acivities	Photoplethysmogram	not available	Moderate-180	Moderate	Moderate
Plarre, et al. [42]	Public Speaking, Maths	Skin Temperature, Accelerometer, ECG, GSR, Respiration	90.2	High-175	Moderate	Complex
Sandulescu, et al. [43]	Physical Activity	HR, Humidity, Temperature	85.7	High-100	High	High complexity
Zhai, et al. [44]	Stroop Color Test	Pupil Diameter, Skin Temperature, GSR, Blood Volume Pulse	90.1	High-100	Moderate	Complex
Begum, et al. [45]	Verbal, Math	Finger Temperature	80.0	Moderate -35	Moderate	Moderate
Choi, et al. [21]	Mental Arithmetic, Stroop Color Test	Respiration, GSR, Heart Rate Monitor	83.0	High -200	Moderate	Complex
Akmandor, et al. [31]	Memory Game, Fly Sound, IAPS, Ice Test	ECG, BP, GSR, RESP, BO	95.8	High -200	High	Complex
Rachakonda, et al. [24], [25]	Physical activity	Temperature Senor, Humidity Sensor, Accelerometer Sensor	95.6	Low -25	Moderate	Less Complex
Stress-Lysis	Physical Activity- climbing stairs, descending stairs, running, walking, sitting, standing, ironing, eating.	Temperature Senor, Humidity Sensor, Accelerometer Sensor	98.3 to 99.7	Low -25	Low	Less Complex with high range of sample size

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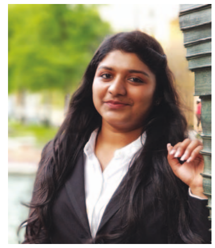

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