Activity Monitoring and Alert System for Elderly People in Smart Homes

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***Abstract*—The rapid ageing of the population poses difficulties for elderly people who live alone. It gets more difficult for people who live in rural areas. As a result, there is an immediate need for real-time monitoring via the internet of things (IoT). In this work, An activity monitoring and alert system are proposed, which monitors health parameters such as ECG, oxygen amount in the blood, fall detection, and the person's activity. The individual monitors his or her heart disease using various wearables. The chest strap is used to read the ECG signal, the wrist strap is used to check the oxygen level in the blood, and the footwear is used to detect falls. To reduce false alarms, three modules are integrated. For activity monitoring, multiple sensor nodes are placed throughout the house. Any deviation from the parameters sends a message to the cloud database, alerting family members, doctors, and emergency services. The proposed system is useful for providing medication and assistance on time.**

***Index Terms*—Activity monitoring, Alert Systems, Ageing people, Health care support, Internet of Things, Smart homes.**

I. Introduction

WHO and World Population Prospects-2019 (United Nations), stated that within 2050, 1 of every 6 individuals in the world will be over the age of above 65, up from 1 of every 11 in 2019. In any case, the number of people aged 65 and more will outweigh kids under the age of five in roughly five years. The number of people aged 65 and older are forecast to rise from 524 million in 2010 by about 1.5 billion in 2050 [1]. Demand for continuous monitoring emerges as older people become more vulnerable to several diseases, such as heart diseases, Alzheimer's, dementia, and diabetes mellitus. A study published in issue of health journal, 'The Lancet', reported, the number of people who died from cardiovascular illnesses (CVDs) rise from 1.3 million in 1990 to 2.8 million in 2016. More than half of total CVDs deaths in 2016 were found in people younger than 70 years [2]. The cost of hospitalisation for such a vast number of people will be prohibitive. So finding effective way of detection and prevention of heart attack is very much necessary to reduce number of deaths due to this. In 2008, WHO had set target of relative reduction of 25 in overall mortality from CVDs by 2015. The elderly, on the other hand, are at risk of losing their freedom if they do not receive adequate care. This has sparked a surge of interest in the field of ambient assisted living (AAL). Hospitalization, cost efficiency, and elderly independence are all concerns that have arisen as a result of the ageing population, and AAL is considered as a model for addressing them. Monitoring activities at home is a well-known practise for providing assistance and supporting the elderly's independence.

Sensors and devices that are seamlessly integrated into the environment, as well as gadgets that the resident wears or interacts with, can be used to collect a wide range of metrics in an AAL setting [3]. The data collected in this context is tied to the vital signs, activities, and physical world things of the residents, which can be used to infer user behavioural traits. In an AAL scenario, recognising and recording activities of daily living (ADL) is essential. It is critical to understand what activities users are performing, how they are performing them, and where they are in the process. The significance of recognising ADL arises from the belief that any lack or abnormal behaviour in the daily activities might suggest critical health problems and serve as significant indicators of illness development [4]. Heart failure and chronic disease, for example, might create disturbed sleeping patterns. Thus, it is more than necessary to analyse elderly people's behaviour and abnormalities in their activities. Because sensor technology is now more widely available, automatic activity recognition has become a reality. As a result, a person's behaviours can be traced and regularly observed by connecting a range of sensors to various things, positions, and the human body.

II. Literature Review

Munkhjargal Gochoo et al. [5] proposed an unobtrusive activity recognition system using binary sensors and deep convolutional neural networks. They employed aruba annotated open dataset and segmented each activity and converted into activity images. They trained activity images using DCNN and 10-fold cross-validation. The limitation is they manually removed overlapping annotated data to improve the accuracy. Tan-Hsu Tan et al. [6] proposed a front-door event classification technique for identifying older persons in smart homes forgetting events. They validated the algorithm by checking the brief-return-and-exit events among the door events and based on results it could be useful for using as a tool for detecting early symptoms of dementia. Das et al. [7] designed a health monitoring kit using raspberry pi (RPi) and thingspeak cloud server. The kit monitors ECG variations, oxygen level saturation, heartbeat, skin parameters, and motion. All sensors are integrated with RPi and send to thingspeak using IoT for visualisation purpose. It lacks any type intimation during emergency.

Trio Pambudi Utomo et al. [8] developed a heart rate monitoring system where they are using 3 electrodes and an AD8232 kit to get the ECG signal. The signal received is processed in Arduino Uno for QRS complex peak detection using the peak threshold method and peak filter method. Then they are sending ECG values via Bluetooth module to an android smartphone where they are displaying ECG signal and heart rate. Here, they are detecting the QRS complex to calculate heart rate. No type of abnormality they are identifying. Abdallah Kassem et al. [9] developed a smart device to detect heart abnormality using R-R intervals. The system is made up of an electronic gadget with electrode sensors attached to certain body areas. The ECG collected is then analyzed with the help of an android application interfaced with the system via Bluetooth. When any abnormality is detected then the intimation is sent to the doctor along with GPS location and ECG graph. Here, the issue with this system is it is unable to detect what type of heart abnormality occurred and also this system is based only on R-R interval. Muhammad E. H. Chowdhury et al. [10] developed a prototype model of a portable and wearable ECG system for real-time heart attack detection. For the analog front end, they used the off-the-shelf AD8232 module. Once the ECG signal received from 3 electrodes is filtered and amplified, the output of AD8232 is given to the RFduino module where the signal is digitized and sent to the detection system via BLE. The received data is preprocessed and P, QRS complex and T features are extracted and compared with pre-trained machine learning algorithms for abnormalities in the ST segment and T segment.

Joseph Masip et al. [11] proposed a study with pulse oximeter as a diagnostic marker for patients having risk of acute myocardial infarction. Their research demonstrates the value of SpO2 as a supplementary tool, and a baseline SpO2 of less than 93 may be a marker of Acute Heart Failure. Sima Ataollahi Eshkoor et al. [12] conducted a study on elderly people suffering from various diseases and observed that due to the negative effect of medications, age, poor nutrition, psychological problems, etc. the risk of falls increases. They observed people with heart disease experienced more risk of falls than people without heart disease. Laura Montanini et al. [13] developed an threshold based algorithm for fall detection using a pair of smart shoes. It has force sensors as well as a tri-axial accelerometer. The footwear analyses the motion and foot orientation of the user and able to recognize any abnormal configuration and notifying it to the supervising system. Because the devised technique is not computationally intensive, it may be simply implemented on the wearable device. They have not applied any machine learning algorithms.

III. Proposed Work

The overall system model of the proposed system is shown in Fig. 1. It is used to analyse the health and behaviour of the person living alone at home. The system consists of multiple modules like a chest strap, wrist strap, footwear, and sensors network, a local server, a local database, an IoT gateway, a cloud server, and an alert system. Each module gathers data from the sensors placed on the body and at different locations in the house. The data is preprocessed and sent to the local server wirelessly. The local server stores those data in the local database and analyses the data to check for any abnormality. If any abnormality is observed, then it sends the information to the cloud IoT server from where the intimation is sent to the concerned family members, doctor, and ambulance. The proposed system is implemented using wearable sensors and ambient sensors. Ambient sensors are used to recognise the activity of the person and wearable sensors are used to monitor the heart attack.

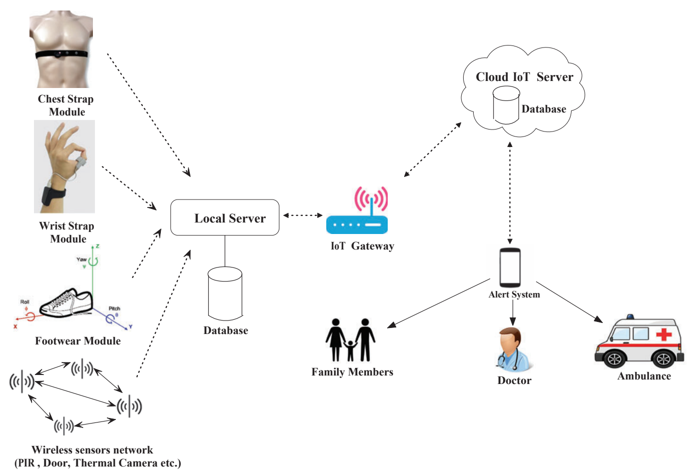

Fig. 1: System Model of Activity Monitoring and Alert System.

A. Activity Monitoring System using Ambient Sensors

The activity monitoring system using ambient sensors is shown in Fig. 2 consists of multiple sensor modules, a local server, a local database, a cloud server, and an alert system. Sensor modules are placed at different locations in the home to recognize the activity of the person. Mainly two types of sensors, motion sensor, and door sensor are used. Whenever any event occurs, the microcontroller sends a message to the local server wirelessly using Message Queuing Telemetry Transport (MQTT) protocol. The server receives the data and stores it in the database. Later the annotated data is converted into activity images and given as test input to the pre-trained Convolutional Neural Network (CNN) classifier which classifies the activity that occurred. The validation is performed using standard parameters like precision, recall, accuracy, F1 score, etc. In this work, mosquito broker is used and raspberry pi acts as a broker. By using this setup, a dataset would be created to perform and recognize different activities performed inside the home. For analysis purposes, pre-generated annotated data is used which is an open dataset collected in Aruba testbed [5] from WSU-CASAS project.

There are a total of 10 activities performed in it. Algorithm 1 describes the conversion of binary sensor data into activity images.

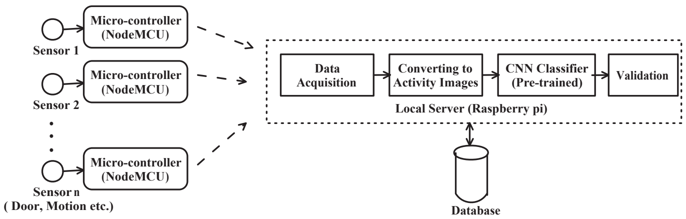

Fig. 2: Activity Monitoring System

Algorithm 1 Binary image generation from sensor data of the activity.

$x \leftarrow sensor\ data\ for\ all\ events$
$y \leftarrow Matrix\ containing\ activity\ labels$
for $i \leftarrow 1, Total\ number\ of\ events$ **do**
  $m \leftarrow Row\ of\ begin\ point\ of\ an\ activity$
  $n \leftarrow Row\ of\ end\ point\ of\ an\ activity$
  $a \leftarrow Create\ a\ zero\ matrix\ of\ size\ 150x250$
  $b \leftarrow Activated\ sensor\ values$ $\rightarrow$ Values of sensors activated between m and n points
  for $k \leftarrow 1, Number\ of\ events\ in\ specific\ activity$ **do**
    $a \leftarrow Replace\ '0'\ with\ '1'\ at\ the\ sensor\ activated$
  end for
end for

B. Heart Attack Detection System using Wearable Sensors

Heart attack detection system using wearable sensors consists of three sub-modules: Chest strap module, Wrist strap module, and Footwear module. All three modules are integrated and contribute to the detection of heart attacks and to reducing false alarms.

1) Chest Strap Module: Fig. 3 shows the block diagram of the chest strap module. It consists of 3 electrodes, an AD8232 module, and a micro-controller. Here, the 3 electrodes are placed at different places on the chest to read the electrical activity of the heart and the sensed signal is given as input to the AD8232 module. The AD8232 module preprocesses the signal such as filtering and amplification of the signal. Then the conditioned analog signal is given as an input to the microcontroller. The microcontroller converts the analog signal into a digital signal using ADC and sends it to the local server wirelessly. On the server side, the acquired data is transformed into images and properly segmented between R-R intervals and given as a test input to the pre-trained CNN model. The CNN model will classify and gives the result.

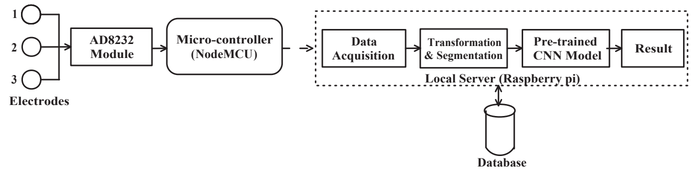

Fig. 3: Chest Strap Module

2) Wrist Strap Module: The block diagram of wrist strap module is shown in Fig. 4. It consists of a MAX30100 module which is a pulse oximeter and can measure the pulse rate and oxygen saturation of hemoglobin in arterial blood. It uses light to measure SpO_2 in blood. If the processed values are less than the threshold [11] i.e SpO_2 value is less than 93 percent then the alert signal is sent to the master microprocessor by using MQTT protocol. SpO_2 is defined as the ratio of the oxygenated Hemoglobin level over the total Hemoglobin level and is represented as shown in equation 1.

$$SpO_2 = HbO_2/(Hb + HbO_2) \tag{1}$$

where HbO_2 is the Oxidized hemoglobin and Hb is the Reduced hemoglobin

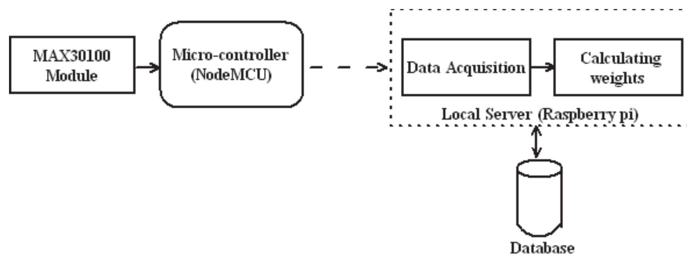

Fig. 4: Wrist Strap Module

3) Footwear Module: The Footwear module as shown in Fig. 5 consists of an Inertial measurement unit (IMU) sensor i.e MPU6050, a microcontroller and a force sensor. The MPU6050 sensor and pressure sensor send the raw data to the NodeMCU to process the data and compared it to the threshold values whether processed data is greater than the threshold values then it is detected as a fall and transmits the alert signal to the Raspberry pi using MQTT (Message Queuing Telemetry Transport) protocol. The Raspberry pi will verify if a fall occurred by checking the alert signal from both the foot module and making a final call.

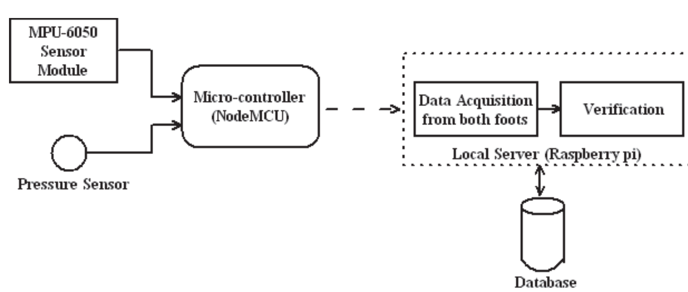

Fig. 5: Footwear Module

Values from the accelerometer and gyroscope are used to compute the roll, pitch, and yaw. Roll angle using the accelerometer output is calculated using following the equation 2

$$R_a = arctan(\frac{A_x}{A_y}) * 180 \quad (2)$$

The pitch angle using the accelerometer output is calculated using following the equation 3

$$P_a = arctan(\frac{A_x}{\sqrt{{A_y}^2 + {A_z}^2}}) * 180 \quad (3)$$

Roll angle using the gyroscope output is calculated using following the equation 4

$$R_g = G_x * dt \quad (4)$$

The pitch angle using the gyroscope output is calculated using following the equation 5

$$P_g = G_y * dt \quad (5)$$

where A_x, A_y, and A_z are the acceleration values in x, y, and z direction respectively and G_x, G_y, and G_z are the angular velocity in x, y, and z direction respectively.

IV. Implementation

The CNN classifier has three convolution layers and pooling layers as a feature extraction component, and flattened neurons with fully connected layers (FCLs) as a classification part, as illustrated in Fig. 6. For the kernel size (feature filter) 2 x 2 layers of pooling is used, so the output size is twice as small as the input value. In the end, 8 and 10 outputs are connected to the neurons in the last row when testing for 8 activities and 10 activities. The annotated Aruba open dataset is used and each activity is converted into binary images and used for training. Several CNN classifiers such as Densenet, VGG16, Resnet50, DCNN [14], [5] is implemented for comparison, with various parameters. Only the parameters of the convolution layers and values of the FCLs are modified. Flattened outputs from the last layer of max-pooling are supplied to the first FCL neurons. In the two FCLs that follow, all of the neurons are coupled together. The neurons in the final layer are connected to 8 outputs and 10 outputs at the end and the softmax activation function is used to classify the activities with probabilistic values between 0 and 1. Experiments are carried out for 8 activities and 10 activities. Activities Leave_Home and Wash_Dishes are excluded as they are affecting the classifier performance.

A. Experimental Results

Fig. 7 shows the accuracy and F1 score of different architectures for 8 activities. The proposed CNN architecture is compared with the existing and popular architectures VGG16, densenet and resnet. It could be observed that the proposed model performs better than existing models and DCNN architecture [5]. Similarly, Fig. 8 compares for 10 activities. Fig. 9 and Fig. 10 shows the graph between number of epochs and F1 score of different architectures. Here also, it could be observed that the proposed CNN architecture outperforms the DCNN [5] and existing architectures.

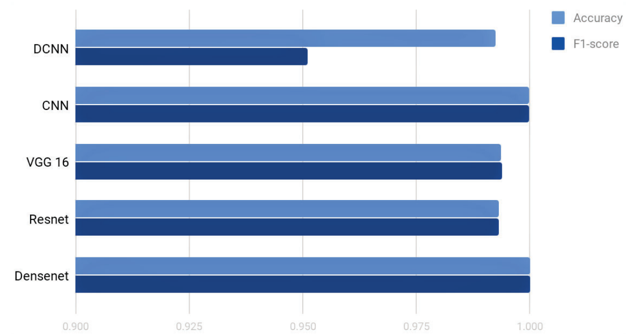

Fig. 7: Comparison of F1 score and accuracy for different architectures(8 activities).

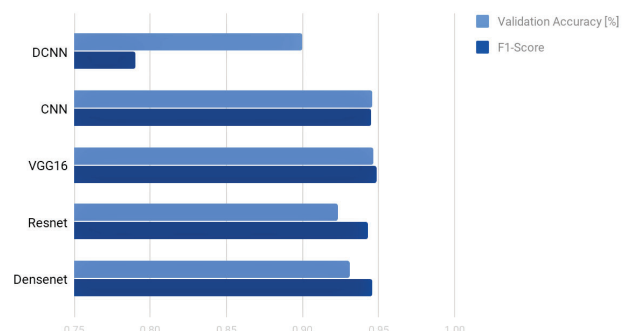

Fig. 8: Comparison of F1 score and accuracy for different architectures(10 activities).

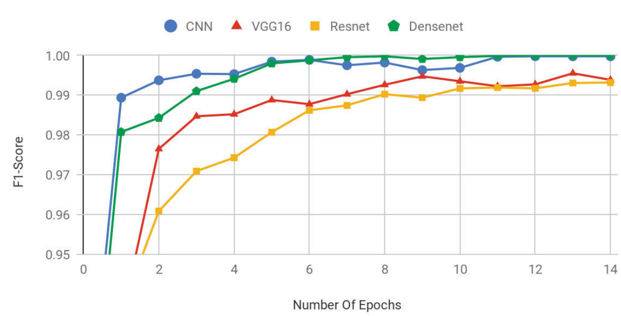

Fig. 9: Number of epochs vs F1 score for different architectures(8 activities).

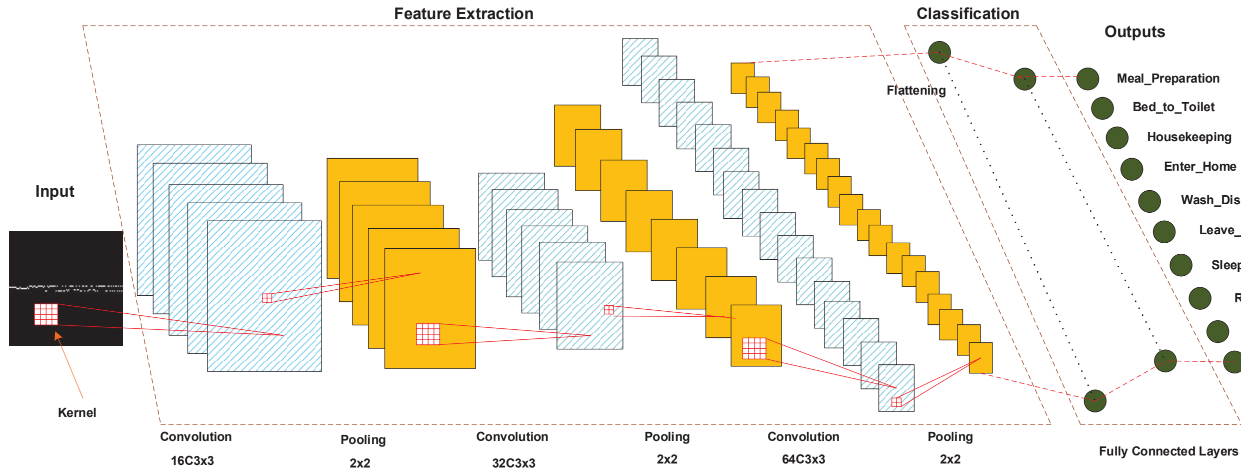

Fig. 6: The architecture of the CNN classifier

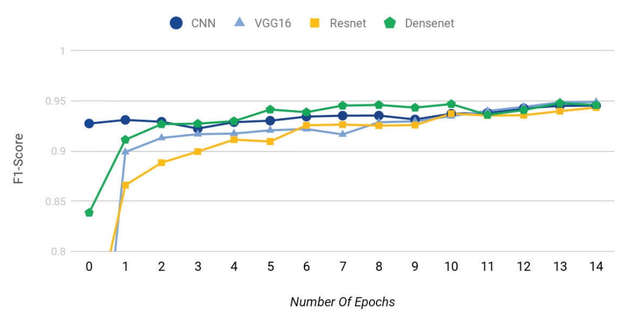

Fig. 10: Number of epochs vs F1 score for different architectures(8 activities).

V. Conclusion

As part of the proposed system, activity images are generated from the Aruba open dataset. Activity images are trained and tested using different architectures. The proposed CNN classifier produces highest F1 score and accuracy as compared to other architectures. Hardware prototype of wearable sensors based heart attack system is implemented. Values from the different sensors are acquired. As a part of future work, based on observation on abnormal values of different sensors, alert can be given to the caretakers and emergency services. Further, natural language processing based techniques would be explored for improving the activity recognition.

VI. Acknowledgement

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