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RESEARCH ARTICLE-COMPUTER ENGINEERING AND COMPUTER SCIENCE

Analysis of Data from Wearable Sensors for Sleep Quality Estimation and Prediction Using Deep Learning

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Abstract
Wearable devices such as smartwatches, wristbands, GPS shoes are increasingly used for fitness and wellness as they allow users to monitor their daily health. These devices have sensors for accumulating user activity data. Clinical actigraph devices fall in the category of wearable devices worn on the wrist determined to estimate sleep parameters by recording movements during sleep. This study aims to predict sleep quality from wearable sensors using deep learning techniques. Three sleep indicators are proposed which are calculated using the data collected automatically from wearable devices. These sleep indicators are Daily Sleep Quality, Weekly Sleep Quality, and Sleep Consistency. Two deep learning models namely Convolution Neural Network (CNN) and Multilayer Perceptron (MLP) have been implemented to predict sleep quality on the basis of the proposed indicators. Two datasets have been used to validate the work proposed in this study which include a dataset comprising sleep parameters using commercial wearable devices and another dataset consisting of sleep data using clinical actigraph device. Systematic Minority Oversampling Technique has been applied for data augmentation with the intent to increase data instances and to alleviate class imbalance. CNN is observed to outperform MLP in predicting sleep quality with the highest accuracy of 97.30%. This study also evaluates the worth of each sleep attribute using Information Gain algorithm in order to identify the most important attributes which contribute to the sleep quality. It has been concluded that in bed awake percentage contributes maximum to the Daily Sleep Quality, average sleep efficiency contributes maximum to the Weekly Sleep Quality and standard deviation of midpoint of in bed and out of bed times contributes maximum to the Sleep Consistency.

Keywords Deep learning · Wearable sensors · Sleep indicators · Actigraphy

1 Introduction

Wearable technology refers to electronic devices and systems incorporated in some part of our body or clothes [1]. Wearables such as smartwatches, activity trackers, sneakers are examples of Internet of Things which include things like electronics, software, and sensors. There has been a great rise in the use of commercial wearable devices as these help individuals to monitor their fitness, wellness and other health related activities. These consumer devices are equipped with sensors and are being used by millions of people collecting huge amounts of rich quality physiological and environmental data. More than 17 sensors in around 140 commercial wearables have been identified in the studies [1,2] which provide high quality, accurate data for analysis. These sensors include heart rate, accelerometer, compass, GPS, microphone, gyroscope, ambient light, barometer, thermometer, altimeter, camera, etc. The data collected through these wearables is also processes by researchers for analytics in order to observe patterns in user activities. The data includes steps walked, calories burnt, exercise time, active time, etc. Many wearables are equipped with sensors used for determining sleeping patterns of individuals based on their movements during the sleep period.

Sleep is an important part of ones daily routine and a good quality sleep is essential for overall wellbeing on an individual. Quality sleep refers to having enough of sleep at the right times and is essential for optimal health as it is important for brain functioning. Sleep disorders may potentially be a symptom of a disease or an indicator of a future disease like depression. There are many research tools to asses sleep of an individual. These techniques can be categorised as self-reporting tools and sensor-based tools.

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Self-reporting are subjective assessment methods which do not essentially need medical aid [3] and are categorised as follows:

- Standardized Questionnaires summarise the observation of a patient about his own quality of sleep. The most common examples include Pittsburgh Sleep Quality Index (PSQI) [4], Mini Sleep Questionnaire [5], Insomnia Severity Index (ISI) [6], Sleep Disorders Questionnaire [7], Epworth Sleepiness Scale (ESS) [8] etc.
- Sleep Diaries are filled by the patients over a period of time. Some examples are Pittsburgh Sleep Diary [9], and Consensus Sleep Diary [10].

PSQI is the most widely used tool in medical and scientific literature. It is a questionnaire-based index which measures sleep quality and disturbances over a period of one month. It consists of 19 questions separated into 7 components.

Sensor-based tools are cutting-edge methods which comprise of wearable and non-wearable sensors, contact and non-contact sensors to monitor human sleep. Most commonly used sensor-based tools for assessing sleep are as follows:

- Contact sensors including wrist band, ankle band, chest band and head band
- Actigraphy comprising of a clinical actigraph worn on the wrist
- Polysomnography (PSG) having multiple sensors for monitoring a patient overnight
- Contactless sensors such as video camera, microphone, infrared thermometer and echo-based devices.

These techniques have varied clinical indications for the analysis of various sleep disorders [11]. PSG is considered as the gold standard for sleep medicine. This technique comprises numerous sensors such as breathing sensors, electroencephalogram, motion sensors, oxygen saturation, and more to monitor a patient overnight [12]. The restrictions of PSG are that it is generally limited to one overnight observation and is complex to perform. [13,14]. Actigraphy is a technique developed in early 1990s to study sleep patterns using wearable devices [15]. This technique uses an actigraph sensor which is worn for a period of time (generally a week) to evaluate the sleep period as well as physical activity of an individual. It has become a widely used tool for sleep evaluation, because of its better reliability, and accuracy than subjective sleep questionnaires and self-reported sleep diaries [16]. Patients can continue their daily routine with the device worn on their body. The technique is significant for studies on groups of people for observing their sleeping patterns where PSG is not feasible [17]. Furthermore, actigraphy allows the continuous longitudinal monitoring of a patient over a period of days in contrast to PSG.

A sleep indicator is an estimation of sleep quality which is calculated using multiple sleep parameters. There are various sleep indicators in the existing literature such as PSQI [4], ISI [6], ESS [8], with PSQI being the most widely used. There are many drawbacks of sleep indicators having questionnaires as the key method of gathering information which include unanswered questions, unconscientious responses, difficulty in understanding and wrong interpretations of questions which lead to inaccurate information. Filling of questionnaires is a cumbersome task for participants and some sleep questionnaires (such as PSQI) require sleep partner to answer some of its questions. Furthermore, technical attributes of sleep such as duration of time spent in various stages of sleep (light sleep, deep sleep, Rapid Eye Movement sleep) are observed by sensors present in wearable devices. Sleep questionnaires cannot acquire these technical attributes by human reporting. Wearable sensors help in better sleep evaluation, as these are more reliable and accurate as compared to subjective sleep questionnaires and self-reported sleep diaries. Not all commercial wearables generate sleep score assessing each nights sleep unlike Fitbit [18]. There is a need for generic sleep indicators which can be evaluated using the data collected automatically from wearable devices. The commercial wearable devices such as smartwatches which help in physical activity and sleep tracking collect motion data similarly to actigraphy devices. Studies have found that these commercial devices are equipped with sensors having similar precision to clinical actigraphy sensors [18]. There are successful examples of the incorporation of physical activity wearable data from smartwatches into eHealth applications [19,20].

Motivated by this, we expound the assessment of sleep quality indicators using the data collected automatically using wearable devices and propose a deep learning model for sleep quality prediction. Deep learning techniques have been achieving state-of-the-art results for predictive modelling on feature-based data [21–23] and have been effectively used in many studies. The objective of this study is to assess sleep using data from wearable sensors without self-reporting from users. We propose three sleep indicators namely: Daily Sleep Quality (SleepQual_D) Weekly Sleep Quality ($\text{SleepQual}_{\text{Week}}$), and Sleep Consistency (SleepCons) which are estimated using the data from wearable sensors. These sleep indicators are further used for sleep quality assessment and two deep learning algorithms, Convolution Neural Network (CNN) and Multilayer Perceptron (MLP) have been implemented to predict sleep quality on the basis of proposed indicators. Two datasets have been used to validate the work proposed in this study. The first dataset has been collected from participants having commercial smartwatches while the second dataset is collected from the National Sleep Research

Resource[1] which consists of sleep data acquired using clinical actigraph device. SleepQual_D is calculated for dataset 1 which consists of daily sleep features of 13 participants using commercial smartwatches worn for 7 consecutive days. $\text{SleepQual}_{\text{Week}}$ and SleepCons are calculated for dataset 2 which contains weekly sleep features of 2237 users from clinical actigraphy. The datasets have been labelled with classes based on these sleep indicators. Systematic Minority Oversampling Technique (SMOTE) has been applied for data augmentation with the intent to increase data instances and to alleviate class imbalance. Performances of the deep learning techniques for prediction of sleep quality based on the proposed indicators have been assessed using performance metrices such as accuracy, precision, recall, and F1-Score. We also evaluate the worth of each sleep attribute using Information Gain (IG) algorithm in order to identify the most important attributes which contribute to the sleep quality. Using this algorithm most important sleep features have been ranked based on their IG value.

The paper is organised as follows: Section 2 presents the review of work in the domain of applications of wearable sensors focussing on sleep quality estimation followed by the contributions of this study. Section 3 discusses the proposed framework of sleep quality prediction using deep learning techniques. Section 4 presents the results obtained followed by Section 5 which concludes the study.

2 Related Work

Wearable technology is a form of ubiquitous computing devices which enables users to do computing pervasively. There are evidences of versatile use of wearable devices for emerging applications in healthcare monitoring [24–26]. Various new sensors for healthcare tracking have been devised in the recent past for different purposes [27–31] and these devices have been used for various applications [32,33]. The commonly acknowledged applications of these wearable devices include mental health assessment [34] and sleep monitoring [35]. There exist substantial research considering technological advancements in development of frameworks for long term mental health monitoring using wearable devices [36,37]. Many wearables have been proposed and developed in the recent past to assess sleep with inbuilt sensors. Kuo et al. [38] propose a low sampling rate actigraph device for in-home sleep quality assessment. Rofouei et al. [39] propose a wearable neck cuff tool to monitor physiological data in real time. Recently, Liao et al. [40] present a wearable portable light weight, scalable and flexible wearable device to monitor sleep physiological signals. RestEaZe, a multi-sensor ankle band that captures leg movements for sleep monitoring presented by Bobovych et al. [41] is also among the recent developments of sleep assessment wearables. Kubala et al. [42] study the agreement between multiple commercial wearable activity monitors and a validated actigraph for measurement of various sleep attributes and conclude that the agreement varied by device. Many primary and secondary studies have been reported in the recent past which propose sleep indicators using wearable sensors. Mendonca et al. [43] review and analyse the methods and devices presented in the literature to assess and estimate sleep quality. They review research articles in literature from 2000 to 2018 to identify methods that have been developed for sleep quality assessment and also study the measures employed by the devices developed to assess sleep quality. de Arriba et al. [44] propose various methods to calculate sleep indicators for students using smartphones and wearables. These sleep indicators include quality sleep, sleepiness level and basic chronotype. Van et al. [45] present a model following a standard close to that of actigraphy by using a wrist-worn device to monitor sleeping trends. Authors in [46] use the accelerometer sensor of a smartphone to track the sleep duration and user movement patterns in order to assess sleep quality. Gu et al. [47] propose a method for sleep quality evaluation by detection of fine-grained sleep stage transition using the accelerometer and microphone sensors of a smartphone.

The intervention of machine learning and deep learning algorithms with wearable technology for healthcare monitoring has been seen recently in a number of studies. Jin et al. [48] propose an attention-based deep learning framework with a multi sensing wearable device for mental wellbeing evaluation in order to do multi-feature classification and fusion analysis. The attention-based deep learning model shows improvement of performance. Tazawa et al. [49] develop a machine learning algorithm to screen for depression and assess its severity based on data from wearable devices. The use of machine learning and deep learning techniques for automation of sleep quality prediction has also been studied by some researchers. In another study [1], authors propose calculation and automation of sleep indicators using off the shelf commercial wearables and machine learning predictor. They apply their model to support self-regulated learning and teaching support in educational environment. Hossain et al. [50] propose a system to identify the microscopic sleep states which indicate good and bad sleeping behaviors in order to do formative assessment of sleep quality. They implement classification algorithms to identify and correlate microscopic sleep states and overall sleep behavior. Sathyanarayana et al. [51] implement deep learning techniques to predict sleep quality from physical activity wearable data during awake time. They consider sleep efficiency as an indicator of sleep quality. Sano et al. [52] implement various machine learning algorithms to

[1] National Sleep Research Resource: www.sleepdata.org.

classify sleep quality, stress and academic performance of students using data from smartphones, wearable sensors and surveys.

This study contributes in the domain of sleep quality assessment using the data from wearable sensors and proposes the calculation of sleep indicators without any self-reporting of participants which makes it superior to the existing studies [1,52] which include self-reporting of individuals for some sleep attributes in addition to data from wearable sensors. This study proposes more reliable indicators of sleep quality as compared to indicators proposed in existing studies. Sathyanarayana et al. [51] consider sleep efficiency as an indicator of sleep quality. Sleep efficiency is the ratio of actual sleep duration to the total time spent in bed [51]. If a person spends 300 minutes (5 hours) in bed and sleeps for only 270 minutes (4.5 hours) at night, the sleep efficiency is 90% but this does not indicate good quality of sleep. Hence, in this study sleep efficiency is used as an attribute which contributes to sleep quality instead of an indicator of sleep quality. Deep learning models, MLP and CNN have been used to predict sleep quality and the performance are evaluated using metrices such as accuracy, precision, recall and F1-Score. Also, worth of sleep attributes has been evaluated using the Information Gain Algorithm in order to identify the major attributes contributing to sleep quality. This has not been reported in any of the existing studies.

3 Proposed Methodology for Sleep Quality Prediction

The proposed framework for sleep quality prediction using deep learning has eight key components, namely, 1. Data Acquisition, 2. Pre-processing to Maintain Parity, 3. Calculation of the Proposed Sleep Indicators, 4. Dataset Labelling 5. Pre-processing using SMOTE, 6. Implementation of MLP and CNN Models for Sleep Quality Prediction, 7. Evaluation using Performance Measures, and 8. Evaluation of Worth of Sleep Attributes. These are explained in detail in the following subsections. Figure 1 describes framework of the proposed work.

3.1 Data Acquisition

The following two datasets have been used in this work for sleep quality prediction.

3.1.1 Dataset 1: Self Collected Participants Data Using Commercial Smartwatches

The dataset 1 is collected from 13 participants using commercial smartwatches. The study has been performed in the normal environment of the participants. The participants were asked to wear their smartwatches, for 7 consecutive nights. 8 out of 13 participants had Samsung Galaxy Smartwatch while 5 participants had Xiomi MI Smartband. The sleep attributes which are collected from participants wearing smartwatches are given in the Table 1.

Here Main Sleep indicates the main time of sleep at night discarding the naps taken during the day. Sleep is conventionally categorised into two types, Non-Rapid Eye Movement (NREM) which comprises four stages of sleep cycle and Rapid Eye Movement (REM) which comprises the fifth stage. The brain progresses sequentially through each stage of sleep: wake, light sleep (stages 1 and 2), deep sleep (stages 3 and 4), and REM (stage 5) periodically. Stages 1,2, and REM constitute to the total light sleep of a sleep cycle.

- Stage 0 Awake Awake time is the time spent in bed not including the actual sleep duration. It generally includes time before and after falling asleep with the short awakenings during the night.
- Stages 1 and 2 Light Sleep Light sleep initiates the sleep cycle with the body muscles beginning to relax, and slowing down of heart rate and breathing.
- Stages 3 and 4 Deep Sleep It is considered as the restorative sleep stage, promoting muscle growth and repair as well as waste removal from the brain. In this stage, an individual has difficulty waking up.
- Stage 5 REM REM sleep is vital in order to re-energize the mind. REM is linked to learning, memory association, dreaming, and problem solving.

3.1.2 Dataset 2: Data from Clinical Actigraphy

The dataset 2 has been collected from National Sleep Research Resource[1]. The dataset named as Multi-Ethnic Study of Atherosclerosis (MESA) is a longitudinal study of features associated with the progression of subclinical cardiovascular disease to its clinical state in Hispanic, and Chinese-American men and women. The study comprises 2,237 participants enrolled in a Sleep Exam (MESA Sleep) which included 7-day wrist worn actigraphy, overnight polysomnography and a sleep questionnaire. In this study, we discard features of the dataset coming from polysomnography and sleep questionnaire and only consider relevant pre-processed features from 7-day wrist worn actigraphy. The Table 2. gives the description of attributes from MESA dataset considered in this study.

We consider only the actigraphy variables from main sleep periods (night) and exclude the variables related to naps in day. The actigraphy data are broken down by weekday days

[1] National Sleep Research Resource: www.sleepdata.org.

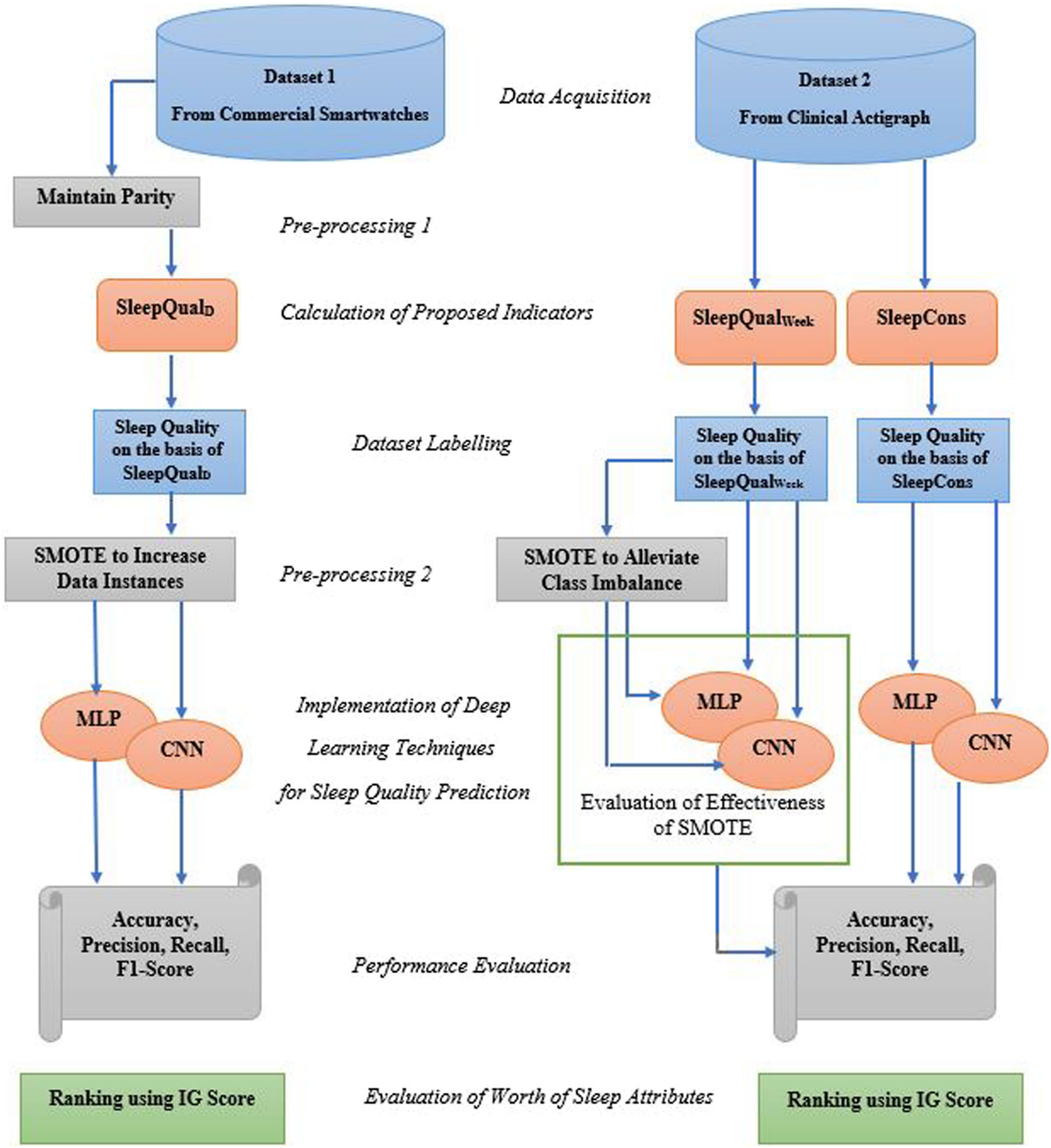

Fig. 1 Framework of the proposed work

(MondayFriday), weekend days (SaturdaySunday), workdays (selfreport), nonworkdays (selfreport). In this study we do not consider workdays and non-workdays data as this data is self-reported and this study concentrates only on digital data.

3.2 Pre-Processing to Maintain Parity

Pre-processing is done on dataset 1 to maintain parity throughout the dataset. Since, the data has been collected from participants with two brands of smartwatches, maintaining parity among the data is essential. In Samsung Galaxy smartwatch total sleep duration indicates total time in bed (in

Table 1 Sleep attributes from Smartwatches

S. no.	Attribute	Description
1.	In bed duration	In bed interval duration from main sleep (Minutes)
2.	In bed time	Clock time to get in bed for main sleep (HH:MM:SS)
3.	Out bed time	Clock time to get out of bed after main sleep (HH:MM:SS)
4.	ActualSleep duration	Sleep duration in main sleep period (Minutes)
5.	Sleep onset latency	Time between getting in bed and falling asleep (Minutes)
6.	In bed awake duration	Total time spent awake during the in bed interval in main sleep (Minutes)
7.	Sleep efficiency	Percentage of time spent asleep during the in bed interval in main sleep (%)
8.	Duration in REM	Duration of time spent in REM stage in main sleep period (Minutes)
9.	Light sleep duration	Duration of time spent in light sleep stage in main sleep period (Minutes)
10.	Deep sleep duration	Duration of time spent in deep sleep stage in main sleep period (Minutes)
11.	In bed awake percentage	Percentage of time spent awake during the in bed interval in main sleep (%)
12.	Percentage REM	Percentage of time spent in REM stage during the in bed interval in main sleep (%)
13.	Percentage light sleep	Percentage of time spent in light sleep stage during the in bed interval in main sleep (%)
14.	Percentage deep sleep	Percentage of time spent in deep sleep stage during the in bed interval in main sleep (%)

bed duration) which also includes minutes spent awake while in Xiomi MI smartband total sleep duration does not include minutes spent awake. In order to maintain parity, we included awake duration in total sleep duration in the data collected from Xiomi MI band users and the time shown on the watch is maintained in the column of actual sleep duration. This changes deep sleep and light sleep percentages too as total sleep duration now constitutes of the awake percentage too. The in bed time and out bed time already sums up to the total duration. The Table 3 shows the changes made. The first row represents the data as collected by the Xiomi MI band and the second row represents the data after changes are made with the changes highlighted.

In Samsung Galaxy smartwatch the in bed duration is divided into 4 stages namely: awake, REM, light sleep and deep sleep while in Xiomi MI smartband the in bed duration is divided into 3 stages, i.e. awake, light sleep and deep sleep. According to the American Sleep Apnea Association[2], In adults, about three-fifths of a nights sleep is light non-REM sleep, one-fifth is deep non-REM sleep, and one-fifth is REM sleep and the REM sleep is a part of total light sleep. So, for Xiomi MI band users the REM sleep duration is calculated as 25% of light sleep duration and actual light sleep duration is reduced by 25%. This additionally changes the percentages of four sleep stages. The Table 4 shows the changes made. The first row represents the data as collected by the Xiomi MI band and the second row represents the data after changes are made where the changes are highlighted.

Also, the data collected through smartwatches does not show sleep onset latency (time to fall asleep after the in bed time). It contains total time spent awake in minutes which also includes sleep onset latency. So, in this study half of the total time spent awake is considered as sleep onset latency. For example, if the in bed awake duration as recorded by the watch is 34 minutes then sleep onset latency is considered to be 17 minutes.

[2] American Sleep Apnea Association: www.sleepapnea.org.

3.3 Calculation of the Proposed Sleep Indicators

Three sleep indicators have been proposed in this study which are calculated using the real time digital data from wearable sensors without any self-reporting of the participants. These sleep indicators are: SleepQual$_D$, SleepQual$_{\text{Week}}$, and SleepCons. SleepQual$_D$ is the indicator used for dataset 1 while SleepQual$_{\text{Week}}$ and SleepCons are the indicators used for dataset 2. This is done because dataset 1 contains the sleep attributes of each night while dataset 2 contains the sleep attributes averaged over a period of one week. Sleep Quality of an individual can be predicted using the proposed sleep indicators. The calculations of the proposed sleep indicators are given in the following subsections.

3.3.1 Daily Sleep Quality (SleepQual$_D$)

Poor quality of sleep at a night negatively affects cognition, concentration, productivity, and performance the following day. The effect of poor sleep or sleep loss on a night has also been linked to reduced activity, increased reaction time and lower problem-solving efforts the next day [53]. So, in this work, we propose a sleep indicator, SleepQual$_D$ which calculates daily sleep quality of participants by considering the real time digital data from their smartwatches and without the use of any questionnaires. The SleepQual$_D$ has six components namely: sleep onset latency, actual sleep duration,

Table 2 Sleep attributes from clinical Actigraphe

S. no.	Feature	Description
1.	Avgefficiency5	Average sleep efficiency in main sleeps across all days (Percent)
2.	Avgefficiencywd5	Average sleep efficiency in main sleeps across all weekday days (Percent)
3.	Avgefficiencywe5	Average sleep efficiency in main sleeps across all weekend days (Percent)
4.	Avginbedduration5	Average in bed interval duration from main sleeps across all days (Minutes)
5.	Avginbeddurationwd5	Average in bed interval duration from main sleeps across all weekday days (Minutes)
6.	Avginbeddurationwe5	Average in bed interval duration from main sleeps across all weekend days (Minutes)
7.	Avginbedtime5	Average clock time to get in bed for main sleep across all days (hh:mm:ss)
8.	Avginbedtimewd	Average clock time to get in bed for main sleep across all weekday days (hh:mm:ss)
9.	Avginbedtimewe5	Average clock time to get in bed for main sleep across all weekend days (hh:mm:ss)
10.	Avginbedwake5	Average total time spent awake during the in bed interval (Minutes)
11.	Avginbedwakewd5	Average total time spent awake during the weekday in bed interval (Minutes)
12.	Avginbedwakewe5	Average total time spent awake during the weekend in bed interval (Minutes)
13.	Avgmainsleep5	Average sleep time in main sleep periods across all days (Minutes)
14.	Avgmainsleepwe5	Average sleep time in main sleep periods across all weekend days (Minutes)
15.	Avgmainsleepwd5	Average sleep time in main sleep periods across all weekday days (Minutes)
16.	Avgonsetlatency5	Average sleep onset latency time in main sleeps across all days in minutes (Minutes)
17.	Avgonsetlatencywd5	Average sleep onset latency time in main sleeps across all weekday days (Minutes)
18.	Avgonsetlatencywe5	Average sleep onset latency time in main sleeps across all weekend days in minutes (Minutes)
19.	Avgoutbedtime5	Average time to get out of bed after main sleep across all days in minutes (hh:mm:ss)
20.	Avgoutbedtimewd5	Average time to get out of bed after main sleep across all weekday days in minutes (hh:mm:ss)
21.	Avgoutbedtimewe5	AAverage time to get out of bed after main sleep across all weekend days in minutes (hh:mm:ss)
22.	Avgrestmidpoint5	Average time midpoint between in bed and out of bed times (hh:mm:ss)
23.	Avgrestmidpointwd5	Average time midpoint between weekday in bed and out of bed times (hh:mm:ss)
24.	Avgrestmidpointwe5	Average time midpoint between weekend in bed and out of bed times (hh:mm:ss)
25.	Sdinbedduration5	Standard deviation of the in bed interval duration (Minutes)
26.	Sdinbeddurationwd5	Standard deviation of the weekday in bed interval duration (Minutes)
27.	Sdinbeddurationwe5	Standard deviation Of the weekend in bed interval duration (Minutes)
28.	Sdinbedtime5	Standard deviation of the in bed time (hh:mm:ss)
29.	Sdinbedtimewd5	Standard deviation of the weekday in bed time (hh:mm:ss)
30.	Sdinbedtimewe5	Standard deviation of the weekend in bed time (hh:mm:ss)
31.	Sdmainsleep5	Standard deviation of sleep time in main sleep periods across all days (Minutes)
32.	Sdmainsleepwd5	Standard deviation of sleep time in main sleep periods across all weekday days (Minutes)
33.	Sdmainsleepwe5	Standard deviation of sleep time in main sleep periods across all weekend days (Minutes)
34.	Sdoutbedtime5	Standard deviation of the out of bed time (hh:mm:ss)
35.	Sdoutbedtimewd5	Standard deviation of the weekday out of bed time (hh:mm:ss)
36.	Sdoutbedtimewe5	Standard deviation of the weekend out of bed time (hh:mm:ss)
37.	Sdrestmidpoint5	Standard deviation of the midpoint between in bed and out of bed times (hh:mm:ss)
38.	Sdrestmidpointwd5	Standard deviation of the midpoint between weekday in bed and out of bed times (hh:mm:ss)
39.	Sdrestmidpointwe5	Standard deviation of the midpoint between weekend in bed and out of bed times (hh:mm:ss)

sleep efficiency, sleep disturbance, percentage deep sleep, and percentage REM. The four components of SleepQual$_D$ align with the components of PSQI indicator [4] while the fifth and the sixth components (percentage deep sleep and percentage REM) are added components used in this study as these are important technical attributes of sleep quality. Deep sleep, is the stage of sleep which one needs to feel refreshed after waking up in the morning. In this stage an individuals body and brain waves slow down and the muscles are relaxed while the body is doing a lot of rebuilding and repairing. Deep sleep has also been shown to help strengthen the immune system [54]. Without a good amount of deep sleep, the symptoms of sleep deprivation kick in. In healthy adults, about 13 to 25 percent of sleep is deep sleep which

Table 3 Changes made in Dataset 1 [a]

Total duration	In bed time	Out bed time	Sleep efficiency	Actual sleep duration	In bed awake duration	REM duration	Light sleep duration	Deep sleep duration	In bed awake percentage	Percentage REM	Percentage light sleep	Percentage deep sleep
347	03:45	09:46	–	–	14	–	282	65	–	–	81	19
361	03:45	09:46	96.12	347	14	–	282	65	4	–	78	18

Table 4 Changes made in Dataset 1 [b]

Total duration	In bed time	Out bed time	Sleep efficiency	Actual sleep duration	In bed awake duration	REM duration	Light sleep duration	Deep sleep duration	In bed awake percentage	Percentage REM	Percentage light sleep	Percentage deep sleep
361	03:45	09:46	96.12	347	14	–	282	65	4	–	78	8
361	03:45	09:46	96.12	347	14	70.5	211	65	4	19.5	58.5	18

varies with a persons age [55]. According to the American Sleep Apnea Association[2] if only 10 percent of an individuals sleep is deep sleep, then he might still be tired each day. REM is an important stage of sleep. If a person cuts his sleep short, most of the sleep that cuts out is REM [56] and less REM sleep can leave the person feeling tired, less able to focus, and might even lead to memory problems. Several medications can also block REM such as most antidepressants can cut REM sleep by half [56]. On the other hand, constantly having too much REM (generally over 25%) could also create problems as it might cause too much brain activation. It may potentially leave a person angry and irritable and may also aggravate symptoms of anxiety and depression [56]. The in bed awake duration is considered as an indicator of sleep disturbance. The calculations of these components are presented in the Table 5.

The SleepQual_D is the summation of the six components as follows:

$$\text{SleepQual}_D = \alpha + \beta + \gamma + \delta + \epsilon + \eta \tag{1}$$

The SleepQual_D has been calculated to rate all the participants each night sleep in the dataset 1 as it comprises of sleep data of each night. Overall score ranges from 0 to 14, where lower scores denote a healthier daily sleep quality. The calculated SleepQual_D includes four out of seven components of PSQI and two additional components. The information on the stages of sleep cannot be provided by self-reporting and are hence not included in PSQI questionnaire. Therefore, SleepQual_D gives a better indication of sleep quality considering the technical features of sleep.

3.3.2 Weekly Sleep Quality ($\text{SleepQual}_{\text{Week}}$)

Consistent lack of sleep or reduced quality of sleep causes sleep deprivation. There are many psychological risks of sleep deprivation which include anxiety, impulsive behaviour, depression, paranoia and suicidal thoughts. In this work, we propose a sleep indicator, $\text{SleepQual}_{\text{Week}}$ which calculates weekly sleep quality of individuals by considering their actigraphy data without the use of any self-reported data. The $\text{SleepQual}_{\text{Week}}$ has four components namely: average sleep onset latency, average actual sleep duration, average sleep efficiency, and sleep disturbance. The average in bed awake duration is considered as an indicator of sleep disturbance. All The four components of $\text{SleepQual}_{\text{Week}}$ align with the components of PSQI score. Though we consider weekly average deep sleep percentage and weekly average REM percentage to be important components of weekly sleep quality as if a person regularly does not get enough deep sleep, this may start to affect the brain but this information is not provided in the MESA dataset so we discard these components. The calculations of the components of $\text{SleepQual}_{\text{Week}}$ are presented in Table 6.

[2] American Sleep Apnea Association: www.sleepapnea.org.

Table 5 Components of SleepQual_D

Component 1: Sleep onset latency (a)	Recorded value	Score (α)
	$a \le 15$ min	0
	15 min $< a \le 30$ min	1
	30 min $< a \le 60$ min	2
	$a > 60$ min	3
Component 2: Actual sleep duration (b)	Recorded value	Score (β)
	$b > 7$ hrs	0
	6 h $< b \le 7$ h	1
	5 h $< b \le 6$ h	2
	$b \le 5$ hrs	3
Component 3: Sleep efficiency (c)	Recorded value	Score (γ)
	$c > 85\%$	0
	$75\% < c \le 85\%$	1
	$65\% < c \le 75\%$	2
	$c \le 65\%$	3
Component 4: Sleep disturbance: in bed awake duration (d)	Recorded value	Score (δ)
	$d \le 20$ mins	0
	20 mins $< d \le 30$ mins	1
	30 mins $< d \le 40$ mins	2
	$d > 40$ mins	3
Component 5: Percentage deep sleep (e)	Recorded value	Score (ϵ)
	$e > 10\%$	0
	$e \le 10\%$	1
Component 6: Percentage REM (f)	Recorded value	Score (η)
	$20\% \le f \le 25\%$	0
	$f < 20$ OR $f > 25$	1

The $\text{SleepQual}_{\text{Week}}$ is the summation of the four components as follows:

$$\text{SleepQual}_{\text{Week}} = \alpha + \beta + \gamma + \delta \tag{2}$$

The $\text{SleepQual}_{\text{Week}}$ has been calculated to determine weekly sleep quality of individuals in the dataset 2. Overall score ranging from 0 to 12, where lower scores denote a healthier weekly sleep quality.

Table 6 Components of $\text{SleepQual}_{\text{Week}}$

Component 1: Avg sleep onset latency (a)	Recorded value	Score (α)
	a $\leq$ 15 min	0
	15 min < a $\leq$ 30 min	1
	30 min < a $\leq$ 60 min	2
	a > 60 min	3
Component 2: Avg actual sleep duration (b)	Recorded value	Score (β)
	b > 7 hrs	0
	6 h < b $\leq$ 7 h	1
	5 h < b $\leq$ 6 h	2
	b $\leq$ 5 hrs	3
Component 3: Avg sleep efficiency (c)	Recorded value	Score (γ)
	c > 85%	0
	75% < c $\leq$ 85%	1
	65% < c $\leq$ 75%	2
	c $\leq$ 65%	3
Component 4: Avg sleep disturbance: Avg in bed awake duration (d)	Recorded value	Score (δ)
	d $\leq$ 20 mins	0
	20 mins < d $\leq$ 30 mins	1
	30 mins < d $\leq$ 40 mins	2
	d > 40 mins	3

3.3.3 Sleep Consistency (SleepCons)

Sleep consistency is an important indicator of sleep as it quantifies how similar a persons sleep and wake times are over a period of time. Sleep inconsistency is typically seen as sleep debt during weekdays followed by oversleep on weekends. It has been studied that students who experience larger sleep inconsistency perform worse in school [57]. In this study, we propose a method to calculate sleep consistency, SleepCons using actigraphy data without self-reporting by an individual. The dataset 2 has the features of sleep both for weekdays and weekend which helps us to analyse the inconsistency of sleep. It is calculated using the Eq. (3).

$$\begin{aligned}\text{SleepCons} &= w1.\text{SDmainsleep}+\\ w2.\text{SDrestmidpoint} &+ w3.\text{SDinbedtime}+\\ w4.\text{SDoutbedtime} &+ w5.\text{IncSleep}\end{aligned} \tag{3}$$

where

- SDmainsleep represents the Standard Deviation of actual sleep duration
- SDrestmidpoint is the Standard Deviation of the midpoint between in bed and out of bed times
- SDinbedtime is the Standard Deviation of the in bed times
- SDoutbedtime represents the Standard deviation of the out of bed times
- IncSleep represents the Inconsistency between weekday sleep and weekend sleep

and w_i are the weights for i=1 to 5 IncSleep is calculated as follows:

$$\begin{aligned}&\text{IncSleep} = |\text{avg weekday in bed time} - \text{avg weekend in bed time}|+\\ &|\text{avg weekday actual sleep dur} - \text{avg weekend actual sleep dur}|+\\ &|\text{avg out bed weekday time} - \text{avg out bed weekend time}|\end{aligned} \tag{4}$$

where actualsleepdur represents the actual sleep duration. All the values are converted in minutes for calculation. The values of weights are taken as follows: w1=0.2, w2=0.1, w3=0.25, w4=0.25, w5=0.2

Consistency is a behavioural parameter and can be improved by consistently following same in bed and out of bed times. So, the attributes such as sleep efficiency, sleep onset and offset times, and duration in various sleep stages are not considered in the calculation of SleepCons. The values of SleepCons lies between 0 and 693.23 (maximum) for the MESA dataset where higher values indicate poor sleep quality based on sleep consistency.

3.4 Dataset Labelling

The instances are labelled with classes using the proposed three indicators of sleep quality, SleepQual_D, Sleep $\text{Qual}_{\text{Week}}$, and SleepCons. The following subsections describe the process of dataset labelling.

3.4.1 Labelling on the Basis of SleepQual_D

SleepQual_D has been calculated for the instances of dataset 1 and the dataset has been labelled with 3 classes as given in Table 7.

Table 7 Labelling based on SleepQual_D

Value of SleepQual_D	Class
$\text{SleepQual}_D \leq 5$	0
$5 < \text{SleepQual}_D \leq 9$	1
$\text{SleepQual}_D > 9$	2

Here, class 0 is an indicator of good daily sleep quality and class 2 is an indicator of poor daily sleep quality.

Table 8 Labelling based on $\mathrm{SleepQual}_{\mathrm{Week}}$

Value of $\mathrm{SleepQual}_{\mathrm{Week}}$	Class
$\mathrm{SleepQual}_{\mathrm{Week}} \leq 4$	0
$4 < \mathrm{SleepQual}_{\mathrm{Week}} \leq 8$	1
$\mathrm{SleepQual}_{\mathrm{Week}} > 8$	2

Table 9 Labelling based on SleepCons

Value of SleepCons	Class
Sleepcons ≤ 50	0
$50 <$ SleepCons ≤ 200	1
$200 <$ SleepCons ≤ 400	2
SleepCons > 400	3

3.4.2 Labelling on the Basis of $\mathrm{SleepQual}_{\mathrm{Week}}$

$\mathrm{SleepQual}_{\mathrm{Week}}$ has been calculated for dataset 2 and based on its values the dataset is labelled with 3 classes as given in Table 8.

Here, class 0 is an indicator of good weekly sleep quality and class 2 is an indicator of poor weekly sleep quality.

3.4.3 Labelling on the Basis of SleepCons

SleepCons has been calculated for dataset 2 based on the weekly sleep attributes of individuals. The dataset 2 has been labelled with 4 classes based on the value of SleepCons as given in Table 9.

Here, class 0 corresponds to good sleep quality and class 3 corresponds to poor sleep quality due to high inconsistency in sleeping patterns.

3.5 Pre-Processing using SMOTE

Synthetic Minority Over-sampling Technique [58] has been used in this study. SMOTE generates synthetic data instances by functioning in feature space. This method works by over sampling the minority class by taking each minority class sample and generating synthetic examples along the line segments joining any or all of the k minority class nearest neighbours. This varies as compared to other oversampling techniques like random oversampling which increases the training data with multiple copies of some of the minority classes like. Pre-processing has been done for two main purposes, to increase the size of the dataset and to alleviate class imbalance. The following subsections describe the process in detail.

3.5.1 Pre-Processing to Increase Data Instances

SMOTE has been used to increase the instances of dataset 1, With the increase in data instances, SMOTE provides an additive benefit of class balance by adjusting the class distribution of the data set which leads to better algorithmic classification and prediction. In the dataset 1, the data instances are increased from 91 to 151 after the implementation of SMOTE by synthetically increasing the instances of the two minority classes.

3.5.2 Pre-Processing to Alleviate Class Imbalance

When the dataset 2 is labelled on the basis of $\mathrm{SleepQual}_{\mathrm{Week}}$, it creates high class imbalance with class distribution ratio as 1716:414:8. Classification using class-imbalanced data is biased in favour of the majority class. SMOTE is implemented on this data and instances of both the minority classes have been increased in order to alleviate the class imbalance to futher improve the prediction performance of deep learning algorithms. The class distribution ratio after the implementation of SMOTE is 1716:1242:864.

3.6 Sleep Quality Prediction using Deep Learning

Deep learning techniques have been achieving state-of-the-art results for predictive modelling on feature-based data [21–23]. The datasets with labels and after the pre-processing have been provided as input to two deep learning models, MLP and CNN for sleep quality prediction.

3.6.1 Multilayer Perceptron

Multilayer perceptron is the most commonly used feedforward neural network architecture. It generally has smaller training set requirements and comprises fast operations [59]. The MLP consists of three sequential layers: input layer, one or more hidden layers and output layer. The output of each hidden layer neuron is calculated as given in Eq. (5).

$$y_j = f(\Sigma w_{ji} x_i) \tag{5}$$

where j is a hidden layer neuron, x_i is the input signal to the hidden layer, w_{ji} represents the connection weight, and f is an activation function.

An activation function can be a simple threshold, sigmoid, or hyperbolic tangent function. In this study, a sigmoid function is used as the activation function. In the work, we use MLP models with varying number of hidden layers for prediction of sleep quality on the basis of three sleep indicators. The details of complete architecture are given in the results section.

3.6.2 Convolution Neural Network

Convolutional Neural Network is a category of neural networks having capability of giving better performance in terms of complexity and memory requirements [60]. CNN extracts features used for prediction and combines the weights of convolution layers with fully connected layers. Every neuron in CNN computes output by evaluating dot products between inputs and weights of the neuron. Nonlinear activation functions are used which help to reduce the number of parameters in a CNN. A CNN architecture is generally made up of three main layers namely: convolutional layer, max pooling layer and fully connected layer.

Convolution Layer: The convolution layer is composed of filters where each filter detects a particular feature at every location on the input matrix. In a given convolution layer, the output from ith feature map, given by y_i^1 , after the convolution operator is computed as Eq. (6).

$$y_i^l = b_i^l + \sum_{j=i}^{m} f_{i,j}^l * y_j^{l-1} \tag{6}$$

where l is the layer having m filters, $f_{i,j}^l$ is the convolution filter, y_j^{l-1} is the output obtained from the previous layer, and b_i^l denotes the bias matrix.

Pooling layer Its function is to gradually reduce the dimensionality of the feature map to reduce the number of parameters. This further reduces computation in the system and helps retain the most significant features. Max pooling has been used in this study which selects the largest element from the feature map.

Non-Linearity (ReLU) ReLU stands for Rectified Linear Unit for a non-linear operation. ReLUs purpose is to introduce non-linearity in the model. It generates a rectified feature map, which is fed to the next pooling layers to reduce the dimensionality of the feature map.

Fully connected layer The results of the last max pooling layer act as input to the fully connected layer. This connection is shown as represented in Eq. (7).

$$y_i^l = g^l . \sum_{j=1}^{m(l-1)} y_i^{l-1}(i) w_{i,j}^l + b_i^l \tag{7}$$

where l is the number of layers, $m(l-1)$ represents the number of filters in the previous layer, $w_{i,j}^l$ is the weight of the connection between neurons of two layers, b_i^l is the corresponding bias, and g^l represents the nonlinear activation function of layer l. One dimensional convolution with ReLU activation function has been used in this study. The number of each type of layers are varied for different models and the architecture of each model is described in the results section.

3.7 Evaluation using Performance Measures

The performances of deep learning models have been evaluated using Accuracy, Precision, Recall and F-Score. Accuracy is evaluated as a proportion of correctly classified instances among all instances. Precision defines the proportion of positive identified instances that are actually correct while Recall defines the ratio of actual positives to the total identified correctly. F-score is measured as harmonic mean of Precision and Recall. The results are represented in the next section.

3.8 Evaluation of Worth of Sleep Attributes using IG Algorithm

Information Gain evaluates the worth of an attribute by measuring the information gain with respect to the labelled class. It does this by determining the contribution of each feature in decreasing the overall entropy. The entropy indicates the degree of impurity [61]. The IG score for every attribute is evaluated as given in Eq. (8).

$$\begin{aligned} &\text{InfoGain(Class, Attribute)} \\ &\quad = H(\text{Class}) - H(\text{Class}|\text{Attribute}) \end{aligned} \tag{8}$$

where $H(Class)$ is the entropy of the class and is given by Eq. (9).

$$H(\text{Class}) = -\sum P_i * log_2(P_i) \tag{9}$$

where P_i is the probability of class in the dataset.

In this work, IG algorithm has been used to calculate work of each sleep attribute contributing to overall sleep quality. We rank the top features with most contribution using their IG score.

4 Results and Analysis

This section summarises the results of the techniques implemented in the study. Section 4.1 represents the results of sleep quality prediction on the basis of SleepQual_D, Sect. 4.2 represents the results of sleep quality prediction on the basis of $\text{SleepQual}_{\text{Week}}$, Sect. 4.3 represents the results of sleep quality prediction based on SleepCons.

4.1 Sleep Quality Prediction on the basis of SleepQual_D

SleepQual_D has been calculated to rate daily sleep quality of participants in dataset 1 and the instances are labelled with 3 classes indicating different levels of sleep quality. SMOTE has been applied to increase the instances of this dataset

Table 10 Performance of techniques for prediction of sleep quality based on SleepQual$_D$

Technique	Acc (%)	Pr	Re	F1-S
MLP	90.06	0.913	0.914	0.913
CNN	91.30	0.904	0.923	0.913

before feeding it into the MLP and CNN models. The dataset has been split into train and test data where 70% of the data is used for training and the rest for validation. The Table 10. shows the results of these deep learning techniques in terms of Accuracy (Acc), Precision (Pr), Recall (Re), and F1-Score (F1-S). Accuracy has been represented in percentage.

It can be observed that CNN outperforms MLP in predicting sleep quality on the basis of SleepQual$_D$ with an accuracy of 91.30%. CNN also achieves better recall and F1-score values while MLP achieves higher precision value.

Architecture of MLP MLP has been used with 2 hidden layers. Backpropagation algorithm has been used with a learning rate of 0.3 and momentum of 0.2. At every hidden layer, the number of neurons is chosen to be half of the total of inputs (attributes) and outputs (classes).

Architecture of CNN CNN model has been used with 2 convolution layers, each followed by a max pooling layer. 32 filters of size 6 are used in the first convolution layer and 32 filters of size 3 are used in the second convolution layer. Pool size of 3 has been chosen for this model. Batch normalization has been used at each convolution layer. Two fully connected layers are used of which one is the output layer. The first fully connected layer comprises 32 neurons followed by the output layer consisting of 3 neurons corresponding to 3 the classes. ReLU activation function is used at all the hidden layers while Softmax activation function is used at the output layer. Moreover, a dropout layer has been used in this model for regularization in order to avoid model overfitting due to less training data. Adam optimizer has been used with categorial cross entropy as the loss function.

The Table 11 represents the comparative architectures of MLP and CNN used.

Accuracy of CNN Model has been recorded at epoch 50. Figure 2 plots model loss with respect to number of epochs where validation loss at epoch 50 is observed to be 0.429.

Figures 3 and 4 represent the confusion matrices of MLP and CNN models repectively on predicting sleep quality on the basis of SleepQual$_D$.

We implement IG algorithm for evaluating the worth of each sleep attribute for its overall contribution in SleepQual$_D$. The Table 12 gives the rank wise list of attributes in decreasing order of IG score.

It can be observed that in bed awake percentage contributes maximum to the daily sleep quality of an individual

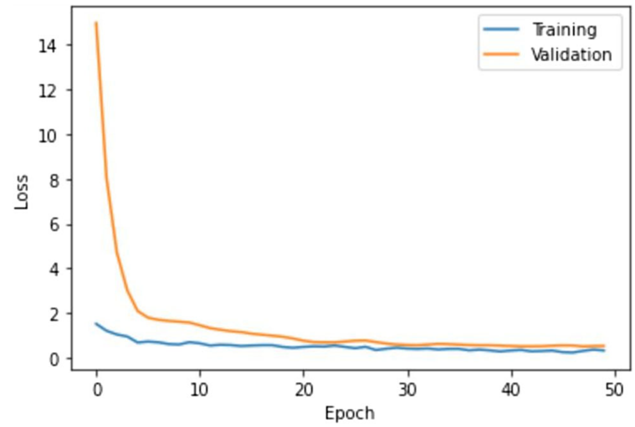

Fig. 2 CNN model loss w.r.t. epochs

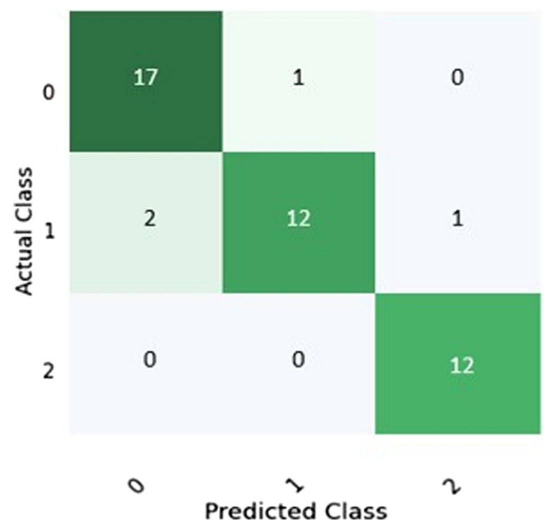

Fig. 3 Confusion matrix of MLP for predicting sleep quality based on SleepQual$_D$

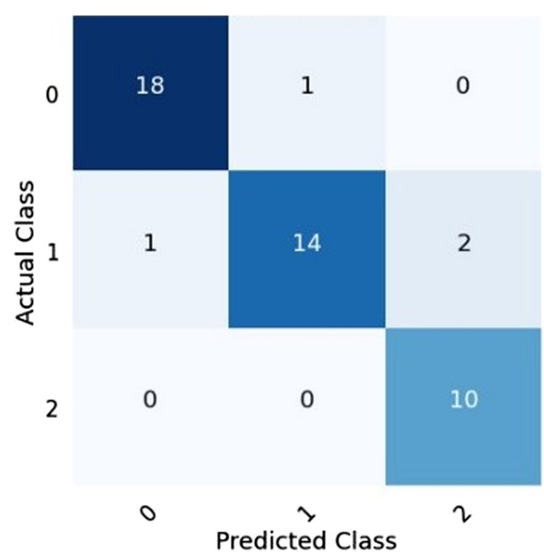

Fig. 4 Confusion matrix of CNN for predicting sleep quality based on SleepQual$_D$

Table 11 Architectures of MLP and CNN for prediction of SleepQual$_D$

Model	MLP	CNN
No. of hidden layers	2	6
Layer 1	8 Neurons	Convolution layer
Layer 2	8 Neurons	Max pooling layer
Layer 3	–	Convolution layer
Layer 4	–	Max pooling layer
Layer 5	–	Dropout layer
Layer 6	–	Dense layer
Output layer	3 Neurons	Dense layer
Network complexity (Number of parameters)	211	4739

Table 12 IG Score of attributes w.r.t. SleepQual$_D$

Rank	Feature	IG Score
1.	In bed awake percentage	1.234
2.	Sleep efficiency	1.176
3.	Sleep onset latency	0.934
4.	Awake duration	0.912
5.	Light sleep duration	0.714
6.	Actual sleep duration	0.625
7.	In bed time	0.472
8.	In bed duration	0.441
9.	Percentage deep sleep	0.342
10.	Percentage light sleep	0.342
11.	Percentage REM	0.335
12.	REM duration	0.312
13.	Deep sleep duration	0.309
14.	Out bed time	0.11

with the highest IG score of 1.234 which is followed by sleep efficiency and sleep onset latency. Therefore, it can be concluded that these three attributes of sleep contribute maximum to the daily sleep quality of an individual.

4.2 Sleep Quality Prediction Using SleepQual$_{\text{Week}}$

SleepQual$_{\text{Week}}$ has been calculated to rate weekly sleep quality of individuals in dataset 2 and the instances are labelled with 3 classes indicating different levels of sleep quality. SMOTE has been applied to this data with an intent to balance the class distribution before feeding it into the MLP and CNN models. The dataset has been split into train and test data 70% of the data is used for training and the rest for validation. The Table 13 shows the results of these deep learning techniques in terms of Accuracy (Acc), Precision (Pr), Recall (Re), and F1-Score (F1-S). Accuracy has been represented as percentage.

CNN performs better in predicting weekly sleep quality of an individual with an accuracy of 97.30%. Also, CNN

Table 13 Performance of techniques for prediction of sleep quality based on SleepQual$_{\text{Week}}$

Technique	Acc (%)	Pr	Re	F1-S
MLP	95.90	0.963	0.962	0.962
CNN	97.30	0.974	0.977	0.975

achieves higher precision, recall and F1-Score values as compared to MLP.

Architecture of MLP MLP has been used with 5 hidden layers. Backpropagation algorithm has been used with a learning rate of 0.3 and momentum of 0.2. At every hidden layer, the number of neurons is chosen to be half of the total of inputs (attributes) and outputs (classes).

Architecture of CNN CNN model has been used with 3 convolution layers, each followed by a max pooling layer. 32 filters of size 6 are used in the first convolution layer and 32 filters of size 3 are used in second and third convolution layers. Pool size of 3 has been use in the first pooling layer while pool size of 2 are used in the following pooling layers. Batch normalization has been used at each convolution layer. Two fully connected layers are used of which one is the output layer. The first fully connected layer comprises of 32 neurons followed by the output layer consisting of 3 neurons corresponding to 3 the classes. ReLU activation function is used at all the hidden layers while Softmax activation function is used at the output layer. Adam optimizer has been used with categorial cross entropy as the loss function.

The Table 14 represents the comparative architectures of MLP and CNN used for the prediction of . SleepQual$_{\text{Week}}$.

Accuracy of CNN Model has been recorded at 40 epochs. Figure 5 plots model loss with respect to number of epochs where validation loss at epoch 40 is observed to be 0.099.

Figures 6 and 7 represent the confusion matrices of MLP and CNN models respectively on predicting sleep quality on the basis of SleepQual$_{\text{Week}}$.

To observe the effectiveness of implementing SMOTE for class balance the accuracies of MPL and CNN models for

Table 14 Architectures of MLP and CNN for prediction of SleepQual$_{Week}$

Model	MLP	CNN
No. of hidden layers	5	7
Layer 1	21 Neurons	Convolution layer
Layer 2	21 Neurons	Max pooling layer
Layer 3	21 Neurons	Convolution layer
Layer 4	21 Neurons	Max pooling layer
Layer 5	21 Neurons	Convolution layer
Layer 6	–	Max pooling layer
Layer 7	–	Dense layer
Output layer	3 Neurons	Dense layer
Network complexity (Number of parameters)	2,646	10,019

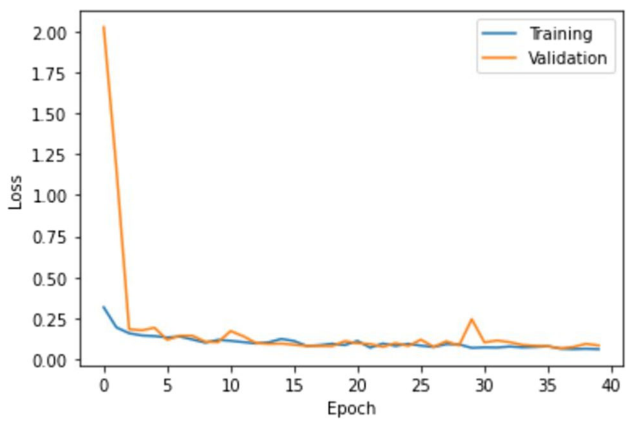

Fig. 5 CNN model loss w.r.t. epochs

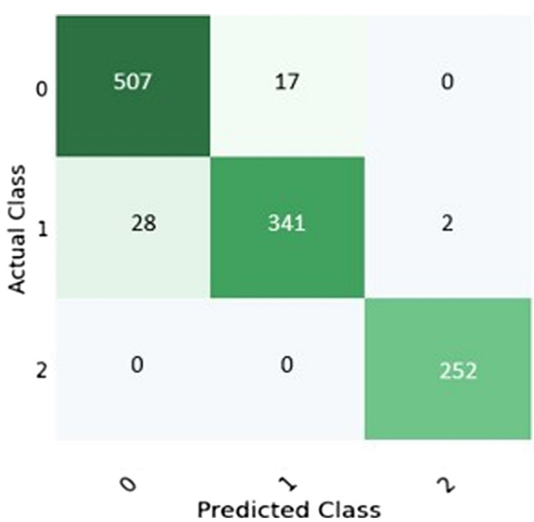

Fig. 6 Confusion matrix of MLP for predicting sleep quality based on SleepQual$_{Week}$

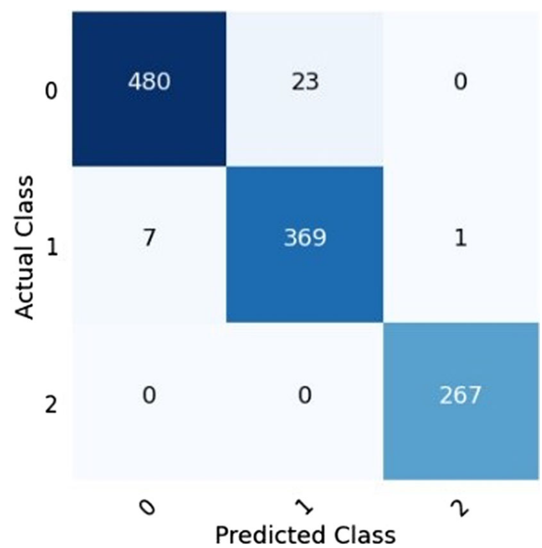

Fig. 7 Confusion matrix of CNN for predicting sleep quality based on SleepQual$_{Week}$

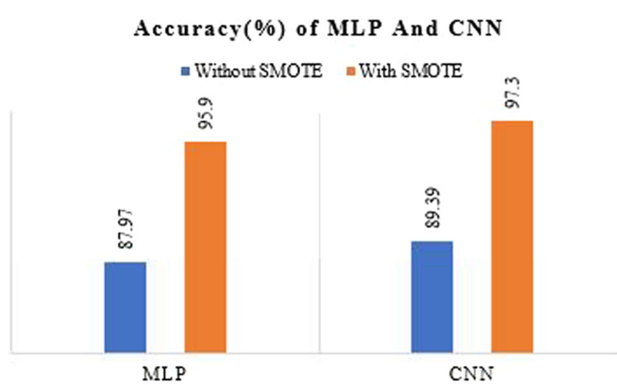

Fig. 8 Effectiveness of SMOTE

sleep quality prediction based on SleepQual$_{Week}$ have been evaluated before and after applying SMOTE on the dataset. Figure 8 represents these accuracies in the form of a graph.

It can be clearly observed that the accuracies of both MLP and CNN models improve after the implementation of SMOTE on this dataset.

Next, IG algorithm has been implemented in order to evaluate the worth of each sleep attribute for its overall con-

Table 15 IG Score of attributes w.r.t. $\text{SleepQual}_{\text{Week}}$

Rank	Feature	IG score
1.	Avgefficiency5	1.107
2.	Avgefficiencywd5	1.0174
3.	Avgefficiencywe5	0.8686
4.	Avginbedwake5	0.7361
5.	Avginbedwakewd5	0.6894
6.	Avgmainsleep5	0.6424
7.	Avgonsetlatencywe5	0.6106
8.	Avgmainsleepwd5	0.5917
9.	Avgmainsleepwe5	0.505
10.	Avginbedduration5	0.4539
11.	Avginbedwakewe5	0.405
12.	Avginbeddurationwd5	0.3514
13.	Avginbedtimewe5	0.3091
14.	Avginbeddurationwe5	0.2933
15.	Avgonsetlatency5	0.2645

Table 16 Performance of techniques for prediction of sleep quality based on SleepCons

Technique	Acc (%)	Pr	Re	F1-S
MLP	84.79	0.826	0.847	0.836
CNN	88.48	0.708	0.761	0.726

tribution $\text{SleepQual}_{\text{Week}}$. The Table 15 gives the rank wise list of top 15 out of 39 attributes which attain higher IG values.

Average sleep efficiency has the maximum IG value of 1.107 followed by average weekday sleep efficiency, average weekend sleep efficiency, and average in bed awake duration. Therefore, it can be concluded that average sleep efficiency and average in bed awake duration over the week contribute maximum to the weekly sleep quality of an individual.

4.3 Sleep Quality Prediction Using SleepCons

SleepCons has been calculated to rate sleep consistency of individuals in dataset 2 and the instances are labelled with 4 classes indicating different levels of sleep consistency. The dataset has been split into train and test data where 70% of the data is used for training and the rest for validation. Table 16 shows the results of these deep learning techniques in terms of Accuracy (Acc), Precision (Pr), Recall (Re), and F1-Score (F1-S). Accuracy has been represented as percentage.

CNN performs better in terms of accuracy with the value of 88.48% while MLP performs better in terms of precision, recall and F1-Score achieving higher values of these measures.

Architecture of MLP MLP has been used with 5 hidden layers. Backpropagation algorithm has been used with a learning rate of 0.3 and momentum of 0.2. At every hidden layer, the number of neurons is chosen to be half of the total of inputs (attributes) and outputs (classes).

Architecture of CNN CNN model has been used with 3 convolutions, each followed by a max pooling layer. 32 filters of size 6 are used in the first convolution layer and 32 filters of size 3 are used in second and third convolution layers. Pool size of 3 has been use in the first pooling layer while pool size of 2 are used in the following pooling layers. Batch normalization has been used at each convolution layer. Two fully connected layers are used of which one is the output layer. The first fully connected layer comprises of 32 neurons followed by the output layer consisting of 3 neurons corresponding to 4 the classes. ReLU activation function is used at all the hidden layers while Softmax activation function is used at the output layer. Adam optimizer has been used with categorial cross entropy as the loss function.

The Table 17 represents the comparative architectures of MLP and CNN used.

Table 17 Architectures of MLP and CNN for prediction of SleepCons

Model	MLP	CNN
No. of hidden layers	5	7
Layer 1	21 Neurons	Convolution layer
Layer 2	21 Neurons	Max pooling layer
Layer 3	21 Neurons	Convolution layer
Layer 4	21 Neurons	Max pooling layer
Layer 5	21 Neurons	Convolution layer
Layer 6	–	Max pooling layer
Layer 7	–	Dense layer
Output layer	4 Neurons	Dense layer
Network complexity (Number of parameters)	2667	10,052

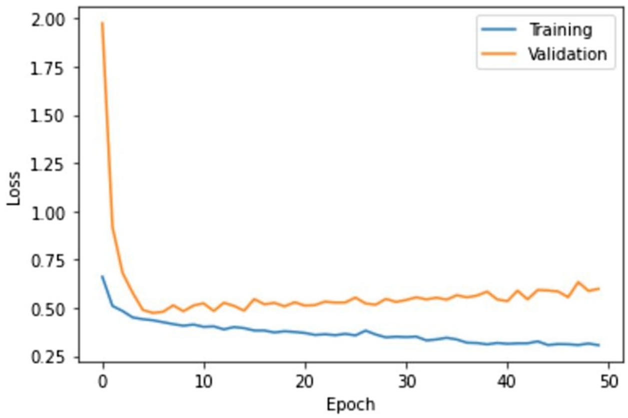

Fig. 9 CNN model loss w.r.t. epochs

Fig. 10 Confusion matrix of MLP for predicting sleep quality based on SleepCons

Accuracy of CNN Model has been recorded at 50 epochs. Figure 9 plots model loss with respect to number of epochs where validation loss at epoch 50 is observed to be 0.539.

Figures 10 and 11 represent the confusion matrices of MLP and CNN models respectively on predicting sleep quality on the basis of SleepCons.

IG algorithm has been implemented in order to evaluate the worth of each sleep attribute for its overall contribution in SleepCons. Table 18 gives the rank wise list of top 15 attributes out of 39 attributes which attain higher IG values.

It is observed that standard deviation of midpoint of in bed and out of bed times achieves maximum IG score of 0.689. It is followed by standard deviation of in bed times and standard deviation of out bed times. So, it can be concluded that these attributes contribute maximum to the sleep quality based on SleepCons.

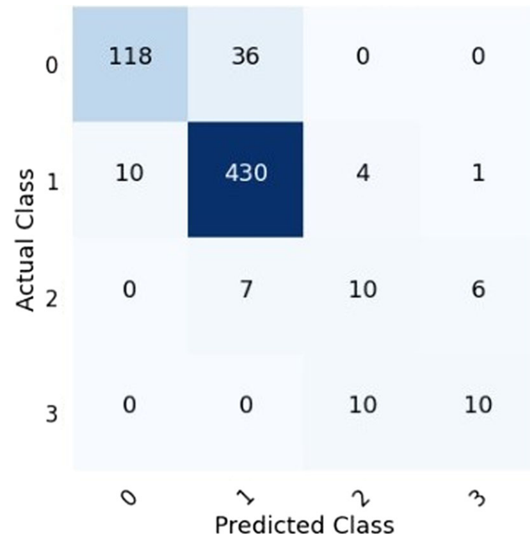

Fig. 11 Confusion matrix of CNN for predicting sleep quality based on SleepCons

Table 18 IG score of attributes w.r.t. SleepCons

Rank	Feature	IG score
1.	Sdrestmidpoint5	0.6892
2.	Sdinbedtime5	0.6103
3.	Sdoutbedtime5	0.6002
4.	Sdrestmidpointwd5	0.4527
5.	Sdmainsleep5	0.4304
6.	Sdinbedtimewd5	0.4272
7.	Sdinbedduration5	0.4203
8.	Sdoutbedtimewd5	0.3949
9.	Sdmainsleepwd5	0.245
10.	Sdinbeddurationwd5	0.2364
11.	Avginbedtime5	0.232
12.	Avgrestmidpoint5	0.2157
13.	Avgoutbedtimewd5	0.2073
14.	Avgrestmidpointwd5	0.2066
15.	Avgoutbedtime5	0.2049

5 Conclusion and Future Work

In this study authors have proposed a technique to predict sleep quality from wearable data using two deep learning models. Three sleep quality indicators are proposed namely SleepQual_D, $\text{SleepQual}_{\text{Week}}$, and SleepCons. SleepQual_D indicates daily sleep quality of an individual, $\text{SleepQual}_{\text{Week}}$ indicates weekly sleep quality and SleepCons is an indicator of sleep consistency. SleepQual_D comprises six components of which four components align with the components of Pittsburgh Sleep Quality Index. $\text{SleepQual}_{\text{Week}}$ is the summation of four components and all these components align with the components of Pittsburgh Sleep Quality Index. The three indicators are calculated using the sleep data obtained from wearable sensors (commercial smartwatches and clinical actigraphy). Two datasets have been used to validate the proposed framework. This includes a self-collected dataset of 13 participants using commercial wearable devices over a period of 7 days and another dataset of 2237 users using clinical actigraph device. Two deep learning techniques, MLP and CNN are implemented to predict sleep quality on the basis of the proposed sleep indicators. SMOTE has been applied to increase the data instances as well as to alleviate class imbalance. It has been observed that CNN performs better than MLP in terms of accuracy in predicting sleep quality on the basis of all the three indicators. CNN achieves an accuracy of 91.30% for predicting sleep quality based on $\mathrm{SleepQual}_D$ on dataset 1. CNN achieves an accuracy of 97.30% on predicting sleep quality based on $\mathrm{SleepQual}_{\mathrm{Week}}$, and an accuracy of 88.48% on predicting sleep quality based on SleepCons on dataset 2. CNN achieves higher values of precision, recall and F1-score on prediction of sleep quality based on $\mathrm{SleepQual}_D$, and $\mathrm{SleepQual}_{\mathrm{Week}}$ while MLP acquires higher values of precision, recall and F1-score on predicting sleep quality based on SleepCons. Also, Information Gain algorithm has been implemented on the datasets in order to assess the worth of sleep attributes and to rank the most important sleep attributes which contribute to the sleep quality prediction. It has been concluded that in bed awake percentage, sleep efficiency and sleep onset latency are the most important attributes contributing maximum to the daily sleep quality, average sleep efficiency and average in bed awake duration over the week contribute maximum to the weekly sleep quality of an individual. It is observed that standard deviation of midpoint of in bed and out of bed times, standard deviation of in bed times and standard deviation of out bed times contribute maximum to the sleep consistency with higher values of Information Gain score as compared to other attributes.

As a future work, the performance of the sleep quality prediction model can be optimized by integrating swarm-based optimization techniques such as particle swarm optimization, elephant search algorithm and wolf search algorithm [62] with deep learning. Also, techniques of fusion of complementary lifestyle features with the sleep features to improve the sleep quality prediction accuracy can be seen as a future work [36,63]. Field programmable gate array-based implementation of deep learning techniques [64] for real time sleep quality prediction can be implemented within smartwatches as a future work to avoid overhead of collection and storage of data before feeding into the prediction model. The authors also plan to study the effects of excessive use of digital technologies on sleep quality using soft computing techniques.

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Compliance with Ethical Standards

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

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