CNN Based Smart Sleep Posture Recognition System

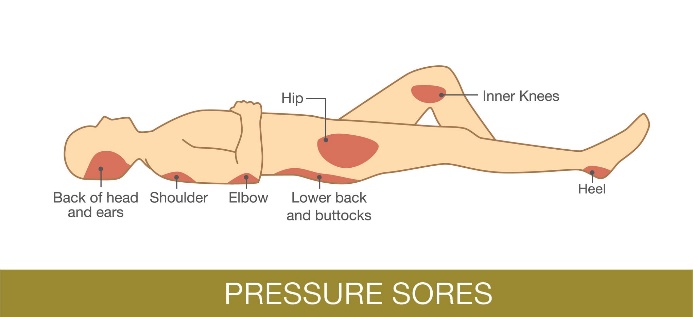
**ABSTRACT:** Sleep pattern and posture recognition have become of great interest for a variety of clinical applications. Autonomous and continuous monitoring of sleep postures provides useful information for lowering health risk. Existing systems are designed based on electrocardiograms, cameras, and 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 to the user alert 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:** *Force-sensing resistor, Sleep posture recognition; Sleep activity; Internet of Things; Machine Learning; Healthcare.*

# Introduction

The population of elderly people is on the rise in the world and the number of elderly people is expected to reach 20% of the total population by 2050 [1]. The prevalence of chronic conditions is also on the rise among the elderly people. They tend to suffer from poor sleep quality and this has effects on their physical health, cognitive function, and overall quality of life [2, 3, 4]. Adequate, restful sleep is important as it allows the body and brain undergo necessary restorative activities. Inadequate sleep leads to reduced alertness and drowsiness [2]. Health issues stemming from poor sleep quality include weakened immune system and cardiovascular diseases[5]. As a result, sleep analysis is a very important step towards the detection and diagnosis of sleep problems.

Another issue prevalent in the elderly population is pressure injuries (PI) that arises due to prolonged sleep in a single posture without moving, as shown in Figure 1. The PI can cause constant pain, loss of mobility, depression, and even death. Studies have found that sleep issues were more prevalent within the residential care population [6, 7]. Furthermore, certain sleep positions and postures are considered to be major cause of sleep apnea [8]. Research has shown that people sleeping in the decubitus position have higher risk of developing subacromial impingement syndrome compared to those who sleep in the supine position [9]. People sleeping in 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 a 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 evidences 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, motivates the need for a system that can 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 [5a], artificial neural network [6a], dual tree [7a], empirical mode decomposition (EMD) [8a], and support vector machine (SVM) [9a]. 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 Netwrok (CNN), redcues the complexity of the network and number of weights because of its shared-weight network structure when compared with the traditional methods, The CNN is widely used in the field of object recognition [10a] and image segmentation [11].

We propose an smart autonomous system that is capable of monitoring sleep pattern, sleep posture, activities, and alerting about potential fall during the sleep. This IoT based solution can be utilized to record patient health data in a securely 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 the 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 [18].

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. System design and implementation are discussed in Section IV. Experimental results are presented in Section V followed by the conclusion at the end.

# Related Work

Sleep is a major part of health and well-being. Researchers have explored diverse techniques on 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 Internet of Things (IoT) and sensing modalities have enabled researchers to more accurately determine the posture and patterns during sleep.

There are numerous solutions available [18-47] 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) [18]. 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* [19] is worn on 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 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 [20-24]. Some of the available Apps are: *Toss 'N' Turn sense* [20], *My Sleep APP* [21], ‘*Sleep as Android*’ [22] and *Runtastic Sleep Better* [23], and *iSleep* [24]. 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 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* [25], *Jawbone UP3* [26], *Zeo*, *SleepImage*, *Lark*, *WakeMate*, *Hexoskin*, *OURA* are popular commercially available wrist worn sleep trackers used for collecting data about sleep [14, 25, 26]. 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 [27]. 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 use common digital 2D, 3D, and infrared cameras to acquire visual data and then apply image processing and machine learning techniques to recognize different postures [28-30]. For example, [28] used a single 2D camera to acquire 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 camera to build a multi-view Eigen model of human body in terms of its constituent body part and then recognize the posture [30]. Versatility of the data captured is augmented by using different sensors in conjunction with the sensors [31-35]. Lee et al. [32] used Kinect camera hanged over the bed to classify six sleep positions. They extracted body joint positions using Kinect V2’s own libraries and used the relative position of hands and knees with respect to the spine for classification using a parametric approach. The patient was not allowed to use the blanket. Evaluation and results were not provided by the researcher. [29] used 3D camera together with Microsoft Kinect sensors for analyzing body positions and monitoring the posture of person in residential care. Torres et al. [33] 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 “BAM” descriptor based on depth information collected from a Microsoft Kinect, which could monitor the sleeping posture and movement data [34]. This work is further extended to recognize high level activities such as removing bed covers [35]. [31] used pressure arrays and a single depth camera to build a 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 “watched” by cameras.

Another approach exclude the use of cameras and instead use 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*) [36] and *MediSense* [37] used the y-axis accelerometer and z-axis gyroscope readings to infer body postures and movement of the patients, respectively. *Wi-Sleep* [38] classifies a person’s respiration, six sleep positions, and rollovers by leveraging Wi-Fi signals, i.e., channel state information (CSI), from a pair of TX-RX. *TagSheet* [39] 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 gray scale snapshot, analyzed it to identify six sleep positions as well as estimated the respiration rate. *SMARS* [40] 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* [41] 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 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 cell to sophisticated pressure sensing mats. The fluid filled cells were placed between the patient and a support for detecting motion via pressure fluctuations [42]. The low-ended load cells were placed under each bed leg to classify 27 pre-defined movements by analyzing the computed forces [43]. 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 occured. A non-invasive pressure-sensitive bedsheet was deployed to monitor different sleep postures by generating high-resolution pressure maps [44]. 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 [45]. However, this work was only useful for point-of-care applications. On the other hand, [46] used a bed pressure sensor array which could detected 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 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 [45]. 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 [48]. These mats used photodiodes of connected to optical fiber for providing light. The light intensity of photodiodes would vary as pressure is applied which is translated to voltage signal indicating the pressure exerted on the mat. Data was 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 [49], a high resolution mattress that contained 2048 sensors. This system could identify only three different postures, namely “supine”, “right side” and “left side”. Similarly, [50] used a sensor mat comprising 1728 resistive sensors for identifying 13 different sleep postures using Gaussian Mixture Model. Image collected form 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%.

According to author’s knowledge, no comprehensive work was dedicated to develop monitoring a sleep quality monitoring and sleep posture recognition system with capabilities of delivering processed data to the end user and 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 high cost. This solution is affordable, and unobtrusive that will enormously decrease the elderly accidents. .

# 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 current posture, and transmits it to the cloud server using Wi-Fi. The data acquisition unit is implemented using the ATmega32u4. 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. A machine learning algorithms is used to perform 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 calssification that incorporates different APIs to build at scale deep learning architectures like Convolution Neural Network (CNN). The data is first loaded into memory, a model is built, a machine learning algorithm is trained, and then posture is estimated.



**Fig. 2** System Architecture

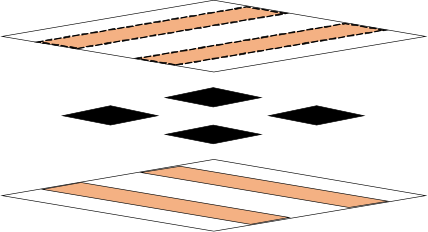
The Android application is provided to the end user (subject or health professional) to interact with the system and retrieve information from the cloud. The information provided is the current sleep posture and statistical data for a specified period of the time. The statistical data contains the overall 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 bed sore 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.

# Design and Implementation

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

## Sensor Design

Force sensitive 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, piezoresistive material, conductive wires, fibre-optical or fibre-gratting material. We implemented an array of FSR’s using Velostat pressure sensitive material was used because it is inexpensive. to capture the pressure distribution of a person’s sleeping posture. 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 the greater surface area has higher resistance, but it still has the same level of sensitivity. This is an important property as we can easily then have sensors designed for different pressure ranges with all of them having the same sensitivity. The square shaped sensor has dimensions of *2cm x 2cm* and contains three main layers which are a top electrode, Velostat, and bottom electrode, respectively as shown in Figure 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 where denotes the pressure sensor at the row and column of the matrix, . The total number of sensors is . The dimensions of the mat are 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 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 application without impose 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

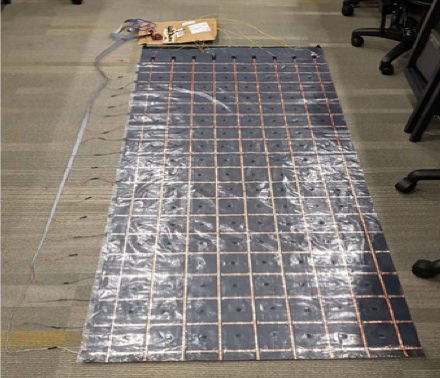


**Fig. 4** Sensor topology with heat map



Figure 6: Bread-boarding and final PCB

**Fig. 8** Bread boarding and PCB



**Fig. 5** PressureSensor mat prototype

## Data Acquisition

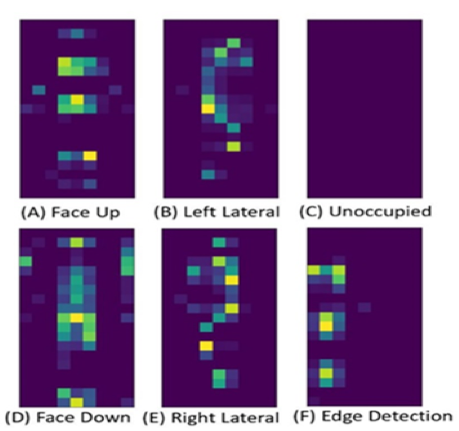
The data capture unit comprises a microcontroller and an electronic circuit connected used to reduce the required pin count as shown in Figure 6 (A). This circuit is connected to a microcontroller kit during development phased. The electronic circuit was put together with the microcontroller on a single printed circuit board (PCB) to reduce the size as well as power consumption. The final completed printed circuit board (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 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, the analog values outputted by all the columns fed to analog to digital converter (ADC) are captured by the controller. The same procedure is repeated for all the rows, and 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.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Algorithm 1:** *Sensor Scanning* | | | | | |
| 1: | ***procedure*** | | | | |
| 2:  3: |  | *clear shift register shift 1 into shift register* | | | |
| 4: |  |  | ***for row i*** *= 0 to* ***I-1*** | | |
| 5: |  |  |  | ***for column j*** *= 0 to* ***J-1*** | |
| 6: |  |  |  |  | *array[i][j] = ADCj value* |
| 7: |  |  |  | ***end*** *for;* | |
| 8: |  |  | *shift 0 into shift register* | | |
| 9: |  | ***end for****;* | | | |
| 10: | ***end procedure****;* | | | | |

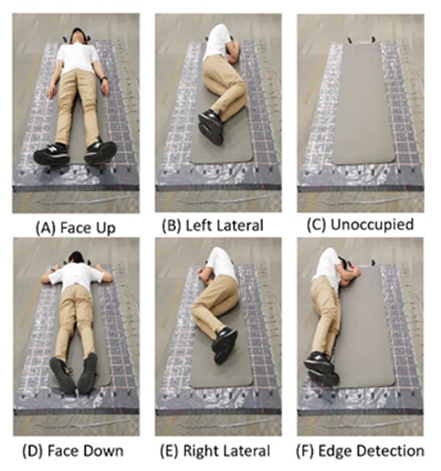
Powering all rows required 19 digital outputs and this was reduced by deploying a shift registers in a daisy-chain configuration essentially creating a single large shift register while using the same common control signals for each chip thus reducing the required IOs.

## Posture Recognition



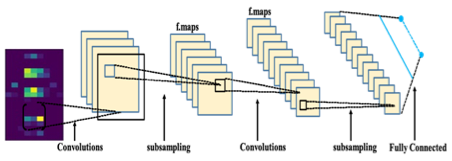
**Fig. 8** Categorical heat map images generated from the pressure readings.

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. 10. The closer to the edge case will alert the caregiver through the Android application (we need to mention the name of the app maybe) that someone may fall off the bed.



**Fig. 7** Identifiable sleep postures

The categorical heat map images generated from the pressure readings Figure 7 shows. Each colored square represents pressure sensor and it has 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 using *TensorFlow* and sleep posture is predicted. A new piece of data is classified when the python script reads a flag set in a text file that is edited by NodeJS. This was to ensure that python script was not continuously polling the database. A method that allows us to start the Python script from the NodeJS was also tested (I believe this part should be removed). However, it was found that it was not the optimal way of classifying data as the Python script will restart every time and was not able to classify data in the given time because the restart of the script will also restart the *TensorFlow* session which creates a significant delay to start. Whenever the server updates the table with new data, the Python script begins to classify it.



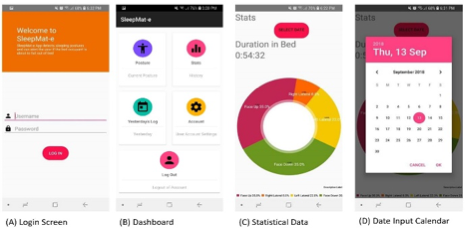
**Fig. 9** CNN process in TensorFlow

This is an image recognition problem and deep learning, specifically Convolutional Neural Networks (CNN), is an effective tool to solve this problem. We make us of *TensorFlow*, an open source artificial intelligence library 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 some aspect ratio. From the 200 collected images for each case, we filtered out the images that were either similar with other cases or were difficult to classify. This was due to the resolution of the mat. Instead of creating whole model again, we retrained existing model with our own data. We adapt a pre-trained network for other classification based on *TensorFlow* Hub module that computes image feature vectors. The Inception V3 model that is used by TensorFlow 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. The training usually took around 10 to 15 minutes depending on the size of the data. Graph file generated from the training session was then transferred to the server and used in a *TensorFlow* session for classifying postures.

The process image classification using *TensorFlow* is shown in Fig. 12. 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. Above step is process is repeated multiple times to create the multiple convolution and pooling layers. The output of convolution and pooling layers is flattened before feeding it to the fully connected layer. 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.

## Mobile Application

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 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 bed sore 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. 10** Mobile application user interface

Fig. 9 shows the screenshots of our Android app. The first screenshot is of the user login as shown in Fig. 9 (A). The user login screen also provides a general description of the application. Once a user has successfully logged in, the user can then access the dashboard (Fig. 9 (B)) from where the user can check the current 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 “Stats” option and then select a date through the calendar menu as shown in Fig. 9 (D). The “Stats” option also provides information regarding overall time in bed (Fig. 9 (C)). This time is measured from midday of the selected date to the midday of the next day; a complete day.

# Results

In order to confirm the validity of the proposed system, we conducted the accuracy test for the recognition algorithm. The controller responsible for measurement was ATMega324. Experiments were conducted by extracting the pressure data generated by the subject lying down on the mat and forming a data set. The subjects who participated in the experiment were a 26-year-old male with a height of 176.8cm and a weight of 62.1kg. In order to confirm the recognition accuracy, we constructed 100 data sets for each posture and executed the algorithm by dividing ten by ten. The following results were obtained by comparing the perceived attitude with the actual dataset.

The developed prototype could identify four different postures namely “Face up”, “Face Down”, “Right Lateral” and “Left Lateral” alongside generating fall warning, bed sore alerts and whether the bed is occupied or not. Our system also has an Android application, which allows a user to get statistical data regarding their sleep. *TensorFlow* machine learning library was used for classification of the pressure images that are generated from the pressure sensors information sent by the microcontroller. The system show a high accuracy which is more than 90% after training with the TensorFlow model as shown in Table 1. The system performed well for all the different cases with the highest for unoccupied and edge, as these cases were the easiest to classify.

**Table 1**: Accuracies of posture categories

|  |  |  |
| --- | --- | --- |
| **Category** |  | **Accuracy (%)** |
| *Unoccupied* |  | *100.0* |
| *Face up* |  | *92.5* |
| *Face down* |  | *90.0* |
| *Left Lateral* |  | *85.0* |
| *Right Lateral* |  | *80.0* |
| *Edge* |  | *95.0* |

Confusion matrix Considering confuse matrix as shown in Figure 4.1, the results of 120 input features achieved accuracy than the 4 input features. In the results of 4 input features, there are ambiguous in two classes i.e. out of bed and sitting. The accuracy of out of bed posture is 99.2% and sitting posture is 93.2%. Figure 4.2 shows the signal pattern of out of bed and sitting postures. Both of signals are quite similar. In sitting posture, pressure sensors are low activation, similar to out of bed posture, but no piezoelectric signals. Therefore, the signals of both postures are look the same at some point. The accumulated signal as 120 inputs can achieve accuracy of 100% for 5 postures classification whereas 4 input type reach only 99.5%. Hence, the accumulated signal can solve the confusion between out of bed and sitting posture. This is because Neural Network can capture more context feature to identify the out of bed posture from sitting posture.

**Table 1**: Accuracies of posture categories

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| *Unoccupied (U)* | U | FU | FD | LL | RL | E |
| *Face Up (FU)* |  |  |  |  |  |  |
| *Face Down (FD)* |  |  |  |  |  |  |
| *Left Lateral (LL)* |  |  |  |  |  |  |
| *Right Lateral (RL)* |  |  |  |  |  |  |
| *Edge (E)* |  |  |  |  |  |  |

The current posture is displayed on the app screen as shown in Fig. 10(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. 13 (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 11** (a) Live posture image (b) fall alert

# Conclusion

Poor sleep and sleep postures poses a great threat to the health of elderly people living residential care. These risks can be reduced by effectively monitoring the pattern and posture of the sleep which is a challenging task. In this paper, we presented a novel system that is unobtrusive, affordable and accessible through a smartphone. Our system can identify four different major sleep postures alongside generating fall warning, pressure sore and unoccupied bed alerts. A cloud server was used for collection and processing of the sensor data. Machine learning is used for the classification. A user-friendly Android application allows users to easily access the statistical data related to their sleep such as posture distribution and generates fall, bed sore and bed unoccupied alert warnings. The system has an average accuracy of 90% in identifying different cases. Further improvements can be made to the system to enhance the overall functionality.

As a future work, we intend to increase the number of postures that can be detected easily and we also plan to develop the algorithm to measure the breathing rate. Development of an Android or iOS application for smartwatch will make the system more flexible, and the health care professionals will be able to view statistical data and get alerts on their smart watch.

**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.

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