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Design of Smart Wearable System for Sleep Tracking Using SVM and Multi-Sensor Approach

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Mohammed M. Abo-Zahhad [1]
Moaz Elsayed [2]
Abdelrahman Fawaz [2]
Ahmed H. Abd El-Malek [2]
Mohammed S. Sayed [2]
Ahmed Sharshar [2]
Mohammed Abo-Zahhad [2]

Keywords

Internet of Things; Wearable electronics; Sleep tracking; Vital signs; Sleep stages; Sleep quality; Support vector machine.

Abstract

Healthcare has been considered one of the main issues to be spotted and improved in a high manner. Thus, many technology trends are customized for healthcare. One of the fields that highly affects health is sleeping. Therefore, the development of a portable and cost-affordable sleep-tracking system has arisen. This could be done by monitoring vital signals that affect sleep quality such as heart rate, blood oxygen saturation, and positioning. Furthermore, these signals are used to detect sleep stages and sleep quality. In this paper, commercial off-the-shelf sensors are used to develop a sleep quality monitoring system. The aim is to make it cheap, portable, lightweight, and easy to use with good sleep quality and sleep stage detection. REM and NREM sleep cases are also investigated based on EEG signals which measure brainwaves. So, two types of delta waves that occur during REM sleep are differentiated. Slower (2 Hz) waves were recorded in the medial-occipital areas that are present in both NREM and REM sleep, and quicker sawtooth waves (2.5-3 Hz), were present in REM sleep only. In the proposed system the heart rhythm is measured by ECG signals using heart-rate sensors. ECG data is used to define REM and NREM by monitoring the heart rate variability (HRV), which changes as a person moves between light, deep, and REM sleep stages. In addition, the market-available Amazfit T-Rex Pro watch is used for data labelling. Comparison with similar systems shows that it performs better given its lower cost, lighter weight, and smaller size. The obtained results indicate that sleep quality and sleep stage accuracy are 97.5% and 67.5% respectively, which are better than similar systems used with commercial off-the-shelf sensors.

1. **Introduction**

Recently, integration between the Internet of Things (IoT) and healthcare has risen and become essential [1]. One of the fields that affect health in a high manner is sleeping, which is why monitoring it was very demandable. Getting enough sleep with good quality is crucial to living a healthy life. Therefore, quality of sleep could be one of the main issues that should be observed to get a better daily life routine. Studies and research have linked the productivity and concentration of people with getting good sleep hygiene. Furthermore, sleeping connects directly with several

[1] Department of Electrical Engineering, Faculty of Engineering, Sohag University, Sohag Governorate, New Sohag City, Egypt. mohamed.abozhad@eng.sohag.edu.eg

[2] Department of Electronics and Communications Engineering, Egypt-Japan University of Science and Technology, New Borg El-Arab City, Alexandria, Egypt. (moaaz.elsayed, abdelrhman.fawaz, ahmed.abdelmalek, mohammed.sayed, mohammed.zahhad}@ejust.edu.eg

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functions performed by the brain such as concentration, productivity, and cognition. Sleep is considered a brain activity used to release exhaustion [2].

The most common method of measuring sleep is polysomnography (PSG), which is regarded as the standard for identifying sleep disorders [3]. SleepScore, the most sophisticated sleep monitor on this list, measures sleeping patterns using sonar technology. According to PSG, there are multiple distinct phases of sleep that alternate between non-rapid eye movement (NREM) and rapid eye movement (REM) phases. Some sleep monitors use heart rate to estimate REM sleep as well as deep and light sleep stages. Although it is well known that heart rate and respiration rate change significantly while we sleep, they are closely correlated with each stage of sleep because the autonomic nervous system has a big impact on both. About 20 to 25 percent of adult sleep time is typically devoted to REM, which appears to be normal during typical sleep cycles. However, sleep research is raising some interesting questions. With time, the disorder frequently gets worse. Movement in response to exciting or violent dreams, such as being followed by an attack, maybe a symptom of REM sleep behavior disorder. This movement may take the form of punching, kicking, flailing arms, or jumping from bed. The brain activity, respiration, heart rate, blood pressure, and eyelids move rapidly while closed during REM sleep. Antidepressants, for example, can reduce REM sleep. People who smoke a lot frequently have light sleep and less REM sleep. After a few hours, they might awaken from the effects of nicotine withdrawal. Around 90 minutes of the entire sleep time, or the restorative sleep stage where dreams take place if one sleeps between seven and eight hours each night, will be spent in REM sleep. Anything more than that puts your health at excessive risk.

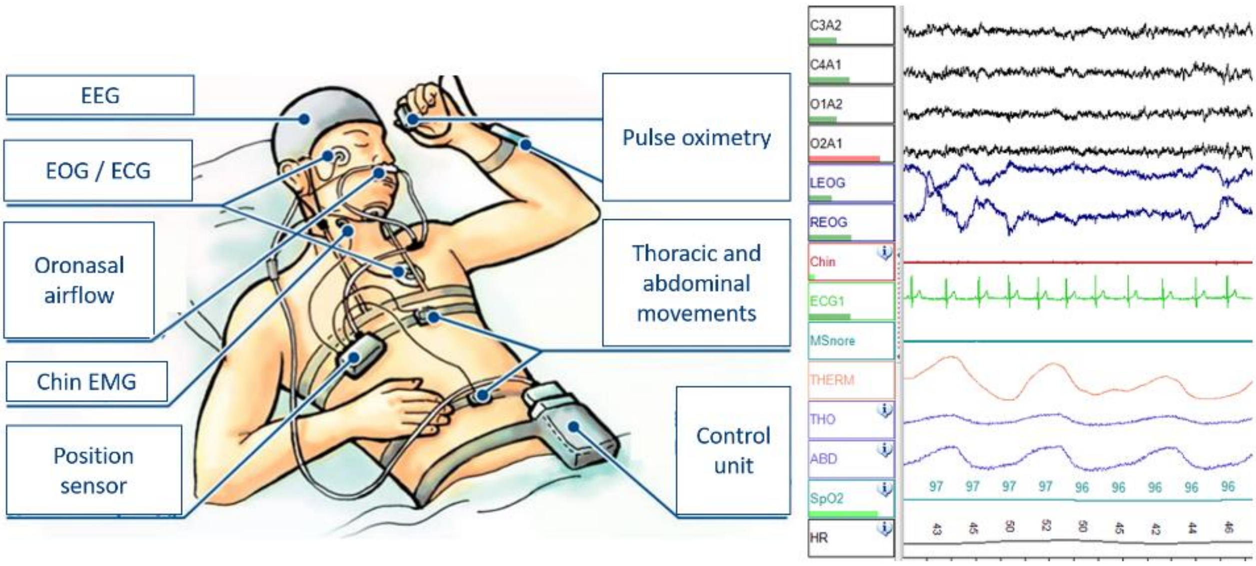


Fig. 1: Graphical representation of traces of the polysomnography technology [5].

Sleep monitoring could be accessed using a wide range of methods or systems that could be wearable or non-wearable devices. One of the concepts that are tracked is sleep quality and it is the measurement of how well you are sleeping—in other words, whether your sleep is restful or restorative. It differs from sleep satisfaction, which refers to a more subjective judgment of how you feel about the sleep you are getting. The most accurate one is the PSG laboratory test, shown in Fig. 1. This test depends on collecting several parameters that characterize sleep patterns. These parameters are brain waves, heart rate, blood oxygen saturation, respiration, besides, positioning, and leg and arm movements. They are used aiming to distinguish between sleep stages. Additionally, PSG could distinguish if the user struggles with any sleeping disorder, and the collected data gives neat information that helps form a treatment plan. This system provides high reliability; however, it is not portable and cannot be used in daily monitoring [4].

On the other hand, wearable devices that are used for sleep monitoring provide mobility and portability while they have less accuracy than PSG. Many commercial sleep monitoring systems vary between monitoring the quality of sleep and detecting sleep stages. The common point between all these commercial devices is that they collect data and then transfer them directly to the smartphone or laptop that they relate to. After that, these devices could perform complex analyses and algorithms to get information from the gathered data [6]. The first proposed system is actigraphy described in [7]. It is a device that looks like a wristband and could be worn on either wrist or ankle. In addition, it has an accelerometer that is used to detect body movements and using them to detect and calculate other sleep parameters. This type of device could figure out when you fall asleep and wake up as well as the interval of sleep. These parameters based on observing movements are useful to detect sleep disorders such as insomnia. People with such disorders have problems with their sleeping habits as they have irregular sleep and wake-up times. On the other hand, actigraphy has many limitations as it has not been confirmed to determine sleep stages. Furthermore, the effectiveness of the system is decreased while monitoring poor sleep quality [8].

The second considered system is Fitbit [9], it is a wrist-worn activity tracker that records everyday activities such as walking, running, swimming, and cycling. A 3-axis accelerometer is used in all Fitbit trackers and watches to detect motion and other movements, with complex algorithms to detect patterns of them. Additionally, it measures heart rate depending on the photoplethysmography (PPG) signal. The data collected is used to detect the quality of sleep with a specified score. Then, the gained information can be viewed via the Fitbit app. Fitbit has an acceptable accuracy in comparison with PSG and could perform better than actigraphy in some cases. It has been found that Fitbit underestimated total sleep time by 6.1 minutes, whereas the actigraphy underestimated it by 31.5 minutes. From another perspective, Fitbit overestimated sleep efficiency by 3.0% and actigraphy by 12.9% [10].

The third system is Oura Ring [11] which is a commercial device based on a smart ring and has the most accurate sleep tracking system in comparison with other commercial systems. This ring has sensors that measure health parameters and collect data that could be translated into information. Then, the data collected is transferred to the company’s customized mobile application called Oura App via Bluetooth. This smart ring gathers readings of acceleration and gyroscope, PPG signal, and body temperature to detect sleep parameters. Oura Ring has high accuracy in determining the four statuses of sleep represented awake, light sleep, deep sleep, and Rapid Eye Movement (REM) [12], [13].

The fourth considered system is a device that uses COS sensors [2]. This system used an ADXL345 accelerometer for determining movements, MAX30100 to monitor heart rate, SpO2, and a MAX9814 microphone amplifier. The system has three steps: 1) the collected data is transferred to the used microcontroller, which is an Arduino, 2) this data is sent to a computer, and 3) the data will be processed using a random forest classifier. These steps are used with the target of determining the quality of sleep. It classified sleep quality as very unpeaceful, unpeaceful, medium, peaceful, or very peaceful. This monitoring system has reached an accuracy of 95% in categorizing the sleep of patients into these classes. However, the system has limitations as it is not a portable system.

Furthermore, replacing Arduino with Raspberry Pi would enhance the system's processing capability without the need for an external computer.

In this paper, the proposed system comes in a similar design to a regular watch which provides portability. Furthermore, it provides an enhancement as it could track sleep stages using COS sensors. We have used a Support Vector Machine (SVM) that leads to better performance and a robust system. The system detects body movements and uses them to detect and calculate sleep parameters such as sleep onset latency (SOL), wake after sleep onset (WASO), total sleep time (TST), and sleep efficiency (SE). The proposed system could figure out when you fall asleep and wake up as well as the interval of sleep. So, based on observing movements, the system could detect sleep disorders such as insomnia. The remaining parts of this paper are arranged as follows. Section II provides the proposed system concepts, functions, and a brief background. Section III presents a detailed description of the proposed system. In section IV, the proposed system prototyping results are discussed. Section V concludes the paper.

2. The Proposed System Functions

In this section, we first provide an explanation of the main concept behind the suggested system as well as all its functions. After spotting challenges and identifying recent advances in the area of interest, many advancements appeared with feasible features and improvements to be considered. We would start defining these features, how they are calculated, and the mathematical aspects utilized in this demand.

2.1 Sleep Quality

As we have mentioned, sleep quality represents a vital parameter that could affect health in many aspects. Thus, the importance of detecting factors that affect sleep quality has arisen considerably. These factors are represented in having an irregular sleep schedule, a bad sleeping environment such as being in a room that has too much noise or its light is blue light which enhances alertness, drinking too much caffeine, and being diagnosed with a sleeping disorder such as insomnia or obstructive sleep apnea (OSA) [14]-[15]. Although the notion of sleep quality has been widely used in sleep medicine, it is not specified to a particular parameter. Many quantitative measures are meant to be part of the concept of sleep quality. Examples of these measures are mentioned in [5] as SOL, WASO, TST, and sleep efficiency (SE).

- SOL: represents the waking required to make the transition from full wakefulness to sleep.
- WASO: symbolizes the intervals of waking during the sleeping period and it could be calculated as:

$$WASO = \sum_{i=0}^{NA} \mathrm{Awd}(\mathrm{i}) \tag{1}$$

where NA represents the number of awakens in the interval between sleep onset (Son) which represents the first time of falling asleep and sleep offset (Soff) which signifies the time of waking up and cannot fall asleep again. Moreover, Awd(i) is the duration of the waking at instance i.

- TST: it is the total time of being asleep during the interval of bedtime. We can figure it out as the duration from sleep onset to awake.

TST = TIB – (SOL + WASO) (2)

where TIB is the bedtime.

- SE: it is defined as the amount of time you spend sleeping while in bed. It could be defined as the percentage between total sleep time and bedtime.

SE = TST / TIB (3)

These parameters and measures are used to target a well understanding of the experience of sleeping which will reflect the quality of sleep.

2.2 Sleep stages

Some fitness monitoring wearable manufacturers, such as Fitbit, have already integrated a sleep detection capability for wearable devices. However, rather than just identifying whether a person is sleeping, a more in-depth study might be performed to track one's health while sleeping. With this type of analysis, the focus has shifted from the number of hours of sleep you get to how efficient and restorative that sleep is. The sleep cycle's seamless passage through four different sleep stages is critical to sustaining a healthy body. Table 1 shows the various stages of sleep. The classification of these stages is based on an examination of brain activity during sleep and the patterns of nerve signals [16]-[17]. Furthermore, the data collected based on heart rate, blood oxygen saturation, and body movement could be an alternate technique to detect these stages. In addition, body temperature is a factor as it got reduced while sleeping. Deeper sleep stages are also distinguished by the reduced amount of oxygen required by the brain, resulting in a lower blood SpO2 level. Another noteworthy aspect is that when stress levels change, so does the time distribution of sleep stages, allowing for a more accurate and exact diagnosis of excessive stress. Additionally, body temperature is decreased during sleep.

Table 1: Sleep Stages

Sleep Stages	Type	Alternative Name	Duration (Minutes)
Stage 1	NREM	N1	1-5
Stage 2	NREM	N2	10-60
Stage 3	NREM	Deep Sleep	20-40
Stage 4	REM	REM Sleep	10-60

2.3 Measuring heart rate and blood Oxygen level

Heart rate is an important characteristic for sleep tracking for a variety of reasons. This is considered crucial for anything from increasing sports performance to regulating stress levels to tracking heart rate. Otherwise, it is considered a vital parameter in detecting stages of sleep without the need to monitor brain activity. A light-emitting diode (LED) is used in heart rate sensors, paired with an LED light sensor. The sensor's output is presented in beats per minute (BPM). The operating premise of the heart rate sensor is to measure the time difference between periodic changes in the volume of blood, knowing that oxygenated blood has more volume than deoxygenated blood. The volume change, which occurs because of an increase in blood oxygen levels with each heartbeat, is followed by a change in the fluid's reflection properties and is thus detected indirectly via an optical sensor.

In [18], an IoT-based smart wearable system for remote health monitoring adopted MAX30100 for measuring heart rate and blood oxygen saturation. However, it suffers from many design problems that make it operate improperly. We upgraded MAX30100 with MAX30102. MAX30102 has higher storage, resulting in higher data transfer as it has 32-bit FIFO in comparison with the 16-bit FIFO of MAX30100. It is more sensitive to changes in IR receiver voltage [19]. Thus, the MAX30102 sensor consists of a pair of LEDs that emit monochromatic red light at a wavelength of 660 nm and monochromatic infrared light at 940 nm. The reason behind selecting these two specific values is that oxygenated and deoxygenated hemoglobin, which is the protein molecule in red blood cells that carry oxygen, exhibits different absorptive properties. This allows us to calculate the proportion of oxygenated and deoxygenated hemoglobin present. Then, a pair of photodiodes measure the portion of light of each wavelength that is reflected by the sensor and convert this to an electrical signal. Using the Beer-Lambert principle, which relates the attenuation of light to the properties of the material through which the light travels, a relation between absorbance and time for both wavelengths is determined. These values are then converted to oxygen saturation levels obtained from experimental data of healthy volunteers. Furthermore, a graph of the changing volume can be plotted as shown in Fig. 2, indicating the change in blood volume with every heartbeat or simply the blood oxygen saturation. Finally, the time difference between each heartbeat is easily calculated by measuring the distances between peaks on the time-saturation graph.

2.4 Body Movements

The main idea of body movements is to detect any activity as it is a vital parameter with heart rate to distinguish between awake or asleep, then, the detection of sleep stages. Furthermore, it could be an indication of sleeping disorders such as OSA that may cause movement of legs or arms while sleeping [20]. Thus, we used MPU9250 IMU which stands for Inertial Movement Unit, and measures velocity, orientation, and gravitational force. This module depends on combining a 3-axis accelerometer, 3-axis gyroscope, and 3-axis magnetometer and these nine different readings could be used as indications for body movements. These nine different readings are correlated aiming to identify movements of the wrist. Detecting these movements represents a vital factor in the process of sleep tracking. First, the accelerometer measures acceleration and vibration. This could be done through two main principles it could measure the displacement of mass or frequency of a vibrating element. Second, since the gyroscope is mounted on a frame, it can detect angular velocity when the frame is rotating. It could be used to detect deviation from the object orientation [21]. The third and last element is the magnetometer, which detects the strength and direction of the magnetic field. This could indicate the orientation [22].

2.5 Body Temperature

Providing a clinical-grade measurement of human body temperature is of substantial importance to the indication of many health deviations. From fever diagnoses to basal body temperature monitoring, the current developments in wearable thermometers have achieved a widespread set of fundamental advantages. Furthermore, it has been monitored that there are slight differences between body temperature in cases of being awake or asleep as it has been shown that while sleeping body temperature is falling by one or two degrees. In this demand, they utilized a touchless temperature sensor to detect the temperature by using an infrared thermometer for the detection of temperature.

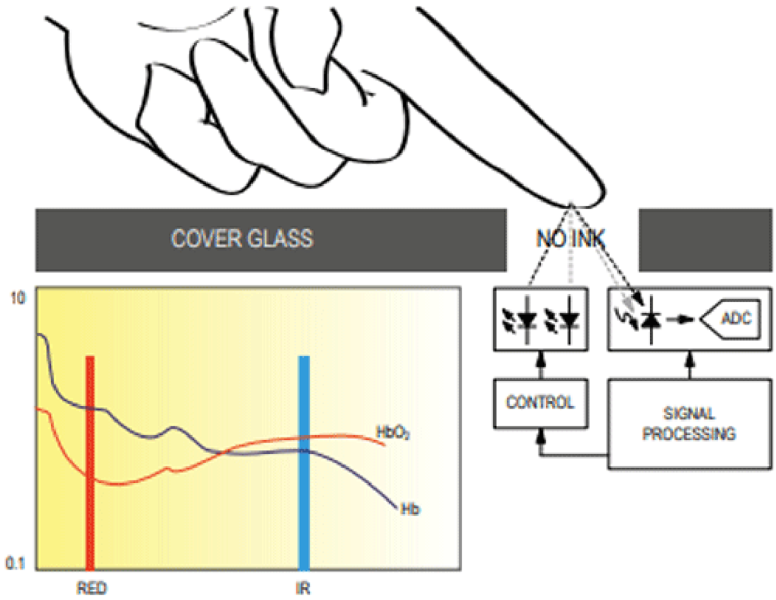


Fig. 2: SpO2 Sensor Working Principle. [19]

3. The Proposed System

Figure 3 illustrates the proposed system architecture. The process of building the system can be broken down into five primary stages: the first, or sensing stage, deals with collecting important health signals utilizing MAX30102, MLX90614, and MPU9250 sensors. The second stage transfers sensor readings using the I2C communication protocol to a centralized unit. This centralized unit represents the third stage, and it is a powerful microprocessor (Raspberry Pi Zero W) that performs the required data processing. In the next stage, we adopted a Support Vector Machine classifier that uses the gained data to be trained to recognize patterns for further data processing. In the following, a detailed description of the custom Printed Circuit Board (PCB), communication with Raspberry Pi, data collection, labeling, pre-processing, and modelling will be described.

3.1 Custom Printed Circuit Board

The proposed sleep-tracking device is implemented on a double-layer PCB. As the need to make it as small as possible to be portable, we customized the dimensions of the PCB to be the same as Pi Zero W of dimension 65mm × 30mm. The used sensors are soldered on the top side to be on the side facing the hand directly to access the data collection, while Raspberry Pi is spotted on the bottom. Furthermore, we have designed and drawn tracks of SCL and SDA on the top layer as shown in Fig. 4.a, whereas tracks of power and ground are on the bottom layer that appeared in Fig. 4.b.

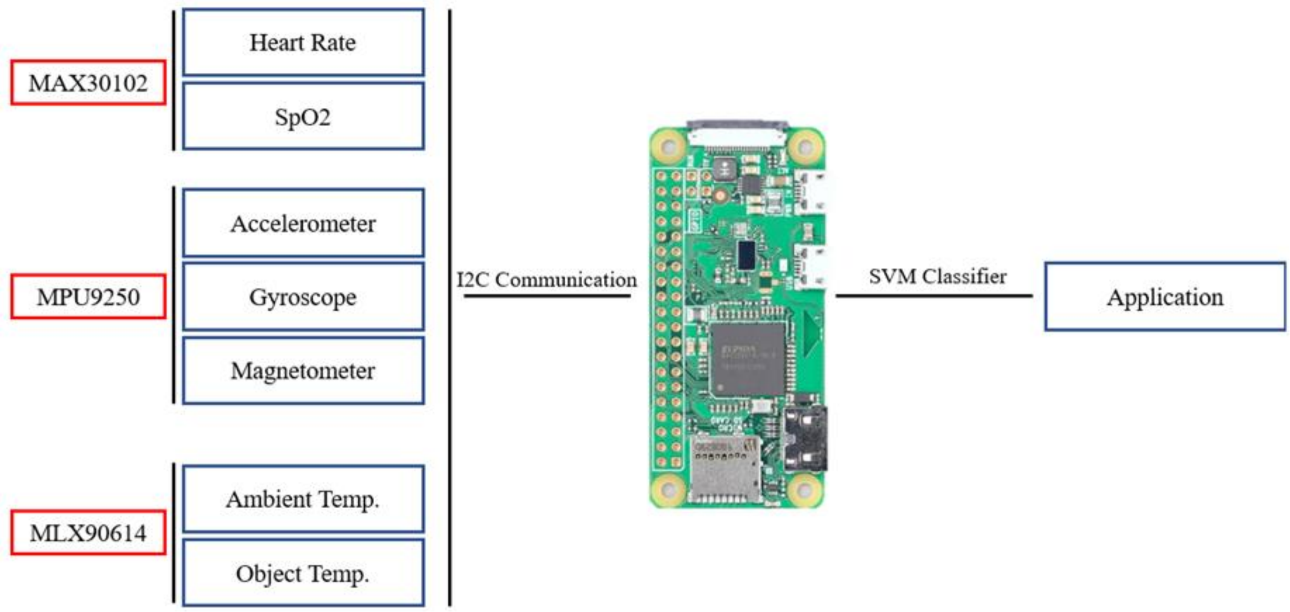
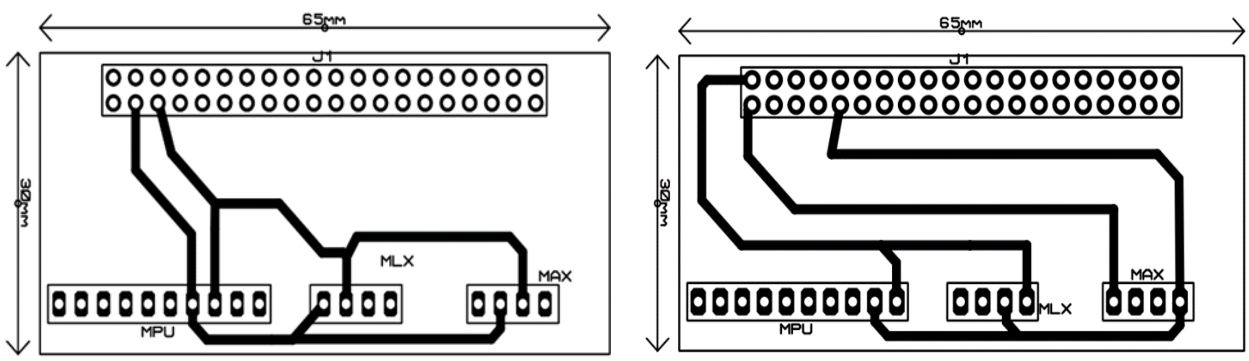


Fig. 3: Sleep Tracking System Architecture.



(a) Top Layer. (b) Bottom Layer.

Fig. 4: PCB Design

3.2 Communication Between Sensors and Raspberry Pi

This stage is considered the second stage in system architecture. The I2C communication protocol is used to establish a connection between sensors and Pi. The two connection lines are SCL and SDA. SCL is the line on which clock signals that are generated by the master devices and used to synchronize the data are sent. SDA is the line that carries the actual data sent from master to slave and vice versa. Every sensor has a specific address as shown in Table 2, as each device is allocated to a unique address, thus, the master could choose the sensor to communicate with [23].

Table 2: I^2C addresses of used sensors.

Device	Address
MPU9250	0x68
MAX30102	0x57
MLX90614	0x5a

3.3 Data Collection

This step is considered the first step in the system architecture. The sensor data collection application is written in Python and uses existing sensor libraries. The application extracts the desired parameters from the registers and saves them as a CSV file for further processing. The collected data is going to pass through data processing aiming to extract information from them. The collected parameters are:

- Accelerometer: (x, y, and z-axis) measured in gravitational force constant (g).
- Gyroscope: (x, y, and z-axis) measured in degrees per second.
- Magnetometer: (x, y, and z-axis) measured in metric gauss (G).
- Ambient temperature in Celsius.
- Object temperature (i.e., skin temperature) in Celsius.
- Heart rate pulses in beats per minute (bpm).
- Blood oxygen saturation (%SPO2).

The collected data has two classifications. The first one distinguishes between being awake or asleep. The importance of this classification is raised from the need to differentiate between being in bed and when you fall asleep. This is necessary to calculate sleep efficiency. The second classification is to differentiate between sleep stages represented in light sleep, deep sleep, and REM. Furthermore, the characteristics of the collected data are represented by the number of samples, average age, and average hours of sleep as illustrated in Table 3.

Table 3: Data Summary.

No. of Participants	Average Age	Average Hours of Sleep
10 Participants	22 years	4 hours

3.4 Data Labeling

In this stage, we needed to use a reference device to label the collected data. Thus, we used Amazfit T-Rex Pro Watch to differentiate between stages [24]. This watch has a heart rate sensor, accelerometer, magnetometer, barometer for measuring air pressure, and ambient light sensors. Most sleep tracker devices have accuracy in detecting stages of sleep that vary between 60% to 65% [11]. However, Amazfit has an overall accuracy of determining sleep at $95.2\% \pm 0.36\%$ in comparison with actigraphy [25]. It could classify data into different stages based on body movement, and heart rate. It is integrated with a mobile application called Zepp to display results. The displayed results show TST by dividing it into stages with the interval of each stage. Then, we labeled data as awake, light sleep (LS), deep sleep (DS), and REM based on reference results.

3.5 Data Pre-processing and Modelling

After finishing data labelling, we started to divide data into packets based on labelling. Data is collected every second and this is the reason why we divided labelled data into packets and each packet has 100 samples. This number of samples in each packet has been considered with the aim of avoiding fluctuations that may occur while the process of data collection. As we have passed through data labelling and utilizing reference data, we used a supervised machine learning model. We trained algorithms based on the labelled data to be able to predict outcomes accurately. In this phase, we used an SVM rather than a neural network, as it provides a robust system and better performance. Moreover, it is better in the demand of the used dataset with a low number of samples because it avoids overfitting. In general, using simpler methods in the smaller dataset is better as it leads to a more generalized model which prevents overfitting.

As the dataset may have many overlapping data, we have moved towards SVM. The idea behind it is to make the best decision boundary that can classify n-dimensional space in a way that makes further categorization for new data points. It may have different and several decision boundaries, however, the best decision boundary is called the hyperplane of SVM. SVM chooses the extreme points/vectors that help in creating the hyperplane. The methodology of it depends on moving data from a relatively low dimension to a higher dimension to be able to classify them. This is done by utilizing kernel functions to find SVM in higher dimensions. Furthermore, we have used a nonlinear classifier as the data are not separated in a linear manner [26].

In the adopted model, we have used a grid search to get the most accurate results indicating the best hyperparameters. This is done through hyperparameter tuning as it has several parameters. This process is based on building and evaluating these different combinations of algorithm parameters. Three major parameters need to be tuned to improve model accuracy. These parameters are:

- Kernels: As we have mentioned, data may appear to be overlapped and this is the reason why we need to move it to a higher dimensional plane, especially in the case of nonlinear separation. The main role of the kernel is to move the low-dimensional data into higher-dimensional data. In our case, we have used a polynomial kernel.
- C: It is considered as the regularization parameter as it is used as the parameter of misclassification or error term. This parameter is used to inform the SVM classifier how many errors are accepted. It is used targeting to manage the trade-off between misclassification and decision boundary. Higher values of C mean better classification of data points; however, a higher chance of overfitting may occur.
- Gamma: It specifies how much the calculation of the line of separation is influenced. If gamma has a higher value, it means a higher influence for nearby points, while lower values mean that faraway points are also considered when determining the decision border.

3.6 REM and NREM Sleep Measurement

A healthy person experiences three to five REM cycles on average each night, with each episode growing longer as the night progresses. The final one could go on for an hour or so. A good target for healthy adults is to spend 20–25% of their time asleep in the REM state. Around 90 minutes of the 7-8 hours of sleep should be REM. The electroencephalogram (EEG), which measures brainwaves, is a simple method for detecting REM sleep. For tracking the signals travelling throughout the brain, a headband is placed on the forehead. Because the normal latency to REM sleep is 100 minutes, which is significantly longer than the average length of a routine EEG recording of 20 to 30 minutes, REM sleep is typically not visible on routine EEGs. A sleep-onset REM period (SOREMP), referred to as REM sleep during regular EEG, is regarded as abnormal when it occurs. They differentiated two types of delta waves that occur during REM sleep: slower (2 Hz) waves recorded in the medial-occipital areas that are present in both NREM and REM sleep, and quicker (2.5-3 Hz), REM-sleep-only sawtooth waves.

In the proposed system the 3-axis accelerometer is used to determine the frequency, duration, intensity, and patterns of the movement. It gathers the data and translates it into digital signals to measure physical activity. This estimates the sleep stages using a combination of movement and heart rate patterns. When you haven't moved for about an hour, your tracker or watch assumes that you're asleep. The ECG measures the heart's electrical activity to find the heart rhythm assessment.

For this purpose, the heart-rate sensor is used, so the system calculates how many times your heart beats per minute (bpm). This data is used to define REM and NREM by monitoring the heart rate variability (HRV), which changes as he moves between the stages of light sleep, deep sleep, and REM sleep.

4. Results and Discussions

To find the system performance, 10 subjects are adopted for training and testing resources. In fact, this number is small to yield good performance matrices. However, it is difficult to find more people that accept the use of the proposed system during their sleep. This number is increased to 200 subjects using data augmentation techniques. To do that, data augmentation is used in this paper by performing various transformations on the collected data. Flipping, rotating, and scaling are used for this purpose to reduce overfitting and improve the model's generalization performance, Briefly, data augmentation is an essential tool for improving the accuracy and efficiency of the proposed model data recognition, and classification [27]. Additionally, when the datasets are unbalanced or the amount of training examples are insufficient to train the suggested model, data augmentation is used. This is done to enhance the quantity and balance the data.
A confusion matrix is used to see how well the prediction model works [28]-[29]. The number of predictions the model made when it properly or erroneously categorized the classes is indicated by each entry in a confusion matrix. Table 4 presents the two classifications model results. It shows that the proposed system has achieved acceptable results in terms of accuracy, precision, specificity, F1 score, and recall.

Table 4: Classifiers results.

Parameters	Awake/Asleep Classifier	Sleep Stages Classifier			
		Deep Sleep (DS)	Light Sleep (LS)	REM	Overall
Accuracy (%)	97.5 %	88.0 %	84.8 %	65.2 %	79.3 %
Precision (%)	97.93 %	64.0 %	100.0 %	44.6 %	69.5 %
Specificity (%)	0.53 %	84.8 %	100.0 %	82.6 %	89.1 %
F1-Score (%)	98.71 %	78.1 %	84.8 %	35.2 %	66.0 %
Recall (%)	99.47%	100.0 %	73.5 %	29.0 %	67.5 %

The first classifier is used to differentiate between being awake or asleep. As displayed in the confusion matrix shown in Fig. 5, if the true label is asleep, the predicted label indicates being asleep. Due to the condition of lying down without being asleep, that will be mistaken for LS, being awake in the true label illustrates that prediction matches the true label with an accuracy of 80%. However, the classifier has achieved an accuracy of 97.5%. After differentiating between sleep status, it could be used to determine intervals of TST and TIB. Based on these intervals, we could measure sleep efficiency.

The second classification is used to detect sleep stages. LS represents a long interval of TST; thus, LS is considered most data of the sample set. Furthermore, REM is only about 20% of total sleep time and the heart rate could go up and down during this stage. Thus, it may be predicted LS while its REM. However, it could differentiate between DS and LS in a high manner as the heart rate significantly gets dropped in the stage of DS. The confusion Matrix that visualizes the results is shown in Fig. 6.

As shown in Table 5, the two classifications have acceptable accuracy. Regarding the first classification, the system has achieved an accuracy of 97.5% in separating between being awake or asleep and consecutively, used in calculating sleep quality. The second classifier has achieved an accuracy of 67.74% in detecting sleep stages comparable to Amazfit [11].

Table 5: Comparison between sleep tracking systems.

Features	Amazfit [11], 2021	Oura Ring [11], 2021	COS System [2], 2020	Proposed System
Sleep Stages	60 % – 65 %	79 %	–	79.3 %
Sleep Quality	95.2 %	–	95 %	97.5 %

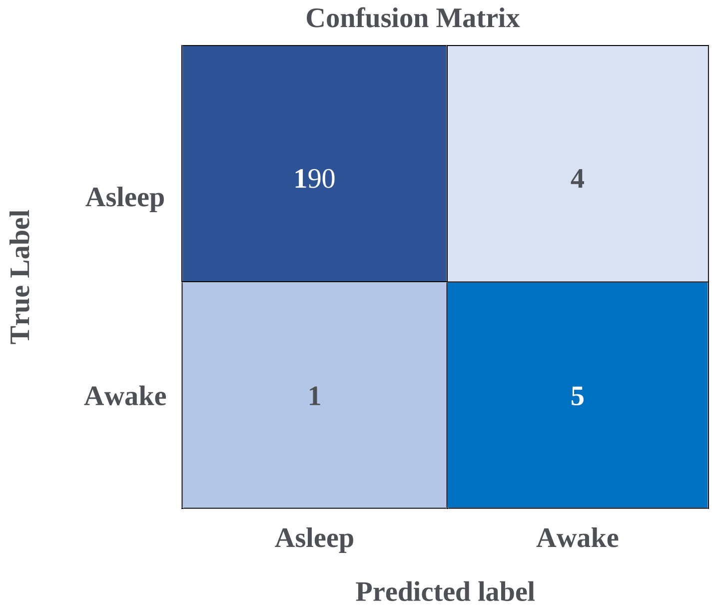


Fig. 5: The First Classifier Confusion Matrix.

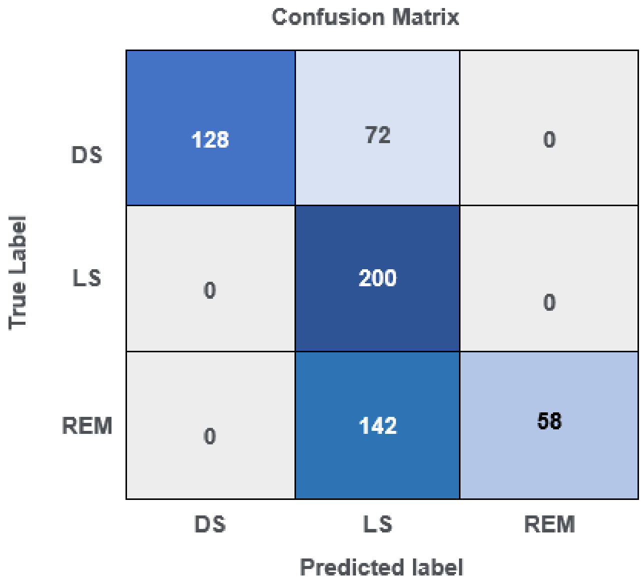


Fig. 6: The Second Classifier Confusion Matrix.

5. Conclusions

In recent years, sleep tracking was recognized as one of the most important applications in health monitoring. In this paper, we proposed a wearable sleep-tracking device using COS sensors that could determine sleep quality and sleep stages. We managed to make a device that meets the design requirements of portability, lightweight, small size, and ease of use. The device comes in a similar design to a regular watch, with the addition of multiple sensors and a powerful processing unit. We used the collected data to build an SVM classifier. Then, we used Amazfit T-Rex Pro as a reference for data labeling. For this purpose, we built two classifiers. The first one is used aiming to differentiate between being asleep or awake and the classifier accuracy was 97.5 %. Based on this classification, we could measure sleep efficiency as it is the percentage between TST and TIB. The second classifier is used to distinguish between sleep stages. This classifier has an accuracy of 67.74 %, which is acceptable as we depend on COS sensors, besides, the most accurate system in this demand achieves an accuracy of 79% [11]. However, the sleep quality of this system is not provided instead the authors considered the heart rate accuracy and the heart rate variability (HRV). The suggested system monitors the HRV or beat-to-beat variations in the user's heart rate, which change as he moves between the stages of light sleep, deep sleep, and REM sleep. The current study can be extended in two directions. First, we might collect information on patients with OSA and insomnia symptoms. This collected data could be used as a reference to estimate if the user is facing any of these problems and based on the answer, it could warn him and direct readings to his doctor. The second direction will be concentrating on improving system efficiency. Thus, we will need to collect more data on people with different sleeping habits. Moreover, we could use PSG as the reference for labelling which will reflect a higher accuracy.

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تصميم نظام ذكي يمكن ارتداؤه لتتبع النوم باستخدام آلة متجهية داعمة ونهج متعدد المستشعرات

تعتبر الرعاية الصحية إحدى القضايا الرئيسية التي يجب رصدها وتحسينها بطريقة عالية. وبالتالي، يتم تخصيص العديد من اتجاهات التكنولوجيا للرعاية الصحية. النوم هو أحد المجالات التي تؤثر بشكل كبير على الصحة. ، لذلك برزت أهمية تطوير نظام محمول لتتبع النوم وبأسعار معقولة. ويمكن القيام بذلك عن طريق مراقبة الإشارات الحيوية التي تؤثر على جودة النوم مثل معدل ضربات القلب، وتشبع الدم بالأكسجين، وتحديد المواقع. علاوة على ذلك، تُستخدم هذه الإشارات للكشف عن مراحل النوم ونوعية النوم. في هذه الورقة، يتم استخدام مجسات تجارية جاهزة للاستخدام لتطوير نظام مراقبة جودة النوم. الهدف هو جعله رخيصًا ومحمولًا وخفيف الوزن وسهل الاستخدام مع جودة نوم جيدة واكتشاف مرحلة النوم. يتم أيضًا فحص حالات نوم حركة العين السريعة (REM) وحركة العين غير السريعة (NREM) استنادًا إلى إشارات تخطيط كهربية الدماغ (EEG) التي تقيس موجات الدماغ. لذلك، يتم التمييز بين نوعين من موجات الدلتا التي تحدث أثناء نوم حركة العين السريعة. تم تسجيل موجات أبطأ (٢ هرتز) في المناطق القذالية الوسطى الموجودة في كل من نوم حركة العين غير السريعة ونوم حركة العين السريعة، وتم تسجيل موجات مسننة أسرع (٢,٥-٣ هرتز) في نوم حركة العين السريعة فقط. في النظام المقترح يتم قياس إيقاع القلب عن طريق إشارات تخطيط القلب باستخدام أجهزة استشعار معدل ضربات القلب. تُستخدم بيانات تخطيط كهربية القلب لتحديد حركة العين السريعة وحركة العين غير السريعة من خلال مراقبة تقلب معدل ضربات القلب (HRV)، والذي يتغير مع انتقال الشخص بين مراحل النوم الخفيف والعميق ومراحل نوم حركة العين السريعة. بالإضافة إلى ذلك، يتم استخدام ساعة Amazfit T-Rex Pro المتوفرة في السوق لتصنيف البيانات. تظهر المقارنة مع الأنظمة المماثلة أن أداءها أفضل نظرًا لتكلفتها المنخفضة ووزنها الخفيف وحجمها الأصغر. تشير النتائج التي تم الحصول عليها إلى أن جودة النوم ودقة مرحلة النوم تبلغ ٩٧,٥٪ و٦٧,٥٪ على التوالي، وهي أفضل من الأنظمة المماثلة المستخدمة مع أجهزة الاستشعار التجارية الجاهزة.