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Certain Investigation on Human Emotion Recognition System using IoT and Deep Learning - A Healthcare Applications

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Abstract

Nowadays the IOT system is widely used in various fields and has attached much attention in the field of healthcare. Emotional recognition is an important subject when talking about human mechanical communication and when analyzing and controlling emotions. Emotions can be detected using a variety of techniques, including facial expressions, speech, body language and psychological signals. Some physiological changes occur in the human body, for example changes in heart rate, temperature, skin conductivity, muscle tension and brain waves. This paper extracts temperature, blood pressure and heart rate values from a temperature sensor, pulse sensor and ECG sensor and uses them to teach in depth learning. Convolution neural network classifier algorithm, which assumes a classification problem based on the conditional probability model and that each aspect is independent of the other, the advantage of using this method is that each person has different patterns based on heart rate. Sometimes the normal body temperature and heart rate of individuals vary. The same database is used to train CNN, for example another classification problem that helps to analyze the algorithm, which is more accurate. In deep learning can help accurately predict each person's emotional state.

Index Terms: Human Identification, emotional recognition, deep learning, health monitoring, IOT.

1. Introduction

Recently, IOT systems have been widely used in variety of fields, including every industry is vertical, it also ranges from the environmental protection of cultural heritage conservation and retail to manufacturing. Recently, the IOT system attenuation in the research field of healthcare every human being behaves differently if different situation so there are no generalized parameters to detect that swings. But there are some unique features that provide accuracy for emotion recognition. Regulating emotions is one of the most important areas of health. There are four basic emotions considered in this paper. Those are Normal, Happy, Anger and Fear. A lot of research has already been done in this area focusing on the detection of emotions using psychological signals such as ECG, body temperature and skin conduction value etc. In this paper focused on emotion recognition using psychological signal. DEEP LEARNING algorithm is applied on the data collected from the sensors.

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As already described above there are many different ways in which emotions are detected. Following are some of the ways: Tone of speech, Facial expression and EEG and ECG. The conditions of this work are as follows: We designed the IOT system for emotional recognition to checking the emotional changes.

1.1 Role of Cloud Computing in IoT

One component that improves the success of the Internet of Things is Cloud Computing. Cloud computing enables users to perform computing tasks using services provided over the Internet. The use of the Internet of Things in conjunction with cloud technologies has become a kind of catalyst: the Internet of Things and cloud computing are now related to each other. These are true technologies of the future that will bring many benefits. Due to the rapid growth of technology, the problem of storing, processing, and accessing large amounts of data has arisen. Great innovation relates to the mutual use of the Internet of Things and cloud technologies. In combination, it will be possible to use powerful processing of sensory data streams and new monitoring services. As an example, sensor data can be uploaded and saved using cloud computing for later use as intelligent monitoring and activation using other devices. The goal is to transform data into insights and thus drive cost-effective and productive action.

1.2 Application of IoT

- Home Automation
- Wearable Health Monitors
- Disaster Management
- Biometric Security Systems
- Smart Cars

Emotional recognition general block diagram is shown in figure.1.

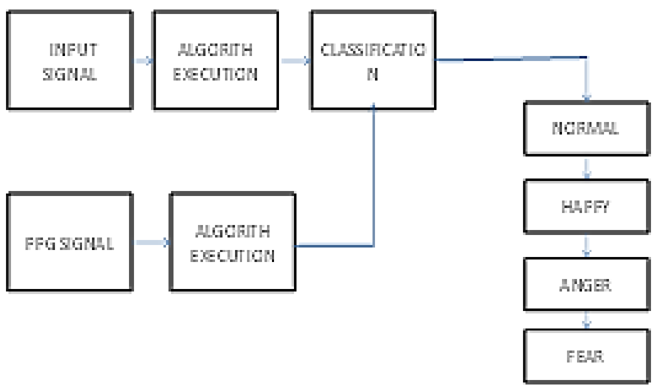

Figure.1 General Block Diagram of Emotion Recognition System

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2. Related Works

Shambhavi S S proposed a method to classify emotions using acoustic features. The Mel frequency cepstral coefficients are the considered features of this purpose. The MFCC features improve the accuracy of classification by the SVM. The emotions are classified and displayed in a mat lab GUI. In the research done by the Milton, classifications of the emotions based on MFCC feature extraction in done using a three-stage SVM.

The studio recordings in Berlin emotion database is classified into seven different emotions here. The SVM used in the experiment makes use of linear and RBF kernels. The linear kernel single-stage SVM claims to have an accuracy of 65% and the three-stage SVM claims to have an accuracy of 68%.In the research done by Marian, A Real time facial action recognition system based on facial action coding system (FACS) is proposed. The system splits the video into subsequent frames and codes each frames based on 20 Action units. The classification done using Adaboost and SVM are compared in the paper. The facial featured are extracted using Gabor wavelets. Gwen Littlewort proposed a fully automated facial expression recognition system. The system utilizes techniques like SVM, Adaboost and LDA for classification of Gabor features. They scaled images into equal dimensions. Features were extracted by convolution of the image with Gabor filters. The system using SVM and Adaboost claims to have a success rate of 93.1%.Carlos Busso proposed a multimodal system combining facial and acoustic features. Two methods discussed in the paper for this are decision level and feature level integration. It is seen that facial expression performed better than acoustic features during emotion classification. The former gave a classification accuracy of 70.9% while the latter gave 85.1% accuracy. Multi-model system provides a 5% improvement over the previous systems. Human Recognition system using smart sensors-A research by Muhammad Tauseef Quazi states that emotion is a mental state that arises and is accompanied by physiological changes. He said studying these emotional changes is very important and can help in identifying at an early stage before they become serious. Human emotions detection using brain wave signals-according to AIMejrad emotions play critical role in rational and intelligent behavior. When people are happy, their perception is based on selection happy events, same in case of negative emotion. So, decisions taken by human beings are highly affected by their emotional states .He studied emotions using brain signals and classified emotions into three type's i.e .motivational, basic and social.

Automated Facial Expression Recognition System-here author studied emotions using facial expression and classified emotions into 6 types i.e. happiness, sadness, fear, surprise, anger and disgust. He later expanded them into more types including relief, satisfaction, embarrassment etc. [5] HERS is a real time system for emotion recognition through analysis of facial expression and speech features. The system simultaneously detects emotion from live video audio streams. The system splits the video stream, into sequence of images, then detects the face of a person from the frames and extracts his/her emotion.

Facial expression, a non-verbal communication plays a vital role in emotion recognition and classifies the human emotion into six basic facial expressions: happiness, sadness, surprise, fear, disgust and anger as researched by Monika dubey and proof. Lokesh Singh. Data analysis by using ML Algorithm on controller for Estimating Emotions-this paper targets GSR with BVP and temperature analysis to detect emotions. According to them, one can't avoid situation but can have awareness when body feel stress or any other emotion.

Materials and Methods

2.1 Methodology

The proposed system has a work flow of four steps which includes

- Sensors and devices layer
- Additionally include the ECG and Blood pressure sensor.
- Automatic feature extraction subsystem using Convolution neural network

The patient health is constantly monitored using parameters such as blood pressure, body temperature and ECG. All of these parameters are sensed by different sensors. The sensed data are then transferred to the cloud. The cloud is mainly used to save and access the data. The Wi-Fi module used to transfer the data between the data and the cloud. The internet gateway acts as a connective layer between the Wi-Fi module and the cloud. The cloud data are stored in the mobile application.

2.2 Dataset

This data set involves three features taken into consideration. i.e blood pressure, body temperature and ECG. Body temperature is measured in degree Celsius and heart rate in beats per minute (bpm). Blood pressure is measured in millimeters of mercury (mmHg), this data is taken among individuals of age group 20-21 and assumption is taken into account about the gender of individual that it doesn't impact the emotion.

2.3 PARAMETERS

- ECG
- Body Temperature
- Blood Pressure

ECG: Each part of the heart data was under two emotional states, the first corresponding to the neutral state and second connected to the target state. We have defined the mean value of the first part data under neurological condition as the basis for eliminating individual difference.

Body Temperature: Our body is like a small furnace. It puts out heat all the time. When it releases more or less heat than usual, it tries to indicate a problem. The average normal body temperature 98.6^{0}F (37^{0}C) some studies have shown that the normal body temperature range

97^0F to 99^0F (36.1^0C to 37.2^0C) in Celsius. Emotional stress activates the neural system (sympathetic), which leads to physical respects, such as a rise in body temperature.

Blood Pressure: Blood pressure (BP) is the pressure of circulating blood against the walls of blood vessels. Most of this pressure results from the heart pumping blood through the circulatory system. When used without qualification, the term "blood pressure" refers to the pressure in the large arteries.

Blood pressure is usually expressed in terms of the systolic pressure (maximum pressure during one heartbeat) over diastolic pressure (minimum pressure between two heartbeats) in the cardiac cycle. It is measured in millimeters of mercury (mmHg) above the surrounding atmospheric pressure.

- The higher number is called systolic pressure.
- The lower number is called diastolic pressure.
- Both pressure are recorded as "mmHg" (millimeters of mercury)

2.4 Convolutional Neural Network

Convolutional neural networks are composed of multiple layers of artificial neurons. Artificial neurons, a rough imitation of their biological counterparts, are a mathematical function that calculate the weighted sum of multiple inputs and outputs an activation value. The behavior of each neuron is defined by its weights. When fed with the pixel values, the artificial neurons of a CNN pick out various visual features. When you input an image into a Cont-Net, each of its layers generates several activation maps. Activation maps highlight the relevant features of the image. Each of the neurons takes a patch of pixels as input, multiplies their colour values by its weights, sums them u, and runs them through the activation function. The first layer of the CNN usually detects basic features such as horizontal, vertical and diagonal edges. The output of the first layer is fed as input of the next layer, which extracts more complex features, such as corners and combination of edges. As you move deeper into the convolutional neural network, the layers start detecting higher level features such as objects, faces and more. Here in our proposed work, data is sent to the cloud solution, where all features are calculated and submitted to the proposed prediction subsystem based on a one –dimensional CNN products the features of the parameters which are classified for analysis. Finally a classification to support the medical diagnosis is presented to the clinical staff.

3.5 Equipment

Sensor: Sensors are an integral part of modern living. A sensor is a device that measures physical input from its environment and converts it into data that can be interpreted by either a human or a machine. Most sensors are electronic (the data is converted into electronic data), but some are more-simple, such as a glass thermometer, which presents visual data. They are commonly used to measure temperature, gauge distance, detect smoke and regulate pressure a myriad of other uses. It generates an electrical signal or optical output signal corresponding to the variations in the level of inputs.

- ECG sensor
- Blood pressure sensor
- Body temperature sensor

Arduino UNO Microcontroller Board: The Arduino microcontroller board contains an Atmega328 microcontroller. It consists of 14 digital pins and 6 analog pins for input/output operations. It can be powered by the USB cable or by an external 9-volt battery, though it accepts voltages between 7 and 20 volts.

ESP8266 Wi-Fi Module: To upload the sensor data in a cloud environment we required a wired/wireless communication module. The ESP8266 Wi-Fi Module is a self-contained SOC with integrated TCP/IP protocol stack that can give any microcontroller access to your Wi-Fi network.

3.6 Cloud Environment

All the collected sensor data will be gathered in Cloud Environment. Cloud computing is the on-demand availability of computer system resources, especially data storage and computing power, without direct active management by the user. The term is generally used to describe datacenters available to many users over the Internet. Large clouds, predominant today, often have functions distributed over multiple locations from central servers.

3. Proposed Model Description

Emotional recognition system helps to identify human emotions and analyze these emotions to control them at an early stage before harming a person’s health. The proposed system consists of a wearable device that has sensors that constantly read body temperature, blood pressure and pulse rate and sends it to the Arduino board on the device. Arduino sends this data to the gateway, all of which will be sent from the gateway to the cloud and stored in the cloud. All calculations and deep learning methods are implemented based on the data collected; we primarily consider four different emotions here as sad, happy, normal and angry.

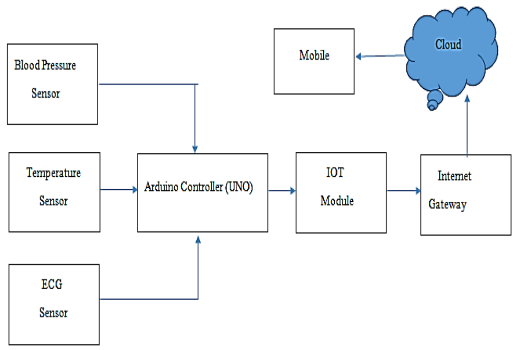

Figure.2 Block Diagram of Proposed Model

4. Results and Discussions

This system will predict emotion of an individual on the basis of his/her ECG, blood pressure and body temperature. For prediction part, the paper used deep learning algorithm, i.e. Convolution neural network classifier. The deep learning algorithm will take parameters like ECG, blood pressure, body temperature from the PPG which is linked with arduino. We have divided different range of heart beat. A temperature value and assigned an emotion class to them. If a person's temperature lies in range of 36.5-37.5^{0}C and 70-90- bpm, then he is normal. If a person's temperature lies in range of (37.0)37.0-38.0^{0}C and bpm lies in range of 90-110 bpm, then he is happy. If a person's temperature lies in range of 36.5 to 38.50C and bpm lies in range of 110-130 bpm, then he is anger. If a person's temperature lies in range of 36.0-37.0^{0}C and bpm lies in range of 110-150 bpm, then he is fear state. Running C script figure shows the result to which class the input variable belongs to and which is accuracy of the algorithm. Input from user will be fed to algorithm which predicts the class to which emotion of user belong.

Test Cases: The IOT server regularly collects the listed measured parameters and plots on graphs with reference of data they measured .Think speak channel settings can be changed as per figure showed.

Figure.3 Output of Combined ECG Analysis

Figure.4 Blood Pressure Level of Patient

Figure 3 The graph indicating temperature status of Patient

Result

- Temperature Output: 37
- ECG: 95
- Body Temperature: 118/75
- State: Happy
- Accuracy (%): 98

Table 1Type of data collected from testing CNN algorithm

Body Temperature	ECG(bpm)	Blood Pressure	State
37	95	118/75	Happy
37	90	120/80	Normal
38	90	132/85	Angry
39	105	95/60	Fear

5. Conclusion and Future Work

In this paper, we developed human recognition system based on data from physiological sensors. This allowed us to provide different limits of these physiological parameters of the testing and simulation system. We created the concept metaphor by taking into account three physiological parameters body temperature, heart rate and blood pressure. Three future work, system development and improvement we can do additional parameters

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such as respiration, perspiration, skin behavior value can help predict a person's emotional state with great accuracy. Also design part of the job is to be able to wearable devices that can be customized for an individual. It cracks an individual's emotions and can be helpful in monitoring his/her health, calculating the threshold for each individual using deep learning technique. Also this type of system can be modified diagnose stress levels with emotions, which further helps an individual to manage stress.

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