*A****bstract— <placeholder>***

**Sleepify: A system towards personalizing and optimising sleeping environments**

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***“***. In your final report, make sure that the importance of temperature for sleep is reflected also in the abstract.”

# Introduction

It is estimated that people spend about one third of their life asleep. Good sleep is important for both the physical and psychological health of a person. For example, sleep aids in the healing and repair of the blood vessels and heart. Studies have shown that sleep deficiency has been linked to an increased risk of stroke, high blood pressure, heart disease and diabetes [2]. Sleep deficiency has also been linked to mental health problems such as depression, bipolar disorder and anxiety disorder. The mechanism of regulating sleep is complex; there are many factors, which affect sleep quality, such as the psychology of a person. In addition, the thermal environment is a key determinant to achieving good quality sleep [3]. Furthermore, disturbed sleep affects not only physical and psychological health status, but also mortality rates in the elderly [4]. Previous studies conducted on human subjects have shown that sleep is strongly linked to thermoregulation - a process that maintains the body’s core internal temperature at a constant level [3]. This mechanism is also controlled by sleep regulation and circadian rhythm. These findings indicate that maintaining a comfortable thermal sleep environment is important for a healthy life. Several other works have also investigated on the effects of room temperature on sleeping pattern in human [3][5].

These findings are our motivation for creating a product that improves sleep quality by monitoring vital physiological data and sleep environment of the user, and applying machine learning on these data to return an optimal and personalized room temperature.

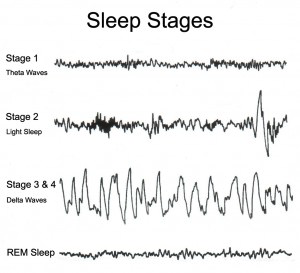
# Sleepify’s Promise

This project aims to provide a better sleeping experience overall from having the room temperature automatically adjust to body and room temperature information from two sensors. Sleepify also promises improved performance and improved machine learning classification accuracy based on prolonged usage of the app. Continued usage of Sleepify is especially important for our machine learning algorithms; thankfully the retention rate of health and fitness apps are the highest among others [1]. Lastly, Sleepify promises to deliver a slick and intuitive app, and web interface for the user to use and interact with, motivating the user to continue using Sleepify regularly; this is crucial to having a low app abandonment rate [2].

# Background

## Sleep

In order to understand how the physical environment affects sleep quality, we must first define what sleep is. Sleep is typically differentiated into five phases; stages 1, 2, 3, 4 and rapid eye movement (REM) [6]. These stages cycle repeatedly during sleep, starting from stage 1 and ending with REM. Electroencephalogram (EEG) measurements are often used to determine these stages as different stages of sleep presents peaks at different region of the signals.



Stage 1 is commonly known as light sleep. During this stage the eyes move very slowly and muscle activity slows. Sometime, we may even experience hypnic myoclonia –a sudden and involuntary muscle contraction. Stage 2 is marked as the onset of sleep where the person becomes disengaged from their surroundings, eye movements stops, heart rate and breathing rate returns to normal, and core body temperature drops.

Stage 3 and 4 is the slow wave sleep (SWS) also called deep sleep stage. In this stage, there are no eye movements or muscle activity. This is the stage where the body repairs and heals itself, muscles are relaxed, and blood supply to muscles increases, blood pressure drops and breathing becomes slower.

REM stage is the final stage of a sleep cycle and it is significantly different from previous stages in that the brain is active. REM EEG waves are very similar to stage 1.

## Sleep and thermoregulation

The sleep-wake rhythm is strongly correlated with the circadian rhythm of the core body temperature (Tcore). Core body temperature decreases upon the onset of sleep due to the circadian rhythm; sleep further enhances this effect by keeping Tcore low [7]. The fundamental driving force behind this decrease in Tcore is due to the peripheral skin temperature. Vasodilatation near the peripheral skin allows rapid decreases in Tcore and promotes onset of sleep [5], [7]–[9]. Studies have concluded that elevated room temperature does degrade sleeping quality [10] [11], as sleep and decreases in skin temperature are related to cardiac activity, it has been suggested that the use of heart rate variability (HRV), skin temperature and galvanic skin response (GSR) can infer to the different stages of sleep and indeed this is how wearable such as Fitbit, and Jawbones detect sleeping patterns.

# Related Work

### Literature

The transition from awake to sleep is indistinctive. Ogilve et al reviewed different studies and concluded entry to sleep is a continuous progress that begins with relaxed drowsiness state until entering stage 1 [3]. Once a person has entered sleep, different stages of sleep can be classified using electroencephalogram (EEG). Davis et al demonstrated this in 1937, where they observed different human brain potential during different stages of sleep [4]. Several works have also observed nervous system activity during sleep [5]. Since then, measurements of EEG to detect sleep have become popular and later forms part of todays’ gold standard in sleep study called polysomnography (PSG). PSG is a combined study that measure EEG, electromyography (EMG), electrooculography (EOG) and electrocardiogram (ECG).

Physiological signals that are used for sleep studies can be put into two groups according to where these signals originate from the nervous system. EEG, EOG, EMG signals originates from the central nervous system (CNS), EEG and EOG are obtained from specialized equipment, which would not be ideal for a normal day person to use and therefore not suitable for our application.

Signals such as ECG, blood pressure (BP), skin temperature, skin conductance and respiration originates from the autonomic nervous system (ANS). These signals are relatively easy to obtain as many commercial wearable contains these sensors [6], although clinical trials and validation for these devices are rare hence they are advertised as “activity tracker”. This inaccuracy in the raw data could potentially affect the performance of the system. Currently, there are a few clinical grade wearable; one example is the E4 wristband by Emptica [7]. Nevertheless, there has been increase in using commercial wearable for researches in the mobile healthcare and medical fields.

Heart rate is well known to decrease at sleep onset [9], it can be obtained from two methods, ECG or photoplethysmography (PPG). ECG measurements requires at least 3 lead electrodes attached across

Einthoven’s triangle, while PPG measures LED absorption when blood flows through the blood vessels. Commercial activity tracker monitors heart rate via PPG sensors, however Lu et al, have shown PPG signals are prone to motion artifacts

[10]. Nevertheless related works primarily focuses on using PPG and other sensors to estimate sleep quality [11], [12].

HRV is a non-invasive and intensively used method to assess the activity level of ANS. It is the inter-change R peaks interval (RR interval) measured from ECG data. It has been observed that the RR interval changes during sleep [13][14][15]. Frequency domain analyses on HRV are common in many works. Power spectrum of high frequency, low frequency and very low frequency were used in Redmond et al works, they used features extracted from these frequency bands to classify different stages of sleep with a subject dependent probabilistic model that achieved accuracy of 87% [16]. The European Society of Cardiology and North American Society of Pacing and Electrophysiology provides a standardized method of HRV, including definitions, methods to obtain features from HRV. These methods are adopted wildly and treated as a gold reference for HRV [17].

Some works have also used accelerometer for sleep quality estimations. Webster et al, developed a scoring based sleep wake recognizer using accelerometer attached to the user’s wrist. Their algorithm summed activity every 2 seconds and was evaluated against sleep / wake status derived from EEG signals. Their algorithm achieved 93.88% accuracy, this suggest the use of accelerometer could be useful [18]. Cole et al, have also presented similar work, their algorithm was able to distinguish sleep from wakefulness for 88% of the time [19].

Body temperature is found to decrease when sleep stage transits from NREM to REM in the third cycle [15]. Secondly, a trend towards a decrease of the low- to high-frequency ratio (LF/HF) derived from the power spectral analysis of Heart Rate Variability is expected to associate with the transition from wakefulness to NREM sleep. Meanwhile, the LF/HF ratio increases during the rapid-eye-movement (REM) sleep[12],[13]. Nevertheless, James W. Mold et.al have concluded that night sweating is associated with several sleep symptoms[16]. Most importantly, body movement monitoring data should be captured as conventional actigraphy method is proved to reach 90% agreement with traditional PSG for nocturnal sleep period [14].

*2) Commercial Products*

There are many sleep trackers on the market that use a variety of ways to track sleep quality. Most sleep trackers monitor the user’s different stage of sleeping, sleeping environment and provide sleep-coaching advice. Majority of the trackers are found in the form of software application for iOS and Android. These applications use the accelerometer found in smartphones to track body movement throughout the sleep cycle. Using this data, “Sleep Cycle” wakes the user up during the lightest sleep phase, preventing the feeling of tiredness in the morning. In addition to the accelerometer, “Sleep as Android” [3] records audio through the microphone to detect snoring, speech, and ambient noise. This can be played back to the user the following morning, and can be a good indicator of sleep disturbances and stress [4]. Additionally, some applications also include the feature of playing soothing sound or music to make the user fall asleep peacefully.

Hardware sleep trackers such as “S+ By ResMed personal sleep solution” contain even more features, such as synchronizing the output music with the respiratory pattern of the user to provide a calming effect [5]. Another interesting feature by “Aura Smart Sleep system” includes a red light to induce the user into sleep [6]. “Sense” has a slow wake up light alarm to gradually wake the user up. Most of the aforementioned also have questionnaires for the user to record their daily behavior to help analyze their sleeping pattern.

However, some of the down sides of these applications include inaccuracy in telling whether the user is just lying in bed or actually sleeping. Some drain the battery of both the device or the phone quickly. Some of the applications lack a snooze alarm function.

Sleepify has taken into account the pros and cons of these existing sleep trackers in the market when prioritizing its aims. In addition to the generic functions such as sleep coaching advice and sleep environment monitoring, it has taken an active role to provide a novel edge to sleep tracking - adjusting the sleeping environment. Sleepify analyses the best sleeping temperature and connects to smart heating devices to adjust the optimum sleeping temperature automatically. Manually changing the start time of the sleep record would also be enabled to prevent the problem of false sleep detection.

# System Design and Implementation

## Overall High Level Design

There are many types of software distribution models. Traditionally, users purchase a piece of software either through a retailer or online, and then install it onto their computer. The user then holds the license to use this piece of software, indefinitely. A drawback of this traditional method is that the user normally has to pay an upfront cost, update availability is subject to the package the user bought, and data only exists locally on the user’s machine [7].

Nowadays, the Software-as-a-Service (SAAS) model is the model upon which most companies are building their products around [8]. The SAAS model gives the consumer the ability to use on demand software that is provided by developer via the web or an app. From Heredia et al., as the user normally pays a subscription fee instead of an upfront fee, the SAAS model guarantees that the user will always be using the most updated version of the software as there is no ‘local copy’ of the software to install [9]. Moreover, SAAS removes the burden of having to configure (and control of) infrastructure for the user. However, SAAS solutions often assume that customers will always like new changes as updates are rolled out to all users [10] – this is not applicable to Sleepify as the timeframe of the project means only developing a minimal viable product (MVP).

Following the SAAS model, Sleepify consists of a front-end and a back-end, each consisting of two parts. The front-end is what the user sees and uses, and consists of an iOS application and the web interface. Updates through the App Store and the website ensure the user will always be using the most updated version of Sleepify. Finally, this front-end connects to the sensors for data collection and temperature adjustment. The back-end consists of the servers, databases, APIs, and machine learning modules – these both provide, and accept information from the front-end applications. The user has no information or control on how the back-end is configured; they need not to.

## Sensors

Based on our findings from both academic and commercial sources stated in related works, it is clear that our chosen wearable should provide physiological signals such as heart rate, rr-interval, skin temperature and GSR. The Data-as-a-service platform for healthy lifestyle and preventive medicine (DAPENE) has provided a comprehensive literature on existing wearable technology, it is clear that only products from Fitbit, Jawbone and Microsoft contain the above sensors [6]. Since the release of the first Microsoft Band, researchers have been using it for various works in different fields such as sleep tracking [20]. It can be seen from the table, Microsoft Band 2 provides an extensive range of suitable sensors and APIs, therefore the Microsoft band 2 was chosen.

|  |  |  |  |
| --- | --- | --- | --- |
| Wearable | Placement | Sensors | Run Time and API |
| The Dash | In Ear | * Right side   + Accelerometer   + Gyroscope   + Magnetometer   + Dual PPG * Left side   + Accelerometer   + Gyroscope | Up to 4 hours,  Depending on usage  Developer Website with API |
| Fitbit Charge 2 | Wrist | * Accelerometer * PPG * Altimeter * Vibration motor | Up to 5 days  Provides API |
| Apple Watch | Wrist | * Accelerometer * PPG * Heart Rate | Up to 2 days  Provide Watch API |
| Microsoft Band 2 | Wrist | * PPG * Accelerometer/grro * GPS * Ambient light sensor * Skin temperature * UV sensor * Capacitive sensor * GSR * Barometer | Up to 48 hours of normal use |

## Backend (Server, Database, API)

The backend is responsible for interfacing with the front-end, in accepting and providing it with the information it needs. It consists of a server on which a database resides, and a Representational State Transfer (RESTful) API which allows the iOS app, web interface, and machine learning sections to communicate with the server and by extension, the database.

### The Server

As the database, the web interface, and the API all reside upon the server, a smart choice needed to be made regarding how the server would be implemented.

Our group had prior experience in setting up a server running a LAMP stack (Linux, Apache, MySQL, PHP) in hacking together a simple custom API and website, but this was judged to be inadequate for Sleepify as trying to hand code PHP without a web framework when creating any sort of advanced web app would take an extremely long time. Laravel, and Yii, both modern PHP frameworks, were initially shortlisted as using a modern web framework would shorten development times drastically. However, the verbose and sometimes confusing syntax of PHP mean getting-things-done is more important than code readability [11]. As Sleepify’s development may continue in the future, reusability and code readability meant the group decided not to go with a PHP framework. In hindsight, further research from Srinivasan et al. also showed PHP to suffer from more security issues compared to other web frameworks [12].

Emphasising code readability and rapid development meant the choice was narrowed down to two programming languages: Python, and Ruby. The most well-known web framework in Python is Django, and in Ruby, Ruby on Rails. Both offer extremely fast prototyping and development, extensive documentation, security measures against common attacks, and multiple libraries to assist development. The final decision was to use Django, the Python web framework, as the ease of use of Python (especially considering the group had extensive C++ and Python experience) and the ample documentation on Django meant decreasing the time needed to create the MVP.

Multiple Django libraries were leveraged to add extra functionality, the most notable being: django-rest-framework, a library which provides the skeleton of the RESTful API; django-rest-auth, which extends Django’s already excellent authentication system with the API; django-bootstrap3, a library which simplifies styling a website using Twitter bootstrap.

### The Database

The main design decision when choosing the database was whether to go with a Structured Query Language (SQL) or a NoSQL database.

SQL databases are known as relational databases, where databases are linked together by keys and values [13], held in entries in database tables. In SQL databases, all the incoming data must match the format of the database table, whilst NoSQL operate on the premise that the incoming data is of a large volume and of a rapidly changing format [14].

The most well known NoSQL database is MongoDB, and it offers several advantages over SQL databases. MongoDB claims scalability and performance improvements in [15], claiming that NoSQL databases are horizontally scalable (add more servers) instead of vertically scalable (have to make the one server more powerful). However, the flexibility of NoSQL data means there exists consistency issues when dealing with many similar data objects – unacceptable for user data. Another important advantage a NoSQL database has is its data format. Nayak et al. goes into more detail, showing the data being held in a binary Javascript Object Notation (JSON) object [16]; this can be accessed using object oriented methods. However, this advantage is nullified with Django as it has its own object oriented wrapper for any type of database. Django supports its own ‘Models’, which abstract away the complicated SQL statements needed to modify the database [17] in favour of treating database tables as objects, nullifying yet another advantage of NoSQL databases.

Hence, the final decision was to use SQL databases. Having a SQL database means structured data (sensor data is of a set format anyway), and relational relationships mean data can be linked with user profiles very easily. There are a few popular SQL databases, the most popular 3 being SQLite, MySQL, and PostgreSQL. The following table shows the pros and cons of each (taken from [18]); the final decision was made to use SQLite, a SQL database that comes shipped with Django by default, with the main justification coming from portability (copy and paste the database across testing machines, committable on Git), and it supporting enough features to not be considered bloated. Scalability issues have been moved down in priority as according to SQLite, they only occur at high volumes of data [19], an unrealistic target for Sleepify. Lastly, NoSQL support is not part of the official Django development effort, and is only supported via third party forks [20].

With regards to user security, the SQLite database is not encrypted now as the database is not reachable through the internet. However, in the future, a Django library known as django-fernet-fields can be utilised to encrypt database fields (unfortunately, floating point numbers are not supported yet).

Table : Comparison of SQL Databases

|  |  |  |
| --- | --- | --- |
| Database | Pros | Cons |
| SQLite | * Extremely portable as the whole database is one file * Feature rich for development and testing | * No in-built user management * Slow for large number of writes |
| MySQL | * Scalable, more feature rich than SQLite, tested * High security | * Reliability issues and discontinued development * Not fully SQL compliant |
| PostgreSQL | * Reliable in terms of data integrity * Supports complex queries | * Overkill for simple databases * Not portable without spending time replicating the database |

### The API

Creating an API was a top priority for the back-end as it enables a consistent communication format between the front and back-ends. Sleepify’s API exposes URLs in which data can be sent or retrieved, including but not limited to the following: machine learning results, raw sensor data, graphs, calendar events, and sending push notifications.

To create the API, a communication format and architectural style had to be decided. Nurseitov et al. compares the two main communication formats, eXtensible Markup Language (XML), and Javascript Object Notation (JSON) [21]. XML follows a rigid pre-defined structure while JSON does not have any pre-defined structures (large companies such as Google, Yahoo, and Microsoft have a web repository of such pre-defined structures but this is by no means compulsory - <http://schema.org/>), so initially it seemed XML was the way forward. However, since everything in XML is stored in strings, parsing the XML data takes relatively more processing power than that of JSON, which can have single entries or arrays of strings or integers – making JSON much more efficient, especially on mobile platforms as demonstrated by Sumaray et al. [22], making it Sleepify’s choice for the data format.

To decide on the architectural style, the pros and cons of Simple Object Access Protocol (SOAP), Representational State Transfer (REST), and Remote Procedure Call (RPC) were compared in the following table [23], [24], [25].

Table : Comparison of API styles

|  |  |  |
| --- | --- | --- |
| Style | Pros | Cons |
| SOAP | * Versatile, can use different protocols other than HTTP | * Extremely complex payload * Way too verbose for simple tasks * Legacy |
| REST | * Uses standard HTTP verbs * Intuitive and clean looking API URLs * Suited for getting data * Embraced by many as the way to go when designing APIs | * Not suited for calling functions or actions (URLs are nouns) * Not easy to do more than one thing in one request |
| RPC | * Uses standard HTTP verbs * Suited for verbs, functions, actions * Can have a custom verb do more than one action at once | * Getting data using RPC architectures is messy and inconsistent * Naming conventions up to the developer |

As SOAP relied on XML, it was not chosen. Based on these results, Sleepify chose to use a mixture of REST and RPC architectures. Data retrieval and insertion would be done using RESTful nouns such as /user/, /raw\_data/, /stats/, while push notifications and the machine learning training would be done using RPC verbs such as /push\_to\_devices/, /migrate\_features/.

As the API is built on the Django server, the django-rest-framework was leveraged to provide the skeleton of the API. Converting functions into RESTful and RPC compliant APIs were as simple as wrapping the function in an ‘APIView’ class. The library also provided an appealing interface to display data retrieved from the API without any added custom user styling. Authentication to the API is done through sessions/cookies, and is supported through defining permission classes in the API functions (e.g. statistics only available to logged in users, user registration, log in/out, open to the public). Another style of authentication is using JSON Web Tokens (JWT), but JWT does not allow pushing notifications to logged in clients as there is no way to know whether a user is logged in or not, as opposed to authenticating using sessions [26].

## Machine Learning

### Sleep quality evalution

The prime objective of sleep quality evaluation module is to allow real time sleep quality evaluation based on sensors’ data. This section reviews the related methods in sleep quality evaluation and their deliverables to our final implementation.

There are three methods, which are widely used in clinical sleep quality assessment: Pittsburgh Sleep Quality Index (PSQI), Polysomnography and Actigraphy [4]. First, PSQI is a questionnaire-based assessment focusing on subjective feedback on medium to long-term sleep quality [5]. Based on subjects’ answers, it generates a score that is inversely proportional to sleep quality. Due to the limitation of long assessment interval, PSQI is not suitable for direct implementation into this module. However, this method is used to evaluate the general performance of our system on sleep quality enhancement and the result will be discussed in the Evaluation section.

Polysomnography analyses sleep quality by using electroencephalograms (EEG), electro-oculograms (EOG) and electromyograms (EMG) of the mentalis and libs [7]. It reflects the precise proportion of each sleep stages during the 24-hours assessment interval and hence provides the most accurate sleep quality evaluation. Despite of its accuracy, it has a few critical disadvantages that prevent its application into our system. First, the sensors required are extremely intrusive to users and all signals required intensive processing algorithms to analyze. Secondly, the data collection process for complete analysis required at least 12 hours. Therefore, this method is not applicable in this case.

Actigraphy monitors the sleep quality by estimating ratio between ‘sleep’ and ‘awake’ patterns. Conventionally, ‘sleep’ and ‘awake’ patterns are defined as minor and intense body movements during sleep by using motion sensing device actometer. The principle behind is that body muscle is completely paralyzed during deep sleep stage but not in others. By extending this principle further, redefining sleep-awake patterns and combining more sensors, several Actigraphy sleep quality evaluation methods have been invented. Mobile application such as iSleep [8], Sleep as android [9] and Toss ‘N’ Turn [10] uses mobile phone as the main sensor to collect data reflecting the sleeping noise, body movement, background light intensity. They determine the sleep-awake ratio in each night to evaluate sleep quality with mean accuracy over 80%. Furthermore, research by Ya-Ti Peng et.al has also shown that introducing heart rate data into normal motion tracking can improve sleep-awake pattern classification [11]. These applications act as a proof of concept for actigraphy validity and correlation between sleep quality and biometrics including body movement, heart rate, etc. Moreover, they demonstrate the method’s compatibility with mobile phone. As a result, we decided to utilize actigraphy as our detection principle. Nevertheless, we leverage machine learning approach for the implementation to provide short-term sleep quality evaluation continuously.

### Clustering Analysis and Features Extraction

Given the sensors provided by Microsoft Band 2, the features generated covers 3 modalities, this is summarized in Table 1. All sensor data is in temporal manner and hence a time interval for feature generation is required. Our final windowing size is 10 minutes of data sampled at 1Hz. This decision provides the best compromise between mobile phone hardware capabilities and feature validity. Typical range of sleep stage transition time varies from 7 to 45 minutes and thus it would be optimal that to generate feature every 45 minutes. However, the window width is constrained by the memory available on mobile phone. Storing 7 sensors reading at 1 Hz for 45 minutes exceeds the available memory and it also causes long delayed in data sending to server. Therefore, a smaller 10 minutes’ interval is chosen as it is proved to be effective in Toss ‘N’ Turn [10].

Features for each modality are chosen by referencing existing signal processing techniques. Previous research has shown that the heat exposure to extreme heat and humid environment can affect sleep quality and mean skin temperature can capture this exposure effect on body core temperature<http://europepmc.org/abstract/med/10505822>. Moreover, temperature tends to decrease at nighttime sleep onset but increase when awake [15] and standard deviation can be used to capture the fluctuation of body temperature within each time window. Therefore, mean and standard deviation of skin temperature were extracted.

Accelerometer reading is used to reflect users’ arm movement.

Instead of using interval average acceleration over time suggested in [18], we extract the data in terms of mean and standard deviation of squared amplitude shown in (1).

The motivation behind is to capture movement information every 1 second. The suggested method is effective when the time interval is around 100 second, which is much smaller than the chosen 10 minutes’ interval. If similar approach is used, the excessive smoothing on 10 minutes of data can remove acute magnitude fluctuations caused by sudden arm movements. Therefore, mean and standard deviation on mean squared amplitude are used to extract overall movement intensity and frequency.

Heart rate variability is proved to be higher in rapid eye movement sleep stage than others < Zemaityte D, Varoneckas G, Sokolov E. Heart rhythm control during sleep Psychophysiology 1984;21:279e89> while mean and standard deviation on RR intervals are shown to be adequate measures of HRV during sleep stages transition < Heart rate variability, sleep and sleep disorders>. Additionally, instantaneous heart rate data is also analyzed in similar manner. Apart from using mean and standard deviation, kurtosis is also used to analyze the extremes. From < "The meaning of kurtosis: Darlington reexamined". *The American Statistician>*, kurtosis is a measure on outlier’s population out of the total samples. The higher the kurtosis is, the sample is less distributed around the statistical median. Hence, it can be a useful tool to quantify the chronic changes in RR interval and heart rate that is removed under mean and standard deviation. Lastly, we have excluded the introduced Galvanic Skin Response reading as input features because of three reasons. First, the sweat production is proven to be independent with galvanic skin response amplitude < INDEPENDENCE OF GALVANIC SKIN RESPONSE AMPLITUDE AND SWEAT PRODTJCTION\* >. Secondly, the galvanic skin response(GSR) sensor required locking system to provide accurate data and the acquisition-locking cycle is difficult to be controlled as it is done by Microsoft Band 2 API. Thirdly, the variance of GSR across different sleep quality is found to be nearly zero from data collected. This demonstrates its insignificance in sleep quality evaluation and hence GSR is excluded in the final feature set.

|  |  |  |
| --- | --- | --- |
| Modality | Sensor Data | Features |
| Temperature | Temperature readings in Celsius | Mean, standard deviation(STD) |
| Movement | 3-axes Accelerometer readings | Mean, STD of root mean squared amplitude |
| Heart rate | Optical Heart Rate readings and RR interval | Mean, STD, Kurtosis |

Table : Initial Feature Set

### Model Selection

We have defined our sleep quality evaluation problem as a binary classification problem after learning from various sleep-awake pattern classifiers < Comparison of Sleep-Wake Classification using Electroencephalogram and Wrist-worn Multi-modal Sensor Data >< https://infoscience.epfl.ch/record/135627/files/EPFL\_TH4391.pdf >. Given the final feature set, it is necessary to select an optimal classifier based on the obtained data. Matlab classification learner is used to perform cross-model benchmarking. From previous testing result as shown in Table 2, a user specific classifier performs better than a unified classifier and hence our final model selection process only focus on optimizing model which is trained on a specific subject. To prevent loss of generality, we carefully selected a subject that has the most uniformly distributed sleep quality. The result is shown in Table 3.

|  |  |  |
| --- | --- | --- |
| Models | All Data Accuracies | Personalized Data Accuracies |
| Best Tree | 78.1% | 90.5% |
| Logistic Regression | 78.1% | 85.7% |
| Best SVM | 75% | 95.2% |
| Best KNN | 84.4% | 90.5% |
| Best Random Forest | 75% | 95.2% |
| Boosted Tree | 81.3% | 85.7% |
| Subspace Discriminant | 60% | 100% |

Table : Feature Analysis Results

|  |  |
| --- | --- |
| Models | Personalized Data Accuracies |
| Decision Tree | 95.8% |
| Logistic Regression | 85.7% |
| Best SVM | 96.4% |
| Best Random Forest | 96.3% |
| Boosted Tree | 95.6% |

Table 3: Model Selection Results

From Table 3, it can be observed that either support vector machine or random forest should be chosen as the implementation model. Apart from model accuracy, training and testing time are also considered as model selection criteria. Thus, random forest is chosen to be implemented due to its efficient training and testing principle. Another drawback from this testing result is that it is based on feature set generated from one specific subject over 1 week due to limited resources such as time and available Microsoft Band 2. Moreover, the limited subject diversity also reduced the available sample size. This is because most of data collected are from good sleepers, which causes imbalanced sleep quality distribution. Nevertheless, the sleep quality labelling on training data is based on assumption that overall night sleep quality can be interpolated into individual interval sleep quality. This assumption should be abandoned if more time and resource are given to perform clinical testing on overnight sleep quality monitoring with the device.

### Machine Learning Model – Server Deployment

To integrate machine learning module into the system smoothly, an implementation of random forest classifier is done on server side in order to provide online estimation upon requests from Sleepify mobile clients.

As we have chosen Python Django for the server development platform, Scikit-Learn [20] is used for our machine learning implementation. Model persistence on server is achieved by binary serialization and recovering using Pickle, a Python object serialization tool. From the preliminary study results, it is necessary that each user requires a specific classification model which is trained by personalized data. Therefore, these binary models files are linked to user entries in database to allow user specific mapping.

To communicate with the mobile application, a RESTFUL API is created to offer three functions; sensor data storage, machine learning model retraining and prediction. When the mobile application sends a packet of new sensor data to the server, this interface will first extract the date, time and user details of the packet and store the data into database under specific user accounts. After that, the packet will be preprocessed into a feature sample. Then, binary model files under the specific user is recovered and prediction method will be called with the generated feature vector. Finally, the prediction outcome is sent back to mobile application in the form of JSON. Moreover, continuous learning is supported by the use of existing models provided by Scikit-Learn. A user specific data tracker is implemented to monitor the accumulated count of untrained data packet. When it exceeds a threshold, the model will be recovered from the binary file and perform online learning. The block diagram for this machine learning server infrastructure is shown in Figure 2.



Figure : Server Architecture for ML model

### Testing

To evaluate the model implementation, an offline model testing is done to demonstrate the practical performance of random forest model provided by Scikit learn. To compare with testing performed by Matlab classification learner, identical hyperparameters such as tree depth and tree numbers are used. Moreover, a similar testing and training set splitting ratio is used which are 0.2 and 0.8 respectively. The result shows that implemented classifier can achieve 90% accuracy, which is similar to Matlab implementation.

## iOS Application

## Web Interface

As per Sleepify’s promise, the web interface should be modern, intuitive, and easy to use.

# Evaluation Criteria and Setup

# Results

# Discussion

# Conclusion

In conclusion, this report highlighted the motivation behind in building a system that is capable to alter the users thermal sleep environment to achieve better sleep quality. We have identified that the thermal environment is a key factor in affecting sleep quality, this justifies our rational in controlling this factor in order to provide better sleep quality to users. We have discussed related works, however to the authors’ knowledge there is no work that has developed a complete system to alter sleeping environments. Finally, we have also presented some of our prelimiarly works.

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