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Feature Extraction and Wearable Sensors Based Patient Monitoring System

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ABSTRACT- A survey on human activity recognition using wearable sensors used wired communication device. For a survey on human activity recognition using wearable sensors used wireless communication device. The recognition of human activities has been approached in two different ways, namely using external and wearable sensors. In the former, the devices are fixed in predetermined points of interest, so the inference of activities entirely depends on the voluntary interaction of the users with the sensors. In the latter, the devices are attached to the user. In the feature extraction technique, the image from the camera is feed into the system, where we use the classifiers to extract the features of the images. We use two techniques in this project, namely (i) Feed forward neural network (ii) General regression neural network. The feature extraction uses two techniques. Testing and training. In the training phase, couple of the user images are processed and updated in the system. So during the testing phase, when images are feed into the system, the system compares with the existing training data and validates the images.

KEYWORDS- Wearable sensors, Patient monitoring system, Feature extraction, FFNN classifier, GRNN classifier

I.INTRODUCTION

During the past decade, there has been an exceptional development of microelectronics and computer systems, enabling sensors and mobile devices with unprecedented characteristics. Their high computational power, small size, and low cost allow people to interact with the devices as part of their daily living. That was the genesis of *Ubiquitous Sensing*, an active research area with the main purpose of extracting knowledge from the data acquired by pervasive sensors. Particularly, the recognition of human activities has become a task of high interest within the field, especially for medical, military, and security applications. For instance, patients with diabetes, obesity, or heart disease are often required to follow a well defined exercise routine as part of their treatments . Therefore, recognizing activities such as *walking*, *running*, or *cycling* becomes quite useful to provide feedback to the caregiver about the patient's behavior. Likewise, patients with dementia and other mental pathologies could be monitored to detect abnormal activities and thereby prevent undesirable consequences . For a survey on human activity recognition using wearable sensors used wireless communication device. The recognition of human activities has been approached in two different ways, namely using external and wearable sensors. In the former, the devices are fixed in predetermined points of interest, so the inference of activities entirely depends on the voluntary interaction of the users with the sensors. In the latter, the devices are attached to the user. In the feature extraction technique, the image from the camera is feed into the system, where we use the classifiers to extract the features of the images. We use two techniques in this project, namely (i) Feed forward neural network (ii) General regression neural network. The feature extraction uses two techniques. Testing and training. In the training phase, couple of the user images are processed and updated in the system. So during the testing phase, when images are feed into the system, the system compares with the existing training data and validates the images.

II.LITERATURE SURVEY

F.FOERSTER, M.SMEJA, AND J.FAHRENBERG explains.,The suitable placement of a small number of calibrated piezoresistive accelerometer devices may suffice to assess postures and motions reliably. This finding, which was obtained in a previous investigation, led to the further development of this methodology and to an extension from the laboratory to conditions of daily life. The intention was to validate the accelerometric assessment against behavior observation and to examine the retest reliability. Twenty-four participants were recorded, according to a standard protocol consisting of nine postures/motions (repeated once) which served as reference patterns. The recordings were continued outside the laboratory. A participant observer classified the postures and motions. Four sensor placements

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(sternum, wrist, thigh, and lower leg) were used. The findings indicated that the detection of posture and motion based on accelerometry is highly reliable. The correlation between behavior observation and kinematic analysis was satisfactory, although some participants showed discrepancies regarding specific motions.

E.KIM, S.HELAL, AND D.COOK explains., In principle, activity recognition can be exploited to great societal benefits, especially in real-life, human centric applications such as elder care and healthcare. This article focused on recognizing simple human activities. Recognizing complex activities remains a challenging and active area of research and the nature of human activities poses different challenges. Human activity understanding encompasses activity recognition and activity pattern discovery. The first focuses on accurate detection of human activities based on a predefined activity model. An activity pattern discovery researcher builds a pervasive system first and then analyzes the sensor data to discover activity patterns.

A.TOLSTIKOV, X.HONG, J.BISWAS, C.NUGENT, L.CHEN, AND G.PARENTE explains., Ambient assistive living environments require sophisticated information fusion and reasoning techniques to accurately identify activities of a person under care. This paper explains, compares and discuss the application of two powerful fusion methods, namely dynamic Bayesian networks (DBN) and Dempster-Shafer theory (DST), for human activity recognition. Both methods are described, the implementation of activity recognition based on these methods is explained, and model acquisition and composition are suggested. It also provides functional comparison of both methods as well as performance comparison based on the publicly available activity dataset. Our findings show that in performance and applicability, both DST and DBN are very similar; however, significant differences exist in the ways the models are obtained. DST being top-down and knowledge-based, differs significantly in qualitative terms, when compared with DBN, which is data-driven. These qualitative differences between DST and DBN should therefore dictate the selection of the appropriate model to use, given a particular activity recognition application.

III.WEARABLE SENSORS

Wearable sensor is a device that is always with the user, and into which the user can always enter commands and execute a set of such entered commands, and in which the user can do so while walking around or doing other activities. This transformation allows it to be worn constantly, with the goal of becoming a seamless extension of body and mind, equipped with various sensors which measure heart rate, respiration, footstep rate etc, and can help in body maintenance. The 'wearable computer' apparatus is embedded within nontransparent clothing which provides shielding

IV.ACCELEROMETER SENSOR

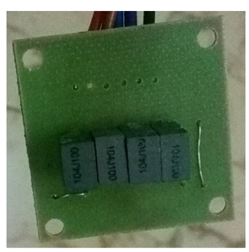

Fig.1 Accelerometer sensor component

In the Fig.1 and Fig.2 An accelerometer is a device that measures proper acceleration, the acceleration experienced relative to free fall. Single- and multi-axis models are available to detect magnitude and direction of the acceleration as a vector quantity, and can be used to sense orientation, acceleration, vibration shock, and falling. Micro machined accelerometers are increasingly present in portable electronic devices and video game controllers, to detect the position of the device or provide for game input. Triaxial accelerometers are perhaps the most broadly used sensors to recognize ambulation activities (e.g., *walking*, *running*, *lying*, etc.) [27]–[29], [34]– [36]. Accelerometers are inexpensive, require relatively low power [37], and are embedded in most of today's cellular phones. Several papers have reported high recognition accuracy 92.25% [29], 95% [38], 97% [35], and up to 98% [39], under different evaluation methodologies

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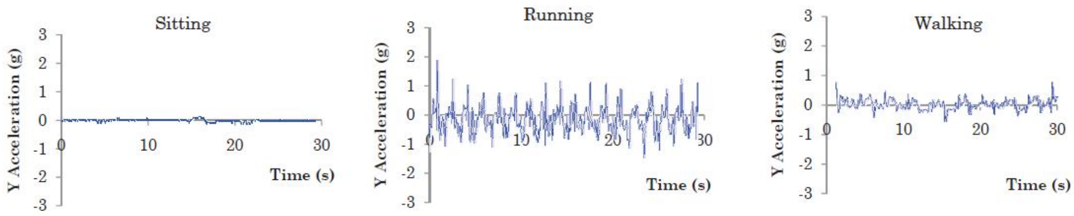

Fig.2 Acceleration for different activities

V.TEMPERATURE SENSOR

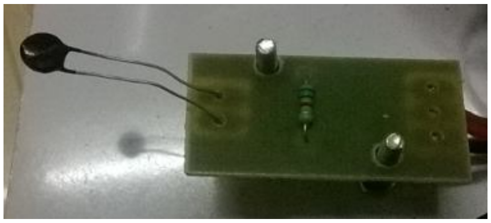

Fig.3 Temperature sensor component

In the Fig.3 A thermistor is a type of resistor whose resistance varies with temperature. The word is a portmanteau of thermal and resistor. Thermistors are widely used as inrush current limiters, temperature sensors, self-resetting overcurrent protectors, and self-regulating heating elements. Thermistors differ from resistance temperature detectors (RTD) in that the material used in a thermistor is generally a ceramic or polymer, while RTDs use pure metals. The temperature response is also different; RTDs are useful over larger temperature ranges, while thermistors typically achieve a higher precision within a limited temperature range [usually −90 °C to 130 °C]. Assuming, as a first-order approximation, that the relationship between resistance and temperature is linear, then:

$$\Delta R = k\Delta T \qquad (1)$$

Where,

- ΔR = change in resistance
- ΔT = change in temperature
- k = first-order temperature coefficient of resistance

$$\alpha_T = \frac{1}{R(T)}\frac{dR}{dT}. \qquad (2)$$

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VI.ELECTROCARDIOGRAM (ECG)

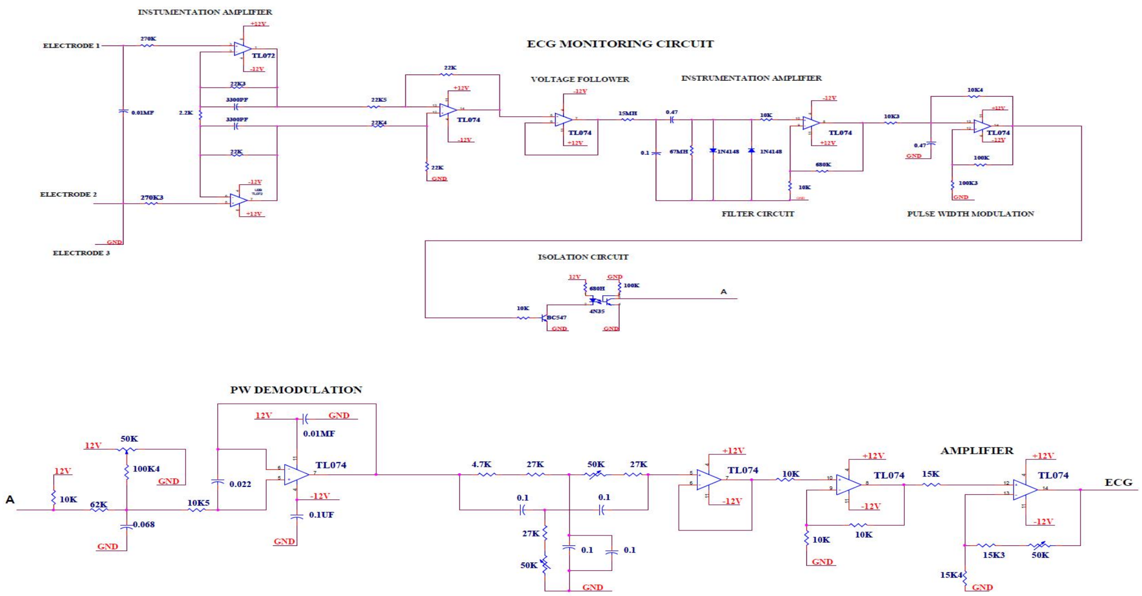

Fig.4 ECG Monitoring

In the Fig.4 An electrocardiogram (ECG or EKG, abbreviated from the German Elektrokardiogramm) is a graphic produced by an electrocardiograph, which records the electrical activity of the heart over time. Analysis of the various waves and normal vectors of depolarization and repolarization yields important diagnostic information. It is the gold standard for the evaluation of cardiac arrhythmias. It guides therapy and risk stratification for patients with suspected acute myocardial infarction. It helps detect electrolyte disturbances (e.g. hyperkalemia and hypokalemia). It allows for the detection of conduction abnormalities (e.g. right and left bundle branch block). It is used as a screening tool for ischemic heart disease during a cardiac stress test. It is occasionally helpful with non-cardiac diseases (pulmonary embolism or hypothermia).

VII.ECG ON GRAPH PAPER

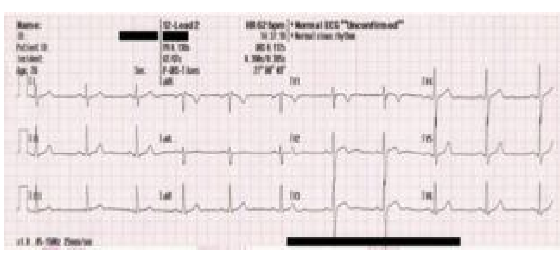

Fig.5 ECG on graph paper

In the Fig.5 A typical electrocardiograph runs at a paper speed of 25 mm/s, although faster paper speeds are occasionally used. Each small block of ECG paper is 1 mm2. At a paper speed of 25 mm/s, one small block of ECG paper translates into 0.04 s (or 40 ms). Five small blocks make up 1 large block, which translates into 0.20 s (or 200 ms). Hence, there are 5 large blocks per second. A diagnostic quality 12 lead ECG is caliberated at 10 mm/mV.

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VIII.POWER SUPPLY

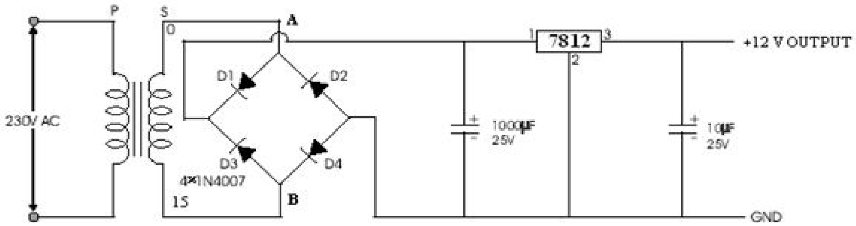

Fig.6 Circuit diagram for power supply

In the Fig.6 The ac voltage, typically 220V rms, is connected to a transformer, which steps that ac voltage down to the level of the desired dc output. A diode rectifier then provides a full-wave rectified voltage that is initially filtered by a simple capacitor filter to produce a dc voltage. This resulting dc voltage usually has some ripple or ac voltage variation. A regulator circuit removes the ripples and also remains the same dc value even if the input dc voltage varies, or the load connected to the output dc voltage changes. This voltage regulation is usually obtained using one of the popular voltage regulator IC units.

IX.RS232 SERIAL COMMUNICATION

In telecommunications, RS-232 is a standard for serial binary data interconnection between a DTE (Data terminal equipment) and a DCE (Data Circuit-terminating Equipment). It is commonly used in computer serial ports. The Electronic Industries Alliance (EIA) standard RS-232-C [3] as of 1969 defines: Electrical signal characteristics such as voltage levels, signaling rate, timing and slew-rate of signals, voltage withstand level, short-circuit behavior, maximum stray capacitance and cable length. Interface mechanical characteristics, pluggable connectors and pin identification. Functions of each circuit in the interface connector . Standard subsets of interface circuits for selected telecom applications. The standard does not define such elements as character encoding (for example, ASCII, Baudot or EBCDIC), or the framing of characters in the data stream (bits per character, start/stop bits, parity). The standard does not define protocols for error detection or algorithms for data compression. The standard does not define bit rates for transmission, although the standard says it is intended for bit rates lower than 20,000 bits per second. Many modern devices can exceed this speed (38,400 and 57,600 bit/s being common, and 115,200 and 230,400 bit/s making occasional appearances) while still using RS-232 compatible signal levels. Details of character format and transmission bit rate are controlled by the serial port hardware, often a single integrated circuit called a UART that converts data from parallel to serial form. A typical serial port includes specialized driver and receiver integrated circuits to convert between internal logic levels and RS-232 compatible signal levels.

X.ZIGBEE

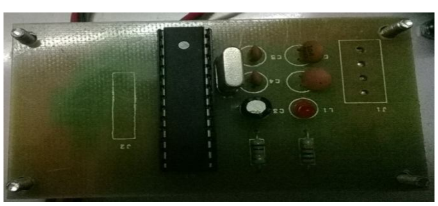

Fig.7 ZIGBEE component

In the Fig.7 Powerful digital features allow building a high-performance rf system. Using an inexpensive microcontroller. Wake-on-radio functionality for automatic low-power rx polling. Burst mode data transmission with high over-the-air data rate. reduces current consumption. Programmable data rate from1. 2-500kbps. Robust solution with excellent selectivity and blocking performance. Ideal for multi-channels operation (50-800khz channels). Full packet handling including preamble generation, sync. word insertion/detection ,add check, flexible packet.

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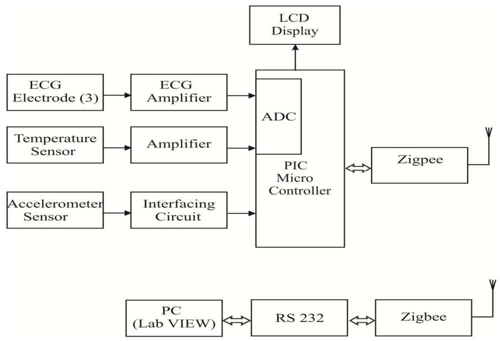

Fig.8 Block diagram for wearable sensors

In the Fig.8 The ECG, temperature sensors and accelerometer sensors were used. To read data the sensors will pass through the amplifier. The output will get in analog form it converted into digital form. The result will appear in the LCD display and the data will transceiver through zigbee. And the output will display in the labview through RS232 serial communication.

XI.FEATURE EXTRACTION

At first we are going to extract the features of the given input images (Eg. Both Normal & Abnormal Images). The features going to be extracted are,[1]Entropy, [2]Energy, [3]Mean/Average Value, [4]Standard Deviation, [5]Variance, [6]Covariance, [7]Kurtosis

1) ENTROPY
   Entropy is a measure of the uncertainty in a random variable
   Entropy is defined as -sum(p.*log2(p))

2) ENERGY
   Energy is also known as uniformity, uniformity of energy, and angular second moment.

$$\sum_{i,j} p(i,j)^2 \qquad (3)$$

3) MEAN/AVERAGE VALUE

$$\bar{X} = \frac{\Sigma X}{N} \qquad (4)$$

4) STANDARD DEVIATION
   The Standard Deviation is a measure of how spread out numbers are.Its symbol is σ (the greek letter sigma).There are two common textbook definitions for the standard deviation s of a data vector X.

   Where

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (5)$$

5) VARIANCE
   The variance is the square of the standard deviation (STD).

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$$\mathrm{Var}(X) = \mathrm{E}\left[(X-\mu)^2\right]. \quad (6)$$

6) CO-VARIANCE

Covariance is a measure of how much two random variables change together

$$cov(x,y) = \frac{\sum_{i-1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{(n-1)} \quad (7)$$

7) KURTOSIS

Kurtosis is a measure of how outlier-prone a distribution is. The kurtosis of the normal distribution is 3. Distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3; distributions that are less outlier-prone have kurtosis less than 3. The kurtosis of a distribution is defined as

$$k = \frac{E(x-\mu)^4}{\sigma^4} \quad (8)$$

XII.CLASSIFIER

Classifier going to be used is Neural network. Neural network consists of two phases. In the training phase we are going to train the network using the features extracted from the input images. In the testing phase, the given input image can be tested whether it is normal or abnormal.

XIII.FEED FORWARD NEURAL NETWORK

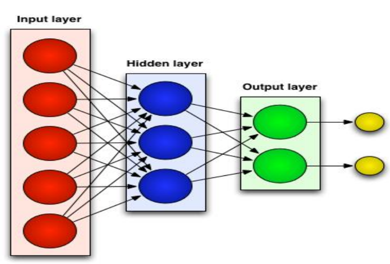

Fig.9 Feed forward neural network

In the Fig.9 A collection of neurons connected together in a network can be represented by a directed graph: Nodes represent the neurons, and arrows represent the links between them. Each node has its number, and a link connecting two nodes will have a pair of numbers (e.g. (1, 4) connecting nodes 1 and 4). Networks without cycles (feedback loops) are called a feed-forward networks(or perceptron). Input nodes of the network (nodes 1, 2 and 3) are associated with the input variables (x1, . . . , xm). They do not compute anything, but simply pass the values to the processing nodes. Output nodes (4 and 5) are associated with the output variables (y1, . . . , yn). Hidden Nodes and Layers. A neural network may have hidden nodes — they are not connected directly to the environment ('hidden' inside the network. We may organise nodes in layers: input (nodes 1,2 and 3), hidden (4 and 5) and output (6 and 7) layers. Neural networks can have several hidden layers. Numbering the Weights.

[a]. Calculate weighted sums in the first hidden layer:

$$v3 = w13x1 + w23x2 = 2 \cdot 1 - 3 \cdot 0 = 2 \quad (9)$$
$$v4 = w14x1 + w24x2 = 1 \cdot 1 + 4 \cdot 0 = 1 \quad (10)$$

[b]. Apply the activation function:

$$y3 = f(2) = 1 \,,\; y4 = f(1) = 1 \quad (11)$$

[c]. Calculate the weighted sum of node 5:

$$v5 = w35y3 + w45y4 = 2 \cdot 1 - 1 \cdot 1 = 1 \quad (12)$$

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[d]. The output is

$$y5 = f(1) = 1 \quad (13)$$

XIV.GENERAL REGRESSION NEURAL NETWORK

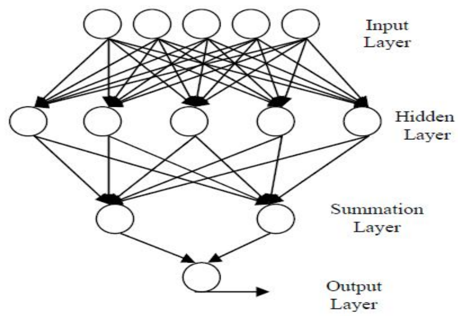

Fig.10 General regression neural network

In the Fig.10 and Fig.11 Extensive effort has been devoted to developing techniques for identification of linear time-invariant systems. The linear identification is based on measured input and output values of the system. Identification for nonlinear systems is also based on measured input and output values, but it is more difficult. A procedure that uses neural networks for identification and control of nonlinear systems. For identification, the input and output values of the system are fed into a multilayer neural network. Although that paper used the back-propagation algorithm for training the networks, the same identification and control framework can be used with neural networks having other characteristics. One disadvantage of back-propagation is that it can take a large number of iterations to converge to the desired solution. An alternative to back-propagation that has been used in classification is the probabilistic neural network (PNN), which involves one-pass learning and can be implemented directly in neural network architecture. This paper describes a similar one-pass neural network learning algorithm which can be used for estimation of continuous variables. If the variables to be estimated are future values, then the procedure is a predictor. If the variable or variables to be estimated relate output variables to input variables, then the procedure can be used to model the process or system. Once the system has been modeled, a control function can be defined. If the procedure is taught samples of a control function, it can estimate the entire control function, and it becomes a controller.

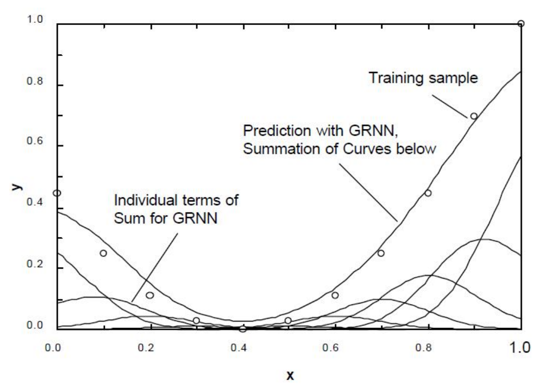

Fig.11 GRNN

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XV.RESULTS AND DISCUSSION

Fig.12 Hardware component

In the Fig.12 These are the hardware component which I will use in this project to evaluate the human activity recognition through wearable sensors.

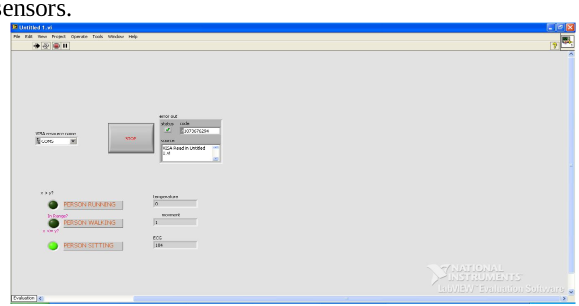

Fig.13 Output for Accelerometer and ECG

In the Fig.13 While using hardware component will connect to the PC through RS232 serial communication to evaluate the value for person sitting and ECG value will appeared. . This project surveys the state of the art in HAR based on wearable sensors.

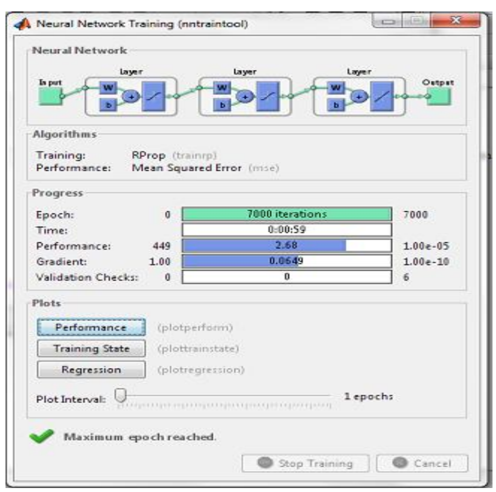

Fig.14 Training phase for input image

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In the Fig.14 In training phase, these are the window to trained the image to iterations.

Fig.15 Testing phase for input image

In the Fig.15 In testing phase, the classifier of the given image to evaluate the image is normal or abnormal.

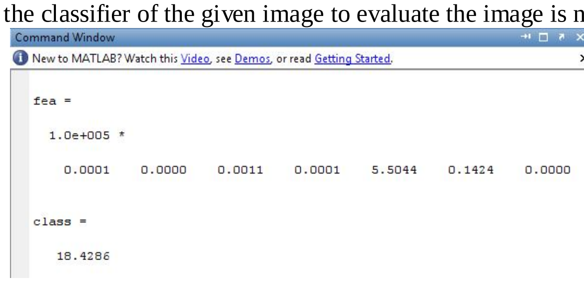

Fig.16 Output from the Testing phase

In the Fig.16 The circles represent the data points or training samples used to predict the solid line going through most of these samples.

XVI.CONCLUSION

In this project, i implemented the state-of-the-art human activity recognition based on wearable sensors. The fundamentals of feature extraction and machine learning are also included, as they are important components of every HAR system. Systems like this will help in improving the field of human healthcare, safety and in many more areas. The recognition of human activities has been approached in two different ways, namely using external and wearable sensors. In the former, the devices are fixed in predetermined points of interest, so the inference of activities entirely depends on the voluntary interaction of the users with the sensors. In the latter, the devices are attached to the user. The feature extraction uses two techniques. Testing and training. In the training phase, couple of the user images are processed and updated in the system. So during the testing phase, when images are feed into the system, the system compares with the existing training data and validates the images.

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