AN AUTOMATED SYSTEM FOR THE MONITORING OF PATIENTS WITH RESPIRATORY DISORDERS

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***Abstract*—Declining birth rates and longer living people are major reasons to increase ageing population. Since they need more concerns and treatments on health, it is becoming a problematic scenario to look after them regularly. Most of the elder people are getting affected by respiratory disorders and monitoring of their health conditions has become a must. The goal of this research is to build an inexpensive system which can monitor multiple necessary facts about the patient's health along with the observation in patient's behaviors, emotions and respiratory sounds. Computer vision and IOT based approach is proposed to monitor the patient, identify the anomalies in the patient and finally alert the responsible person with an appropriate alerting system. Process of patient monitoring at the domestic level is hardly been implemented via a proper technological solution, hence the system implemented as the result of this research can be effectively used for the monitoring of the patient.**

Keywords - Patient Monitoring; Respiratory Disorders; Behaviors; Emotions; Heart Rate; SpO_2; Respiratory Sound Analysis

I. INTRODUCTION

One of the major challenge for future is the ageing of the population, and how the health of old people can be preserved. Since the rate of the growth in ageing population is too high, there should be different ways to tackle the problem. Approximately percentage of older people is projected to be more than double the worldwide over the next half century [1].

With the ageing, older people are restricted to bed due to various kinds of diseases and eventually they are becoming bedridden patients. Majority of the elderly patient are getting directly affected by the air pollution in the domestic environment due to limited outdoor activities. Since the respiratory disorder for elderly people are common, they have been untreated to some extent [2].

Elderly patients who are getting treatments under their own roof need a help of a caregiver to get the attention, care and monitoring. Caregiver's role is to help patients by preventing occurrences of breathing problems. At the same time caregiver need to report the identified problems to doctor in order to ensure the correct directions for the treatments are followed [3]. Caregiver has to continuously monitor vital changes in elderly patient in order to identify the anomalies in an appropriate manner. High concentration level is required even for well trained and qualified caregivers to monitor the patient in every single second. Continuous monitoring of the patient is no more required with the luxury of an automated monitoring system. Family member can even become a caregiver to look after the patient since all the monitoring tasks is done through the system. Family caregiver only has to provide care and attention when requires. System will eventually eases up the duties of the family caregiver by taking care of the patient.

Vital changes in the health parameters such as pulse rate, Saturation of Oxygen in the blood (SpO2) along with changes in behaviors, emotions and lung sounds of the patient are essential when monitoring a patient with respiratory disorders. Monitoring mentioned parameters and motions of the patient helps to identify anomalies in order to minimize adverse events [4].

The rest of the research paper will unfold as follows: Section two will present background and related work while section three focuses on methodology. The section four will show the results of the work carried out and the discussion is followed in section five.

II. BACKGROUND

Electronic Health has been with the people for many years and has been defined as use of Information and Communication Technology. With the arrival of many technologies, concept of the patient monitoring system has emerged. The typical approaches to patient monitoring include monitoring of major health parameters such as pulse rate, SpO2 and respiratory rate [5-8]. Existing computerized monitoring systems lack many mandatory features worth to their extreme cost. Requirement of monitoring emotions, behaviors and the inner sounds of the patients have hardly been addressed. Systems which are capable of tracking and monitoring the behaviors of patients, lack the component of monitoring mentioned health parameters [9, 10].

This research addresses the issues related to human monitoring and introduce an inexpensive system which can monitor multiple necessary facts about the patient's health.

III. PROPOSED SYSTEM

The system comprises of four major components.

a) Abnormality detection of behaviors
b) Abnormality detection in emotions
c) Sensor configuration and anomaly detection via sensor inputs
d) Respiratory Sound Analysis

All the component will perform constant monitoring expect for Respiratory Sound Analysis. Caregiver will have the freedom to utilize Respiratory Sound Analysis component whenever it requires. Components will independently run within the system and alert the caregiver through a text message along with an alarming sound in case of an abnormal situation occurs.

A. Abnormality Detection of Behaviors

High-resolution CCTV camera will be mounted in the patient's room to track the abnormality of behaviors and the captured video will be send to the PC. On living beings with visual ability, this continuously changing image appears in the retina while artificial systems, thus it is captured by a light sensor in the camera. As the very first step, system will identify and track the patient (Fig 1) by analyzing the captured video. For the tracking of the patient, the first thing is to remove colors of other extra objects in order to identify the patient. Thus, used background subtractor model. It is a must to strictly monitor the patient in his/her early discharged period. Thus the system will allow to adjust some parameters like threshold and sensibility. With the aid of those adjusted parameters, it will be helpful to focus the patient on every simple motion. Time to time patient's health condition can be changed. According to several conditions that have occurred, the system can be used by adjusting the relevant parameters.

Figure 1 : Identification and tracking of the patient

As the next step collect the data related to behaviors of the patient including all abnormal and normal behaviors. Image subtraction is used for motion detection. For a second, there are 24 to 30 frames will be captured. Image subtraction is performed in order to identify a motion as soon as motion is detected. The basic thing behind motion detection is consider two frames and check whether if there any difference between those two frames. If there is, assume that motion is occurred. Time to time this will happen iteratively, current frame become the previous and next become the current one. After the motion detection, system will consider about the abnormalities of those identified motions. Same disease can be affected by several ways to a patient. According to the detection of motions and adjusted parameters system will alert the caregiver about the motions through an alarm and a text message. And it will maintain a log of pictures (Figure 2) of every movement of the patient thus it will helpful to doctor when examine the patient.

Figure 2 : Detection of every movements will be saved for future purposes

B. Abnormality Detection in Emotions

High resolution CCTV video camera will be used to detect the abnormality in emotions of a bedridden patient. To get the continuous video from the video camera, it should be escalated on the top of the wall directed to the patient's bed in the room. The captured video will be sent to the PC in order to detect the abnormality.

Making of dataset

Dataset is mainly divided in to two different folders as normal facial expressions and abnormal facial expressions. CK+ (Cohn-Kanade) repository is used to obtain normal facial emotions of the people. Separate repository was made for abnormal facial emotions using a captured video of patients.

Training and classification

Database was separated to two parts for the training and prediction purposes. First 80% of the images from the image file list were taken for the training and last 20% were taken for predictions. Frontal face detector and shape predictor of the dlib library is used to detect the face of the patient and identify landmarks respectively. Frontal face detector returns an object detector which is configured to find human faces that are looking more or less towards the camera. It is created using the scan fhog pyramid object which is used for running a fixed sized sliding window classifier over an image pyramid. Especially scan fhog pyramid slides a linear classifier over a HOG pyramid.

Face is detected from the capturing video and get coordinates for each detected face. Facial landmarks were taken from the shape predictor of the dlib library. If the face of the captured image is titled, classifier is confused. Therefore the correction should be done assuming that the bridge of the nose in most people are more or less straight, and offset all calculated angles by the angle of the nose bridge. This rotates the entire vector array so that titled faces become similar non-titled faces with the same expression [11]. The following figure [11] shows how to do the calculation of the face offset correction by taking the tip of the nose and finding the angle the nose makes relative to the image, and thus find the angular offset β that need toapply apply.

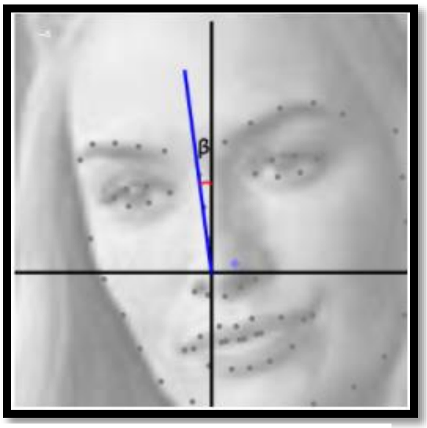

Figure 3: Titled image

Then the images will be classified using support vector classification in support vector machine. Only three parameters of the support vector classification were used in this scenario: kernel, probability and tolerance. Here the linear kernel was selected as the kernel type and default tolerance level was used for the tolerance.

When the system detects the patient's facial emotion, it will recognize whether the patient is having a normal facial emotion or an abnormal facial emotion, if it is an abnormal emotion it will be informed to the care giver through the mobile application.

C. Anomaly Detection via Sensor Inputs

Pulse rate is a main parameter to analyze the health of a person regardless of age or gender. Monitoring such thing in patients with respiratory disorders is as much as important due to frequent changes in heart rate. Very low heart rates, frequent fast heart rates or irregularity in heart rate are mostly due to abnormality of the patient's body and caregiver should inform the doctor in case of such incident. Sp02 or the percentage of the oxygen amount in the blood is another health parameter which can be advantageous in monitoring the patients with respiratory disorders. It is a must to identify the normal SpO2 level of such patient with the help of a doctor and keep monitoring it to avoid adverse events. Patients with respiratory disorders lack the ability to take oxygen in to their bodies easily hence they have to put extra effort in breathing to gain more oxygen. Tool such as SpO2 can be used to monitor how effectively the body is taking oxygen [12].

The MAX30100 is an integrated pulse oximetry and heartrate monitor sensor solution (Figure 4) Advanced Functionality of the sensor Improves Measurement Performance such as capability of fast data output and high sample rate [13]. MAX30100 pulse oximeter and heart rate sensor is being used to capture Pulse Rate and SpO2 for further analysis. Arrhythmia of the heart rate (HR) and deviation of peripheral capillary oxygen saturation (SpO2) are monitored using sensor inputs transmitted through pulse oximeter and heart rate.

Figure 3 : MAX30100 Pulse Oximeter and Heart rate Sensor

As a preprocessing technique, noises of the acquired data will be filtered removing DC (Direct Current) signal and allowing only the AC (Alternative Current) to read heart rate and SpO2 value properly.

Mean median filtration method is used to get the differential of signal to further improve the ability of detecting pulses and to highlight the sudden changes of the signal with a large value. Butterworth filtration method is used to remove higher level harmonies in low pass filter configuration.

Max30100 sensor gives relatively clean signal to calculate the heart rate. Difference between two timestamps will be measured by calculating the delay between two beats. Same concept being applied to calculated BPM (Beats per Minute). Millis function in Arduino gives the timestamp in milliseconds which can be used to get the BPM value [14].

$$BPM = \frac{60000}{current\ beat\ timestamp - previous\ beat\ timestamp} \quad (1)$$

SpO2 level can be calculated using following equation [14].

$$SpO_2 = \frac{HbO_2}{Tot\ Hb} \quad (2)$$

Once DC levels of the signal match, SpO2 level will be calculated by dividing the logs of the RMS (Root of Mean Square) values [14].

$$R = \frac{AC_{RMS\ RED}/DC_{RED}}{AC_{RMS\ IR}/DC_{IR}} \quad (3)$$

Heart rate of a normal person is between 60% - 100% while SpO_2 is between 94% - 99% [15]. But SpO2 value of patients having respiratory problems can be reduced up to 90% [16]. If it reduced more than that, then it will be detected as an abnormality. When those parameters are measured, all of them are transferred to a personal computer (PC) via Bluetooth to display the results with a user friendly manner. Output will be stored in a 10 seconds data buffer and check for abnormal situations. If an arrhythmia of the heart rate (HR) or unnatural deviation of the SpO_2 is detected, system will identify it as an anomaly and caregiver will be alerted.

D. Respiratory Sound Analysis

Auscultation or the listening to the internal sounds using a stethoscope is an effective way of diagnosing the respiratory sounds and identify related diseases in the respiratory system [17]. But identification of respiratory sounds and separate them as normal and abnormal is not an easy task to perform. It requires a skill level of a well-trained physician to listen and understand the sound for classification.

Respiratory sounds or Lung Sounds can be mainly divided in to normal and abnormal lung sounds. Four lung categories namely, bronchial, vesicular-bronchial, vesicular and tracheal can be identified as normal. Meanwhile abnormal lung sounds can be categorized as wheezing, crackles and rhonchi. R2016a version of MATLAB is being used to carry out the implementation. R.A.L.E. [18] repository along with a GitHub repository [19] were used to construct a proper dataset which was further separated in to Testing set and Training set. The sampling frequency of the acquired recordings was 11025 Hz.

An inexpensive stethoscope and a condenser microphone are being used to directly capture the lung sounds of the patient. Condenser microphone has the capability of capturing both lower and higher frequencies. Stethoscope was able to detect the both heart sounds and lung sounds properly. Y-shaped section of the stethoscope was removed and stethoscope head was integrated with the condenser microphone to make the final device for the auscultation process. Figure 5 shows the implementation of the modified stethoscope. Stethoscope collects the lung sounds and condenser microphone records the lung sounds which are transferred to the PC for further processing and analysis.

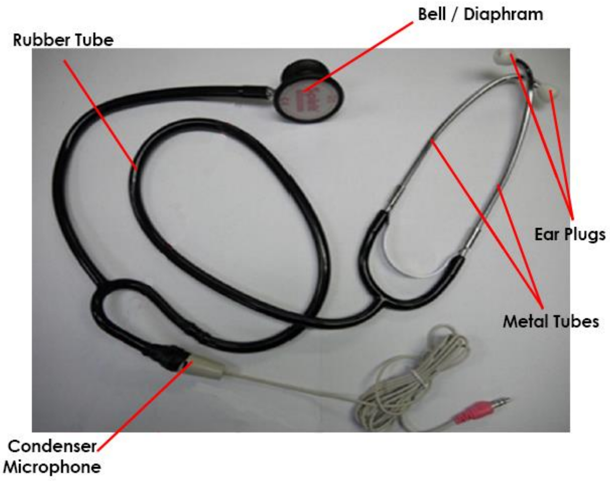

Figure 4 : Stethoscope

As the first step of the implementation, Fast Fourier Transformation (FFT) was applied to convert the signals from its original domain to frequency domain. Analysis process becomes much easier with the application of FFT function.

The following sections discuss each stage of the Respiratory Sound analysis process.

Normalization process

Normalization process is being applied to remove all the differences among signals acquired from various subjects at different time points from the same location. Normalization of signals can be achieved through different ways. Here all the signals are individually divided by maximum data value for that particular signal to complete the normalization process.

Filtration

Lung sounds used in this work were filtered with a band-pass filter to cover the major frequencies of lung sounds, 100 Hz and 2000 Hz cut-off frequencies, canceling out undesired frequencies such as those coming from heart sounds. Audacity software was used to compare the output signals with original signals of respiratory sounds. Wavelet technology is being used to de-noise the signal while preserving useful signals.

Feature extraction

Mel frequency cepstral coefficients are now being used as a highly effective algorithm in speech recognition. Furthermore promising results have been achieved by previous researches by applying MFCC to extract features in signal processing [14, 15]. MFCC is not highly robust with noise, but normalization process will eliminate the influence of noisy effects. Parameter capturing process of MFCC is started with framing. Framing is being performed to select sampling points of signal in order to observe signal characteristics. Energy of each frame will be calculated as the next step in MFCC. In the transferring process of the signal, high frequencies can be attenuated. Pre-emphasis method is utilized to reimburse the high frequencies by applying a high pass filter. Hamming window with overlapped is in use to prevent sudden changes of the signal. Triangular band pass filter is needed to calculate Mel frequency cepstral coefficients from the Fast Fourier Transform coefficients. Linear frequency can be converted to Mel- frequency by applying Eq. (4).

$$Mel(f) = 2595 \log_{10}(1 + \frac{f}{700}) \tag{4}$$

Classification

Classification is the next process follows after feature extraction. Classification is completely based on the representation of the extracted features. Artificial Neural Networks are used as classification method to achieve higher accuracy rate. ANN gives high performance for any given features, but requires fully optimized features for classification. Feed forward neural network (Figure 6) was used as input layer was a matrix with size 1 x 39. There were 3 hidden layers and neuron of each are 13, 11 and 13. 80% of the dataset is used in the training phase while remaining as the test and validation data set.

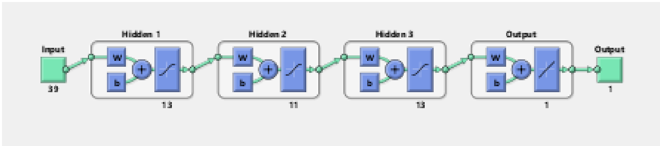

Figure 6: The structure of the neural network used in this study

Immediately after the classification, lung sounds will be graded according to the health condition of the patient such as Good, Warning, Bad or Serious. Grading will be based on classification and segmentation. Sound frame will be segmented in to 10 frames and it will be categorized as normal and abnormal. Normal lung sounds are stated as 0 while 1 is assigned for abnormal lung sound. Proportion of the abnormal lung sounds in the recording will be taken in to a percentage. According to the percentage level, severity of the patient will be displayed in the system.

IV. EXPERIMENTS

Experimental Data for Respiratory Sound Analysis

The training data set was constructed using R.A.L.E. repository and a GitHub repository. Dataset was consisted with 80 lung sound recordings in which all the lung sound categories were having 20 each. Training data contained 39 dimensions of MFCC. Testing dataset was consisted with 60 lung recordings.

Experiment 1

Experiment 1 was performed assuming recording environment was ideal without any interference. Training dataset was used for the evaluation. Table 1 lists the results with identification rates.

TABLE I. IDENTIFICATION RESULTS OF LUNG SOUND TRAINING DATASET.

Lung Sound Category	**Number of recordings**	**Identification Rate**
Normal	20	100%
Crackle	20	100%
Wheeze	20	100%
Rhonchi	20	100%

Experiment 2

Experiment 2 was performed targeting noisy environment. Test dataset was used for the evaluation. Test dataset was consisted with 20 Db Additive White Gaussian Noise. Table 2 lists the results with identification rates.

TABLE II. IDENTIFICATION RESULTS OF LUNG SOUND TESTING DATASET.

Lung Sound Category	**Number of recordings**	**Identification Rate**
Normal	20	100%
Crackle	10	50%
Wheeze	20	100%
Rhonchi	10	80%

Experimental Data for Abnormality detection in emotions

Testing set was consisted with 20% of the dataset. Result will be based on the state of emotion, whether it is a normal emotion or abnormal emotion.

Experiment 3

Experiment was performed using 3 classifiers for the Abnormality detection in emotions component. Mean accuracy for each classifier is listed below in Table 3.

TABLE III. IDENTIFICATION RESULTS OF EMOTION TESTING DATASET.

Classifier	**Mean Accuracy**
Support Vector Classification	96.1 %
Support Vector Regression	17.3 %
Logistic Regression	90.5 %

V. RESULTS AND DISCUSSIONS

Continuously monitoring every single behavior of the patient is a must second in domestic environment. As discussed under Abnormality detection of behaviors component, caregiver will be alerted regarding abnormal situation via a text message and ringing an alarm. Abnormality detection and alerting process will take 3 or 4 seconds according to the time estimation. Rather than alerting one way, the system will alert the motion detection in two ways and it will not miss any simple motion of the patient.

Experiment 3 was performed under Abnormality detection in emotions component in order to identify most appropriate classifier. Support Vector Classification was able to achieve the best result out of all 3 classifiers with an accuracy rate of 96.1%. Good results was shown under Logistic Regression classifier with an accuracy rate of 90.5 % while Support Vector Regression achieved poor results with an accuracy level of 17.3 %. Based on the results, Support Vector Classification was selected as the best classifier to perform the implementation and achieved same good results in real time monitoring.

As mentioned in Experiments, Respiratory Analysis component was able to achieve 100 % accuracy with the training data while testing data achieved an accuracy level 0f 88.33 %. Identification rate of the crackles was 50 % and it was bit low compare to other classes. But it can be neglected since the testing was performed adding White Gaussian Noise to the lung sounds. Main reason behind adding noise is to test whether the component can eliminate the Gaussian noise in order to make sure the results remain accurate. Hence the component has the capability to remove the noises and perform the analysis.

VI. CONCLUSION

Patient Monitoring has not been addressed with a complete solution with novel technology similar to this research study conducted. In this research human monitoring has been eliminated while introducing an automated system for patient monitoring. With this system it is expected to detect anomalies in the patient health parameters, lung sounds and motions. This system can reach its targeted audience easily since the proposed solution is inexpensive and efficient. System has the capability to alert the responsible person in order to minimize adverse events. Cost and time that requires to attend at hospitals and clinics can be reduced through this solution.

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