CNN Based Smart Sleep Posture Recognition System

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ABSTRACT: Sleep pattern and posture recognition have become of great interest for a variety of clinical applications. Autonomous and continuous monitoring of sleep postures provides useful information for lowering health risk. Existing systems are designed based on electrocardiograms, cameras, and pressure sensors, which are expensive to deploy, intrusive to privacy, or uncomfortable to use. We propose an unobtrusive and affordable smart system based on an electronic mat called Sleep Mat-e for monitoring the sleep activity and sleep posture of individuals living in residential care facilities. The system uses a pressure sensing mat constructed using piezo-resistive material to be placed on a mattress. The sensors detect the distribution of the body pressure on the mat during sleep and we use Convolution Neural Network (CNN) to analyze collected data and recognize different sleeping postures. The system is capable of recognizing the four major postures Face-up, Face-down, Right Lateral, and Left Lateral. A real-time feedback mechanism is also provided through an accompanying smartphone application for keeping a diary of the posture and send alert to the user in case there is a danger of falling from bed. It also generates summaries of postures and activities over a specified period of time. Finally, we conducted experiments to evaluate the accuracy of the prototype, and the proposed system achieved a classification accuracy of around 90%.

Keyword: *Sleep posture recognition; Internet of Things; Convolutional Neural Network; Machine Learning; Healthcare.*

1. Introduction

The population of elderly people is on the rise and the number is expected to reach 20% of the total world population by 2050 [1]. They tend to suffer from poor sleep quality which leads to myriad problems and affects their physical health, cognitive function, and overall quality of life [2- 5]. Therefore adequate and restful sleep is important as it allows the body and brain to undergo necessary restorative activities. The quality of sleep seems to be a common problem among the elderly and needs attention. Sleep analysis is a very important step towards the detection and diagnosis of sleep problems. In addition to sleep quality, sleep posture is another prevalent issue among elderly and may cause pressure injuries (PI) if they have prolonged sleep in a single posture without moving, as shown in Fig. 1. The PI may result in constant pain, loss of mobility, depression, and even death. Studies have found that sleep issues are more prevalent within the residential care population [6, 7]. Furthermore, certain sleep positions and postures are considered to be the major causes of certain diseases [8]. Elderly sleeping in the decubitus position have a higher risk of developing sub-acromial impingement syndrome [9] and those sleeping in a supine position are more likely to develop the symptoms of sleep paralysis [10]. Similarly, sleeping on the right side poses a higher risk of development of transient lower esophageal sphincter relaxation, which is the main factor in nocturnal gastroesophageal reflux [11]. Finally, falling out of bed during sleep is another major risk to the elderly, resulting in injuries and even death in extreme cases.

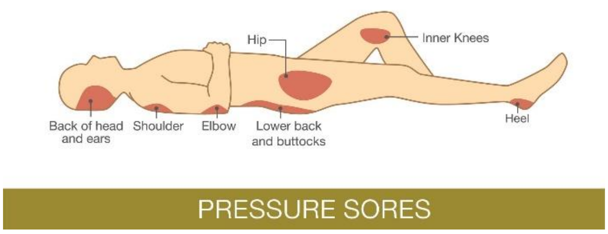


Fig. 1 Pressure Sore Face Up [12]

The aforementioned risks can be mitigated if staff actively and regularly monitors the patient at the elderly care facilities. Clinical shreds of evidence suggest that body posture during sleep serves as a diagnostic indicator for a variety of chronic diseases and as an aid in medical therapies. Detecting and monitoring these symptoms can be challenging and may also require the use of extra staff resources. This will lead to increased healthcare costs and can be a significant source of stress for the patients. The healthcare community has also emphasized the need and importance of a long-term sleep tracking system to identify trends and help people create personalized sleep goals.

The challenges, rising costs of care and effects of sleep-related issues on the elderly motivate the need for a system that could assist medical practitioners and caregivers in residential-care in monitoring patients more efficiently. The Internet of Things (IoT) technology enables and facilitates remote monitoring of patients who don't have ready access to effective health monitoring. The IoT is a network of smart devices and other objects, integrated with electronics, software, sensors, and network connectivity that allows these objects to obtain and exchange data [13, 14, 15]. It also helps thoroughly reduce costs and promote health by increasing the availability and quality of care. On the other hand, there are several methods for sleep posture classification, including -means clustering [16], artificial neural network [17], dual-tree [18], and support vector machine (SVM) [19]. However, these traditional methods require substantial manual features extracted from the preprocessed signals and are prone to local optimization. Recently, researchers proposed a deep learning model named Convolutional Neural Network (CNN), reduces the complexity of the network and number of weights because of its shared-weight network structure when compared with the traditional methods, CNN is widely used in the field of object recognition [20] and image segmentation [21, 22].

The objective of this study is to devise and implement a system for monitoring the sleep health of the elderly people living in hospice. We propose a smart autonomous system that is capable of monitoring sleep pattern, sleep posture, and producing alerts about potential fall during the sleep. This IoT based solution can be utilized to record patient health data in a secure manner from several sensors, apply deep learning algorithms to analyze the data and then distribute it through wireless connectivity with medical specialists who can make suitable health recommendations. This can also help people learn about their sleep habits and find ways to improve sleep health by obtaining feedback on their sleep postures and activities. This can reduce the cost and burden on the health system by providing caregivers and healthcare professionals with sleep-related data so that they could implement preventative measures to reduce and manage the risks of poor sleep as necessary. The system can be used to assess sleep efficiency (the ratio of total sleep time to time spent in bed), sleep latency (the duration from bedtime to the onset of sleep). These measures can help physicians detect and diagnose sleep-related disorders such as insomnia and sleep apnea [23].

This paper is organized as follows: The following Section provides the research carried out in the related areas and Section III gives a detailed description of the overall system architecture. Methodology is discussed in Section IV. Experimental results are presented in Section V followed by the conclusion at the end.

2. Related Work

Sleep is a major part of health and well-being. Researchers have explored diverse techniques for capturing and providing feedback on aspects related to sleep health. In many early studies on sleep postures, an empirical approach was favored and data was collected by interviewing subjects. In recent years, advancements in the IoT and sensing modalities have enabled researchers to more accurately determine the posture and patterns during sleep.

There are numerous solutions available [24-53] that in one way or another try to quantify the quality of sleep or sleep posture. These solutions use different techniques to acquire data for an individual′s sleep. In a clinical sleep assessment setting, the current ′gold standard for diagnosing sleep disorders and issues is the use of polysomnography (PSG) [24]. This method involves the measurement of multiple physiological parameters, such as brain activity, blood oxygen level, heart rate, breathing, and leg and eye movements. It also requires a number of sensors and equipment to be physically attached to the patient′s body. Although this method provides accurate results and insight into one′s sleep, it is obtrusive, disruptive, expensive, and requires monitoring in a highly controlled and unnatural setting. Therefore, it is only suitable for medical-supervised evaluations and not feasible for daily use. A similar device called *WatchPAT* [25] is worn on the wrist by the subject and comes with a finger clip. It monitors the sleep of the patients within the comfort of their own home and usual sleeping environment. This method is much more informal, however, it is still intrusive in nature as it requires the device to be worn on the wrist tightly. This may cause discomfort in subjects, especially, elderly persons.

Nowadays, smart-phones have become a fundamental part of our daily life, including the healthcare domain. A lot of people are using mobile Apps to help improve their health and fitness. There are a plethora of readily available smartphone applications that can monitor sleep patterns using built-in sensors [26-30]. Some of the available Apps are: *Toss 'N' Turn sense* [26], *My Sleep APP* [27], ʹ*Sleep as Android* [28] and *Runtastic Sleep Better* [29], and *iSleep* [30]. A number of commercial smartphone applications are also available which include: *Smart Alarm Clock*, *MotionX*, *Sleep Cycle*, *Sleep Bot*, *Sleep Cycle*, *Sleep Tracker*, *Sleep as Android*, and *Sleep as Android Paid*. While smartphone applications are easily accessible and convenient for everyday users, they are infeasible as the smartphone is required to be placed on the bed meaning one phone is required for each user. This would not be very economical when there are a lot of patients. Furthermore, they require user intervention to start and stop the application. Also, they are very susceptible to motion artifacts because they need to be located on the subject's bed. These motion artifacts might arise from a bed partner and/or interference from blankets. As a result, the quality of the signal obtained by the phone's accelerometer can potentially be degraded.

Wearable sleep tracking devices include smartwatches, wristbands, and headbands. These are powerful devices in terms of the sensors that are embedded in it. Sleep sensing using these devices can lower the burden of manual sleep tracking and improve the accuracy of sleep inference at home. The *Fitbit Charge2* [31], *Jawbone UP3* [32], *Zeo*, *SleepImage*, *Lark*, *WakeMate*, *Hexoskin*, *OURA* are popular commercially available wrist-worn sleep trackers used for collecting data about sleep [14, 31, 32]. The major drawback of such devices is their incapability to recognize the posture thus limiting their use to tracking the sleep. They have limited functionality and can monitor only movement and heart rate, which can be used as the basis for tracking sleep, but their accuracy is questionable [33]. Therefore, data obtained from such sleep tracking devices are not intended for routine diagnosis of sleep disorders. In addition, wrist-worn devices are battery-powered and often require Bluetooth connectivity to gather information meaning that it still requires the use of a smartphone for storing and analyzing data. This would result in extra tasks for the caregivers to complete within their daily routines.

The wearable devices might not be the optimal solutions for older adults, since these devices need to be placed on some parts of the body, such as wrists, arms, etc. The elderly people might forget to wear the devices. Other than that, these devices might annoy people that use them. Alternatively, there are other nonintrusive technologies to sleep patterns and recognize the posture of the subject. They are based on pressure sensing or camera based visual data. The latter used common digital 2D, 3D, and infrared cameras to acquire visual data and then applied image processing and machine learning techniques to recognize different postures [34-36]. For example, [34] used a single 2D camera to acquire an image, applied the background subtraction to extract the foreground human body, used projection histogram, and applied support vector machine (SVM) algorithm for posture classification. Some researchers used multiple calibrated cameras to build a multi-view Eigen model of the human body in terms of its constituent body part and then recognize the posture [36]. The versatility of the data captured is augmented by using different sensors in conjunction with the sensors [37-41]. Lee et al. [38] used Kinect camera hanged over the bed to classify six sleep positions. They extracted body joint positions using Kinect V2ʹs own libraries and used the relative position of hands and knees with respect to the spine for classification using a parametric approach. Unfortunately, researcher did not provide any evaluation results. [35] used a 3D camera together with Microsoft Kinect sensors for analyzing body positions and monitoring the posture of a person in residential care. Torres et al. [39] used a combination of depth and infrared cameras together with a pressure mattress to classify among different sleeping postures. Only one scenario with a fixed camera above the bed is used, thus ignoring the alignment problems. Martinez et al. proposed ʺBAM" descriptor based on depth information collected from a Microsoft Kinect, which could monitor the sleeping posture and movement data [40]. This work was further extended to recognize high-level activities such as removing bed covers [41]. [37] used pressure arrays and a single depth camera to build bed aligned maps (BAMs) al. Although, these computer vision and camera-based methods may appear to be suitable for posture recognition and fall detection field, several problems do exist. They are expensive, sensitive to light, require installation, and infringement of personal privacy is a concerning issue and elderly people may worry that they are being ʺwatched" by cameras.

Another approach excluded the use of cameras and instead used smart bed-type devices in the form of sensors installed on or near the mattress for sleep posture monitoring. These devices comprised inertial Measurement Unit (IMU) sensor and wireless technology (Wi-Fi and RFID) to identify sleep quality and sleep postures. Wireless identification and sensing platform (*WISP*) [42] and *MediSense* [43] used the y-axis accelerometer and z-axis gyroscope readings to infer body postures and movement of the patients, respectively. *Wi-Sleep* [44] classifies a personʹs respiration, six sleep positions, and rollovers by leveraging Wi-Fi signals, i.e., channel state information (CSI), from a pair of TX-RX. *TagSheet* [45] used passive RFID tags taped under a bed-sheet or on the surface of mattresses on a bedsheet. Passive tags were powered by radio frequency (RF) signals from an RFID reader, and they communicated with the reader by backscattering the RF signals. By observing the RF signal variance amongst all tags, the reader constructed a coarse-grained grayscale snapshot, analyzed it to identify six sleep positions as well as estimated the respiration rate. *SMARS* [46] exploited ambient radio signals to recognize sleep stages and assess sleep quality. It used a statistical model that accounted for all reflecting and scattering multipath, allowing an accurate and instantaneous breathing estimation and sleep stages, including wake, rapid eye movement (REM), and non-REM (NREM). *SleepSense* [47] used a Doppler radar-based system that could monitor and classify the sleep-related events by detecting the on-bed movements during sleep based on the radar signal. The Doppler radar sensor is a specialized radar that can measure target displacement remotely by using the Doppler Effect. Above mentioned techniques can detect the activities but do not possess the capability to recognize postures.

More recently, research has shifted to pressure sensing techniques as it leveraged to not only identify sleep patterns but recognized postures as well. These techniques made use of different types of pressure sensors that are unobtrusive and did not interfere in the comfort of users. The sensor ranged from simple fluid cells to sophisticated pressure sensing mats. The fluid-filled cells were placed between the patient and the support for detecting motion via pressure fluctuations [48]. The low-ended load cells were placed under each bed leg to classify 27 pre-defined movements by analyzing the computed forces [49]. A more popular approach is to place a small sensing mat between the mattress and bed-sheet. The bedsheet deployed pressure sensors captured pressure mapping images and different postures could be recognized using classifiers. Alternatively, dispersed pressure sensors embedded in the mattress could record when changes in body posture occurred. A non-invasive pressure-sensitive bedsheet was deployed to monitor different sleep postures by generating high-resolution pressure maps [50]. Similarly, a pillow sensor system based on polysomnography that employed a 3x3 sensor array of FSR (force sensing resistor) based on polymer thick film device was used for classifying and recognizing sleep posture [51]. However, this work was only useful for point-of-care applications. On the other hand, [52] used a bed pressure sensor array which could detect changes in the contact pressure between a subject and the bed. It automatically selected the sensor with the best respiratory signal, determined the respiratory rate, and counted the number of sleep apneas and body position changes through the night. Use of fast responsive triboelectric active sensor (TEAS) with adjustable pressure measurement range allowing both gentle pressure detection and large scale pressure sensing [51]. Through integrating multiple TEAS units into a sensor array, the fabricated TEAS matrix was capable of monitoring and mapping the local pressure distribution applied on the device with distinguishable spatial profiles.

The pressure-sensitive mats manufactured by S4 sensors (formerly Tactex Sensors) recorded the patient′s movement between different postures [54]. These mats used photodiodes connected to optical fiber for providing light. The light intensity of photodiodes would vary as pressure applied is translated to a voltage signal indicating the pressure exerted on the mat. Data were transferred to a computer for processing via Bluetooth, and linear and SVM classifiers were used for categorizing data. Apart from being expensive, this system was not able to detect multiple postures and relay the recorded information to the user in real-time. Force Sensing Application pressure mattress [55], a high-resolution mattress that contained 2048 sensors. This system could identify only three different postures, namely ″supine", ″right side" and ″left side". Similarly, [56] used a sensor mat comprising 1728 resistive sensors for identifying 13 different sleep postures using a Gaussian Mixture Model. The image collected from the mat was processed by various filters for highlighting the pressure areas using a low pass Gaussian filter. For identifying the positions of a user′s limbs, pressure sensor data from specific regions on the mat were clustered together. This information was combined with the previously collected information from pressure sensors to obtain the posture classification. KNN linear classifier was used for supervised training using the collected datasets. The reported system was very efficient in terms of the posture classification given the high accuracy of 91.6%. There are few other recent solutions which make use of the pressure sensors and machine learning for identifying different postures [57-62].

According to the author's knowledge, no comprehensive work was dedicated to develop a sleep quality monitoring and sleep posture recognition system with capabilities of delivering processed data to the end-user and a health professional in real-time with a high level of accuracy by using CNN. The proposed system overcomes this drawback by accompanying a smartphone application where the user or medical staff can visualize the data in real-time and can also access the previously collected for analyzing and diagnosing different medical conditions. Some of the solutions used high-resolution mats that could categorize fewer postures but they were not affordable for most consumers due to the high cost. This solution is affordable, and unobtrusive that will enormously decrease the elderly accidents.

3. System Architecture

The system architecture shown in Fig. 2 provides the conceptual model defining the structure of the system. It comprises a sensing mat made up of pressure sensors used to capture data related to the sleep position of the subject. The data acquisition module integrated into the mat collects the data from the pressure sensors providing the snapshot of the

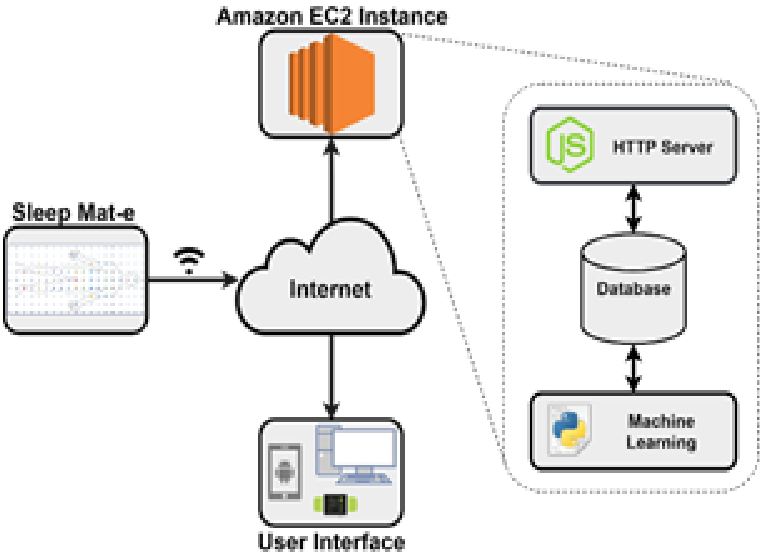


Fig. 2 System Architecture

current posture, and transmits it to the cloud server using the Wi-Fi. The data acquisition unit is implemented using the ATmega32u4 micro-controller. The firmware performs initialization, collects data from sensors, arranges data, and transmits the data to the cloud server using Wi-Fi module. Data received by the cloud server is then stored in the server database. We use a central server design, which performs the data storage, data processing and user authentication.

The server can read the recently added data to the table in the server database for classification. Machine learning is used to perform a statistical analysis of the data obtained from the data acquisition unit and classify different postures. The data is continuously received by the server and classified. Google's deep learning library, *TensorFlow*, is used for classification that incorporates different APIs to build at scale deep learning architectures like CNN. The data is first loaded into memory, a model is built, a machine learning algorithm is trained, and then posture is estimated.

An Android application is provided to the end-user (subject or health professional) to interact with the system and retrieve information from the cloud. The information provided is the current sleep posture and statistical data for a specified period of time. The statistical data contains the overall time in bed and the posture distribution over time. The application also generates fall warning alerts when the user is sleeping closer to the edge of the mat. The fall warning may help in preventing any potential fall injuries. If a user sleeps in one posture for a prolonged period, a bedsore alert generation option is also provided for the caregivers so that they can attend the patient and help change their posture. Bed unoccupied alert is generated when the user leaves the bed which is also helpful for caregivers.

4. Methodology

The Sleep Mat-e system comprises sensors, mat, data acquisition system, and a mobile application.

4.1. Sensor Design

Force-sensing resistors (FSR) are simple tactile sensors [51] that are used in applications where changes and differences in pressure need to be detected. These are constructed using conductive polymers, elastomers or semiconducting polymers, piezo-resistive material, conductive wires, fiber-optical or fiber-gratting material.

We implemented an array of FSR′s using Velostat pressure-sensitive material was used because it is inexpensive. Furthermore, they are cheap as they involve low-cost electronic components and for these reasons, they are widely used in such applications. Velostat-based FSRs have an exponential decay resistance to pressure curve having a significant drop in the resistance of the material within a small region of the pressure range allowing to distinguish between high and low-pressure regions. An FSR sensor with a larger surface area has higher resistance, but it still has the same level of sensitivity. This is an important property as this allowed the designing of the sensors for different pressure ranges having similar sensitivity. The square-shaped sensor has dimensions of *2cm x 2cm* and contains three main layers which are a top electrode, Velostat, and the bottom electrode, respectively as shown in Fig. 3.

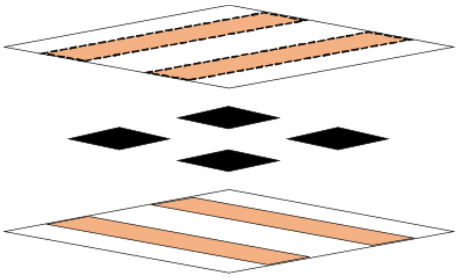


Fig. 3 Three layered FSR design

Mat design

Our sensing mat is designed using an array of sensors attached to a thin plastic film under the sheet, making it easy to deploy on the mattress and unobtrusive to users. As shown in Fig. 4, a total of *171* sensors are placed in a *19x9* grid structure. The sensors are organized in rows and columns, forming an I-by-J rectangular matrix $P = \{p_{i,j}\}$ where $p_{i,j}$ denotes the pressure sensor at the i_{th} row and j_{th}column of the matrix, $1 \leq i \leq I, 1 \leq j \leq J$. The total number of sensors is $I \times J$. The dimensions of the mat is the same as that of a single mattress i.e., *100 cm by 200 cm*. The end-to-end clearance between two sensors is around *8 cm*. We use the equally spaced sensor topology as opposed to a few

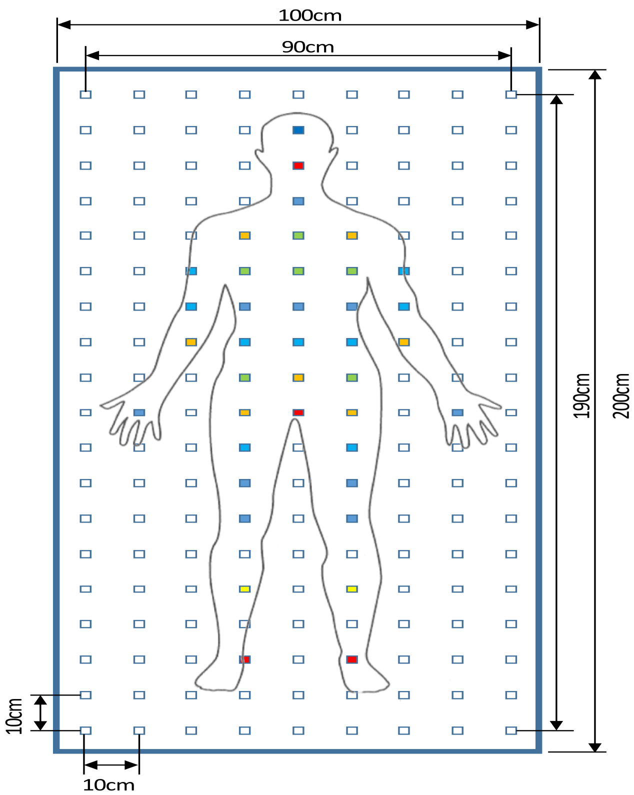


Fig. 4 Sensor topology with heat map

other sensor topologies such as the placement of sensors depending on the regions on the mat expected to have certain pressure values. We preferred this topology as it was more generic and would fit all the different types of major applications without imposing any restrictions on the user for the usability of the map. Two different plastic layers can be seen in Fig.5 with copper tapes applied on the bottom black plastic layer of the mat run perpendicular to the copper tapes applied on the top transparent plastic layer. The Velostat sensor cutouts were placed on the copper tapes on the bottom plastic sheet that can be seen in as black dots along the entire stretch of each copper strip.

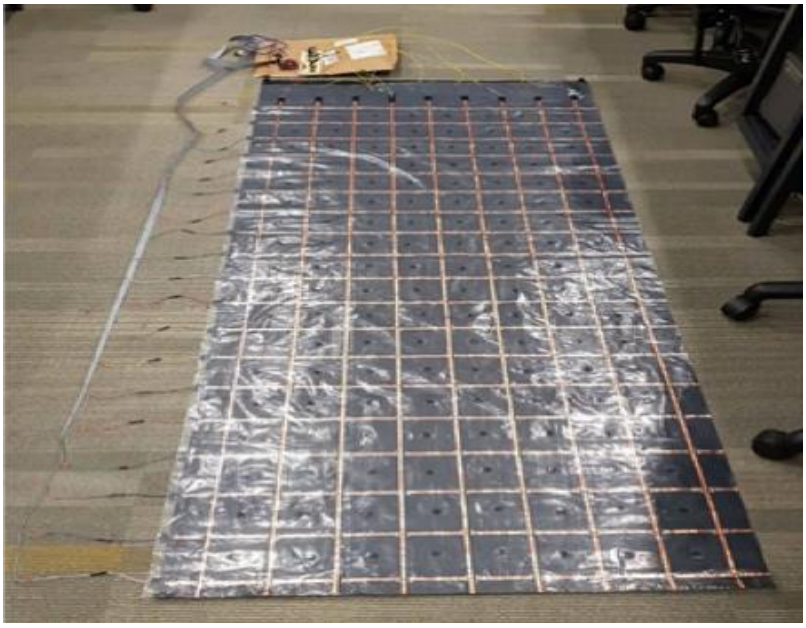
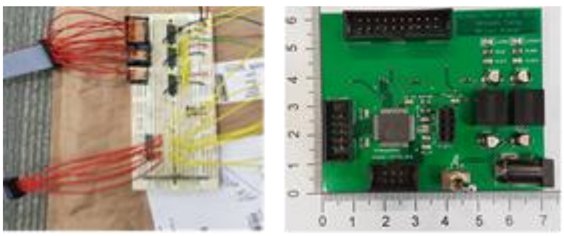


Fig. 5 Pressure Sensor mat prototype

4.2. Data Acquisition

The data capture unit comprises a microcontroller and an electronic circuit connected used to reduce the required pin count as shown in Fig. 6 (A). This circuit is connected to a microcontroller kit during development phased. The electronic circuit was put together with the microcontroller on a single printed circuit board (PCB) to reduce the size as well as power consumption. The final completed PCB is shown in Fig. 6 (B) and has the dimensions of *7cm x 6.4cm*. It also contains other auxiliary circuitry such as voltage regulator for supplying power to the WiFi module.

The data acquisition unit captures a snapshot of sensor mesh (the values of all the FSR′s on the mat at an instance) and sends it wirelessly to the cloud database. We use sensor matrix scanning strategy and this is done by pulling up one row, $i = 1$, the analog values outputted by all the columns, $1 \leq j \leq J$, fed to an analog to digital converter (ADC) are captured by the controller. The same procedure is repeated for all the rows, $1 \leq i \leq I$, and the pressure values of all nodes are captured. This is used to construct the snapshot of the pressure profile of the person at a given instance.



A B

Fig. 6 Bread-boarding and final PCB

Algorithm 1: *Sensor Scanning*

```
procedure
    clear shift register
    shift 1 into shift register
        for row i = 0 to I-1
            for column j = 0 to J-1
                array[i][j] = ADC_j value
            end for;
        shift 0 into shift register
    end for;
end procedure;
```

Powering all rows required 19 digital outputs which were too many to handle for a low-end microcontroller. The important aspect to note is that only one digital output needed to be active at any given time during scanning process. We exploited this fact and reduced the pin count by deploying shift registers in a daisy-chain configuration essentially creating a single large shift register while using the same common control signals for each chip and this solution was even cheaper than using multiplexers [63].

4.4. Posture Recognition

We identify six different cases based on positions a user could be in when on the mat. These positions are identified as “Face Up”, “Facedown”, “Right Lateral”, “Left Lateral”, “Unoccupied” and “Closer to the Edge” as shown in Fig. 7. The closer to the edge case will alert the caregiver through the Android application called *SleepMat-e* that someone may fall off the bed. The categorical heat map images generated from the pressure readings is shown in Fig. 8. Each colored square represents a pressure sensor and it has a color which is based on the magnitude of the pressure applied to the FSRs. The brighter color (yellow) indicates the highest pressure. The data stored in the database is classified and sleep posture is predicted. The database is polled periodically to check for new data, and when a new piece of data is received, the system performs the computations to classify new posture. This not only reduces the workload but also lowers the power consumed by the system. Posture recognition is an image recognition problem and deep learning, specifically CNN, is an effective tool to solve this problem. CNN (or ConvNet) is a class of deep neural networks widely used to analyze visual imagery. CNNs are regularized versions of multilayer perceptrons which are fully connected networks where each neuron in one layer is connected to all neurons in the next layer. The "fully-connectedness" of these networks makes them prone to overfitting data. ConvNets were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex [71]. CNNs use relatively little pre-processing compared to other image classification algorithms.

We make use of an open-source artificial intelligence library, *TensorFlow*, which uses data flow graphs to build models. More precisely, it is an image classifier, type of image recognition algorithm that takes an image (or part of an image) as an input and predicts what the image contains. The output is a class label, which is one of the postures here. The dataset comprises 200 images for each of the six possible cases i.e. classes. Each image has three channels and all images have same aspect ratio. From the 200 collected images for each case, this does not include images that were either similar to other cases or were difficult to classify as some of them were not valid images due to glitches, for example, image taken during the posture change period. This was due to the resolution of the mat. Instead of creating the whole model again, we retrained the existing model with our own data.

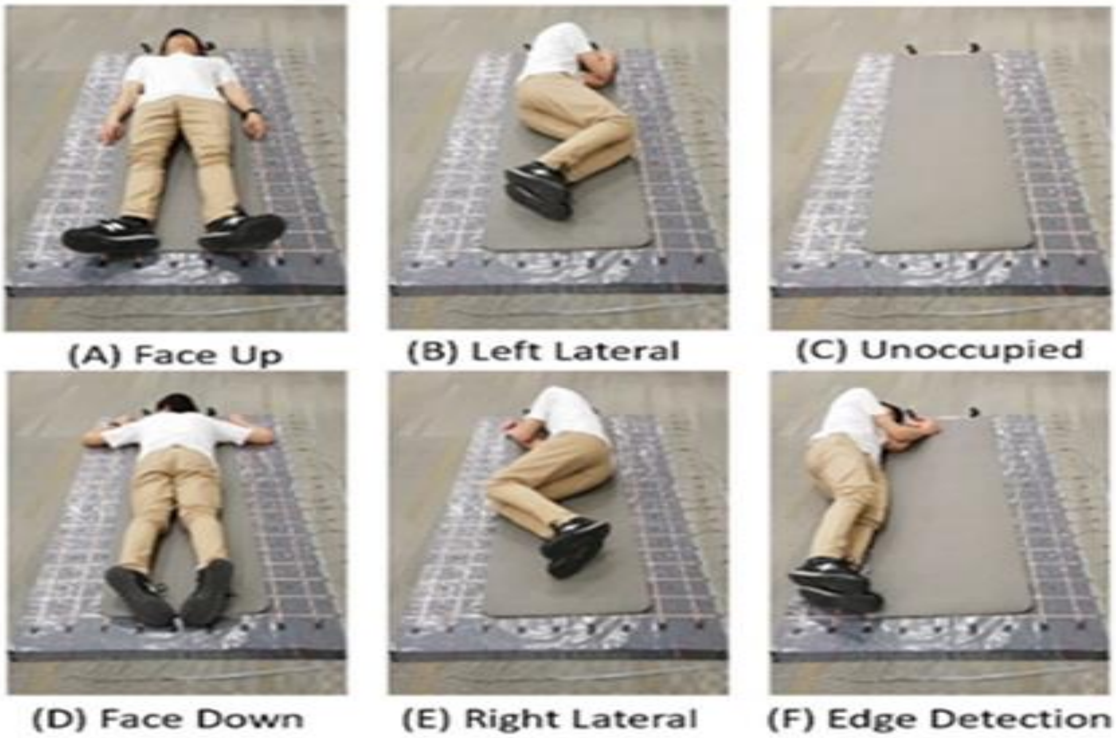


Fig. 7 Identifiable sleep postures

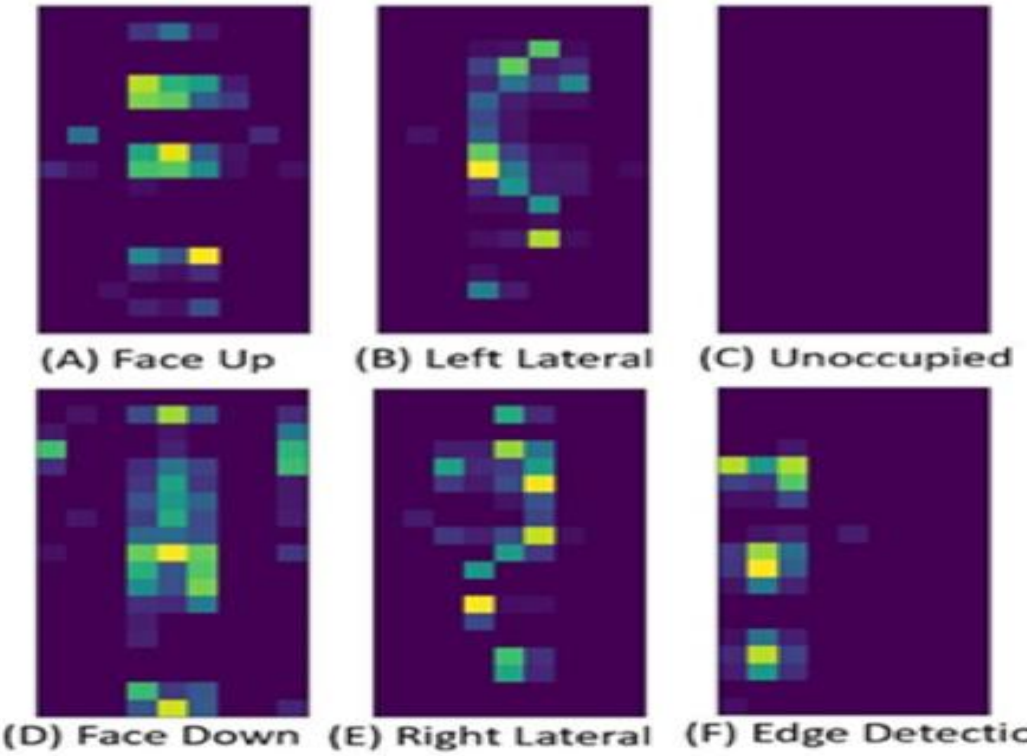


Fig. 8 Categorical heat map images generated from the pressure readings.

We adapt a pre-trained network for other classification based on the *TensorFlow* Hub module that computes image feature vectors. Inception-v3 [66] is a pre-trained convolutional neural network model that is 48 layers deep and has an image input size of 299-by-299. This pre-trained network can classify images into 1000 object categories resulting in network learning rich feature representations for a wide range of images. The model extracts general features from input images using CNN in the first part and classifies them based on those features with fully-connected and softmax layers in the second part.This model has been trained over millions of images, but the last layer of the network has been left untrained. We could supply our own dataset to complete the last layer of training. After training, a graph file is created, which contains information regarding nodes and weighting. This is the advantage of *TensorFlow*, as the training dataset is not needed after the graph file is produced. By default, it uses the feature vectors computed by Inception V3 (CNN) trained on ImageNet, thus taking advantage of the existence of this model for a custom image classification task. This is referred to as transfer learning (TL) as knowledge gained when solving a problem is used to solve a different but related problem [67]. This is a super-effective technique for classification a relatively small dataset is available. As mentioned earlier, neurons are organized in layers in a CNN. Each of these layers may perform different kinds of transformations on the inputs and, in this way, input travels from the first layer to the last one after traversing the layers many times. The last layer has accumulated enough summarized information to provide the next layer which does the actual classification task as illustrated in Fig. 10. Transfer learning may have very limited effect when you switch the dataset from one modality to another one.

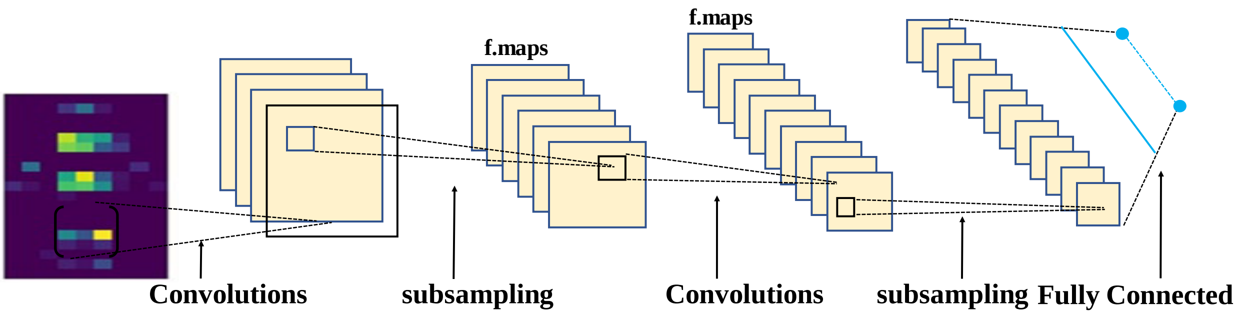


Fig. 9 CNN process in TensorFlow

The Transfer Learning allows to build a new model to classify original dataset by reusing the feature extraction part and re-train the classification part with original dataset. Training feature extraction part is the most complex part of the model, skipping it allows to train the model with less computational resources and training time. The training usually took around 10 to 15 minutes depending on the size of the data. The graph file generated from the training session was then transferred to the server and used in a *TensorFlow* session for classifying postures.

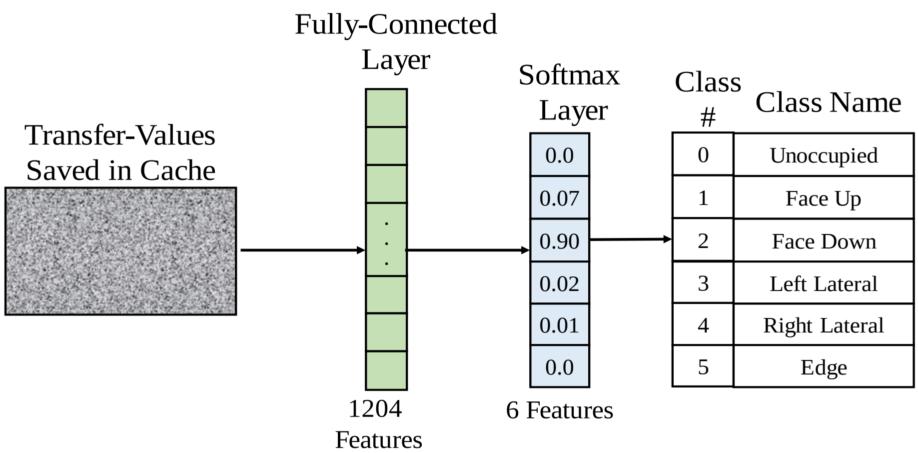


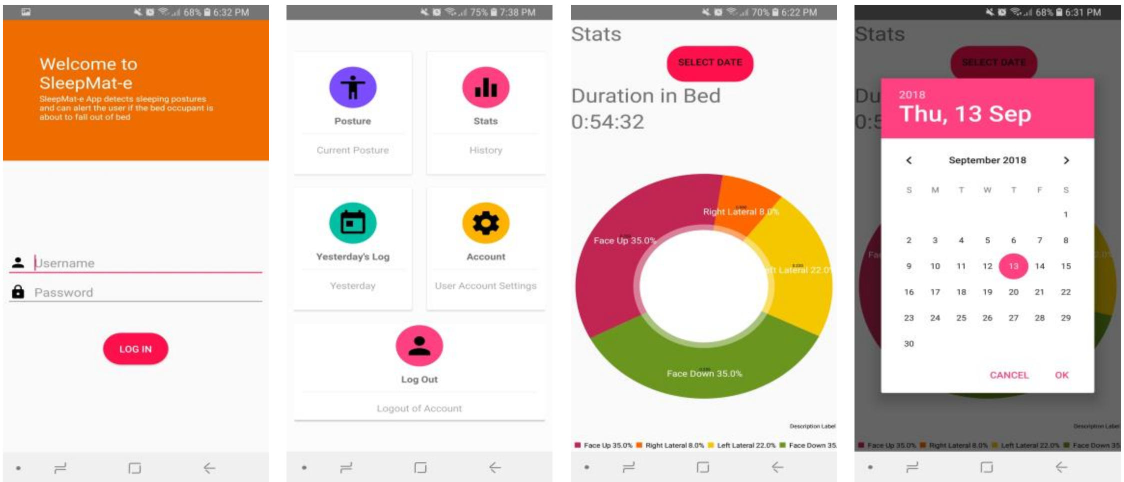
Fig. 10 Inception V3 model transfer learning

The process image classification using *TensorFlow* is shown in Fig. 9. First, we pre-process data to generate the input of the neural network. Then, we reshape input and create a convolutional layer, followed by the creation of a pooling layer. The above steps in the process are repeated multiple times to create the multiple convolutions and pooling layers. The output of convolution and pooling layers is flattened before feeding it to the fully connected layer as shown in Fig. 10. A fully connected layer is created and an activation is also added. Lastly, a final layer for class prediction is created and weights and biases are stored using *TensorFlow* variables.

4.5. Mobile Application

Mobile applications have been used in assistive healthcare and other medical related cases [68-70]. The final stage of our solution was to display the processed data to the user using a smartphone. The Android application then provides the processed information to the end-user. The information provided is the current sleep posture and the statistical data for a specified date. The statistical data contains the overall time in bed and the posture distribution. The application also generates a fall warning alert when the user is sleeping closer to the edge of the mat. The fall warning will help in preventing any potential fall injuries. If a user sleeps in one posture for a significant amount of time, a bedsore alert is generated for the caregiver so that they can attend the patient and help change their posture. Bed unoccupied alert is generated when the user leaves the bed which is also helpful for the caregivers.

Fig. 11 shows the screenshots of our Android app. The first screenshot is of the user login as shown in Fig. 11 (a). The user login screen also provides a general description of the application. Once a user has successfully logged in,



(a) Login (b) Dashboard (c) Posture Breakdown (d) History Date Selection

Fig. 11 Mobile application user interface

the user can then access the dashboard as given in Fig. 11 (b) from where the user can check the current occupancy status of the mat of whether someone is on the mat or not. "Posture" option when clicked uses cartoon images as an indication of the current posture of the occupant. To get more details regarding the sleep posture for a given night, the user can select the "Stats" option and then select a date through the calendar menu as shown in Fig. 11 (d). The "Stats" option also provides information regarding the overall time in bed as demonstrated in Fig. 11 (c). This time is measured from midday of the selected date to the midday of the next day; a complete day.

5. Experimental Results

In order to confirm the validity of the proposed system, we conducted the accuracy-test for the recognition of the postures. The mat was placed over the bed and unobtrusive to users. The controller responsible for measurement and collection of data was ATMega32u4. Experiments were conducted by extracting the pressure data generated by the subject lying down on the mat and forming a data set. The subject simulated his sleeping postures by lying on mat for a period. In order to confirm the recognition accuracy, we constructed 200 data sets for each posture, and the following results given in Table 1 were obtained. The ground truth was recorded by a camera and checked manually. The output of the original Inception-v3 network contains 1,000 classes, but we had only 6 classes; therefore, we changed the number of output channels of the last layer from 1,000 to 6. we divided the dataset randomly into training data and test data for each posture type according to a ratio of approximately 10:1. Also, we ensured that there was no overlapping of the original images between the two datasets. In order to resuce the storage capaciy on cloud, we ensured that not duplicated data is sent to the cloud. For this reason, we take the accumalted value of all sensors outputs in a snapshot and subtract it from the preceeding frame. The snapshot is transmitted with time stamp if differential exceeds a certain threshold. This technique resuced the amount of data transmitted, computation and storage required on cloud, and the power consumption at both ends.

Table 1: Numbers of images in the training and test groups

Category	Training	Test	Total
Unoccupied (U)	180	20	200
Face Up (FU)	180	20	200
Face Down (FD)	180	20	200
Left Lateral (LL)	180	20	200
Right Lateral (RL)	180	20	200
Edge (E)	180	20	200

The developed prototype could identify four different postures namely ʺFace up”, ʺFace Down”, ʺRight Lateral” and ʺLeft Lateral” alongside generating fall warning, bedsore alerts, and bed occupancy status. Our system comes with an Android application, which allows a user to get statistical data regarding their sleep. *TensorFlow* machine learning library was used for the classification of the pressure images that are generated from the pressure sensors information sent by the microcontroller. The system exhibited a high accuracy of more than 90% when trained with the *TensorFlow* model as shown in Table 2. The system performed well for all the different cases with the highest for unoccupied and edge, as these cases were the easiest to classify. Those Image-Net pre-trained networks are mainly trained from natural images which are different from the original images used. Although, model is fine-tuned through TL, the accuracy of the model can be further improved by fine tuning of the final layer with larger dataset.

Table 2: Accuracies of posture categories

Category	Accuracy (%)
Unoccupied (U)	100.0
Face Up (FU)	93.0
Face Down (FD)	90.0
Left Lateral (LL)	85.0
Right Lateral (RL)	80.0
Edge (E)	95.0

The confusion matrix shows detailed analysis of classification outcomes from single annotated test data of a particular subject for 6-postures (including unoccupied). By analyzing the confusion matrices from different classifiers, the weights specified in voting fusion matrix are shown in Table 3. There are two cases where confusion mainly occurs, that is, FU vs FD and LL vs RL and this may be due to variations of spatiality among subjects. The LL image is incorrectly identified as RL and vice versa. This typical kind of error can be explained from the pressure map that is extended behind the subject's back, thus misclassifications can occur since the pressure image looks like a RL image. Similarly, FD and FU have 7% to 10% chance to be erroneously classified into the other. That is because these two postures have extremely similar snapshots due to the bilateral symmetry. Edge is also erronously taken as unoccupied as in both cases majority of the sensors are not active.

Table 3: Confusion matrix of posture classification

	U	**FU**	**FD**	**LL**	**RL**	**E**
U	100	0	0	0	0	0
FU	0	93	7	0	0	0
FD	0	7	90	2	1	0
LL	0	0	2	85	10	3
RL	0	2	2	12	80	4
E	3	0	0	1	1	95

The current posture is displayed on the app screen as shown in Fig. 12 (a). Fall Alert is triggered when the system detects that the user is close to either the left or the right edge of the mat, which can be seen in Fig. 12 (b). When the user leaves the bed, the "Bed Alert" is triggered for the caregiver. This notifies the caregiver that the bed occupant has left the bed. Both alerts are intended to inform the android application user about the possibility that the user may fall or has fallen out of bed.

Fig. 12 (a) Live posture image (b) fall alert

6. Conclusion

This study presents an IoT enabled smart sleep posture recognition system which uses CNN for classifying the postures alongside generating fall warning, pressure sore, and unoccupied bed alerts. The system is unobtrusive, affordable, and accessible through a smartphone. By continuously monitoring the sleep posture, potential pressure hot spots of the subject can be identified and appropriate interventions can subsequently be implemented. The design, implementation and evaluation of sleep posture classification approach and methodologies were presented in details. The experiments were conducted to evaluate the classification accuracies and system efficacy, and the results demonstrate that sleeping postures can be classified up to 90% accuracy. A user-friendly Android application allows users to easily access the statistical data related to their sleep such as posture distribution and generates fall, bedsore, and bed unoccupied alert warnings. The current posture recognition method may be further enhanced and validated by taking into account random sleep postures, testing with real patients in actual care settings.

Compliance with ethical standards

Conflict of interest
The authors declare that they have no conflict of interest.

Ethical approval
This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent
Informed consent was not necessary for this review.

Financial interests
The authors have no relevant financial or non-financial interests to disclose.

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