Deep learning approach to analyze Sleep & Apps usage pattern to predict Problematic Smartphone Usage (PSU)

MSc Research Project
Data Analytics

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MSc Project Submission Sheet

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Deep learning approach to analyze Sleep & Apps usage pattern to predict Problematic Smartphone Usage (PSU)

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Abstract

Problematic Smartphone Usage (PSU) and its relationship with poor sleep quality has been the rising concerns on mental and physical health. This study aims to develop deep learning techniques to analyze sleep duration and apps usage pattern to predict PSU. The objective is to compare all the models built to accurately predict PSU. Two distinct datasets have been employed in this research, one for analysing the sleep quality and another for apps usage. Deep learning models like Feedforward Neural Networks (FNN), Convolution Neural Networks (CNN) and Recurrent Neural Networks Long-Short Term Memory (RNN-LSTM) were developed and evaluated. Hyperparameter tuning is used for the sleep data to optimize the model performance. For the sleep quality dataset, the RNN-LSTM and CNN model with hyperparameter tunning has outperformed the other models with highest accuracy of 94%. On the other hand, FNN has slightly less accuracy with high level of precision. For the app usage dataset, FNN and RNN has achieved 99.87% & 99.80% accuracy. The CNN was slight less in accuracy 98% and showed lower precision. RNN-LSTM model emerged as a consistent model for both the dataset by offering balanced approach to predict PSU. Hyperparameter tuning has helped to increase model performance only for the CNN model.

1 Introduction

1.1 Background

In recent years, the usage of smartphones has significantly increased in everyone's life. The easy access towards internet via smartphone plays a significant role, which includes communication, work, education, searching information and entertainment. In addition to these advantages, there has been growing negative effects of the excessive usage which impacts the sleep quality. Sleep is essential for maintaining wellness and overall health. Sleep disruption can lead to various health issues such as depression, heart diseases, obesity and other mental disorders.

The Korea Internet and Security Agency (KISA), Korea's government agency conducted a survey which revealed 27% of users spend more time on smartphone, 5.8% feels anxiety when they don't use phone and 22.6% of users tried to reduce the usage multiple time but they failed in every attempt. 21% of users says they experienced excessive usage of smartphone affected their concentration power.

During the COVID-19 pandemic, to control the spread of virus people are forced to lock them at their homes. During the lockdown, traditional way of school and office working method has been changed to online and remote. Due to these individuals spent more time staying inside homes and used smartphones for work, education, social interaction and entertainment irrespective of the age. This has increased the screen time, especially during the bedtime which has impacted the sleep patterns.

Studies have shown a stronger relationship between the increased screen time and disturbed sleep quality which is very complex and multifaced. The non-productivity apps like social media, video streaming and games have negative effective on the sleep quality.

Also, the nighttime usage and total screen time plays a major role in how smartphone affects the sleep. There is a significant gap in understanding the clear way in which the smartphone usage particularly during nighttime affects the sleep quality and how effectively to overcome it.

1.2 Motivation

The increasing usage of smartphone and rising concerns of sleep related issues for the people at their young age has motivated to conduct this research to develop strategies to overcome Problematic Smartphone Usage (PSU). This research has employed deep learning techniques to analyze sleep patterns and apps usage data to predict PSU and develop targeted interventions.

1.3 Importance

The compulsive usage of smartphone is called PSU which becomes a major health concern, and it is highly important to develop an effective method to identify and handle the PSU. This research has employed deep learning techniques to analyze sleep patterns and apps usage data, which can handle complex and large datasets to find the patterns present in the data. By developing models such as Feedforward Neural Networks (FNN), Convolution Neural Networks (CNN) and Recurrent Neural Networks (RNN-LSTM) it will provide accurate and detailed analysis of the relationship between the smartphone usage and sleep quality.

The novelty of the study is to advance the previous research by examine the smartphone apps usage and sleep data particularly during the nighttime. This approach aims to explain how the sleep is affected based on the smartphone usage and to develop a predictive model that can identify PSU. The outcome of the research may help to create a tool to find whether the person is affected by PSU and provides the level of addiction.

1.4 Research Question

How deep learning techniques be efficiently implemented to analyze sleep duration and app usage patterns, aiming to accurately predict the Problematic Smartphone Usage (PSU). How can these predictions be used to improve sleep quality and reduce PSU.

1.5 Objectives

To address the research question following objectives has been formulated:

- **Research on current studies:** Conduct an in-depth investigation on the current research on sleep quality, smartphone usage and deep learning approaches to identify key findings, gaps and trends.
- **Design Robust model:** Develop a robust model to collect, clean and preprocess the data to make it suitable to building the deep learning model.

- **Evaluation:** The model's performance will be evaluated based on the metrics such as accuracy, precision, recall and F1-score to determine the model's efficient approach to predict PSU.
- **Compare Models:** Based on the evaluation metrics compare the performance of each model built in predicting PSU based on sleep duration and app usage data. Suggest the best model which has more accuracy and overall performance.

1.6 Document Structure

The research document is divided into seven sections, each of which offers a detailed information on the specific component of the investigation. The second section is Literature review which reviews the existing research on the sleep quality based on the smartphone usage. The third section is methodology which details about the data collection, preprocessing and model implementation. The fourth section explains about the design specification, fifth section explain about the implementation, sixth section explain about the evaluation techniques used and discussion. Finally, seventh section talks about the research report summarizes significant findings and discusses future studies.

2 Related Work

Problematic Smartphone Usage (PSU) which is nothing but over usage of smartphone compulsively for non-productive purposes. This literature review explores the relationship between the smartphone usage and sleep data to understand and predict the impacts of PSU using the advanced deep learning techniques.

2.1 Sleep Disorder due to screen time

Sleep disorder is a health condition known as disturbance in sleep which affects the length of the sleep duration. Due to disturbed sleep during the nighttime, can make sleep during the daytime or inactive during the day. Prolonged sleep disorder may be led to heart disease and mental disorders. Young age people are affected by the sleep disorder due to more screen time especially before the bed.

Exposure to long screen time and using smartphone before sleeping have the tendency to delay the sleep and which in turns affects the sleep wake cycle. *Yue et al (2023)* examined the survey conducted from 4000 adolescents and identified more screen time & blue light emitted from the smartphone affects the melatonin hormone, which is responsible for sleep wake cycle. In their research they suggested to reduce the screen time before going to sleep, which improves the sleep quality. *Nagata et al (2023)* analyzed the connection between screen time and sleep quality of 10000 children's aged between 10 -14 and found that the children's who has TV, mobile phones or any device connected to internet faced trouble in sleeping and sleep disturbance during the nighttime. Activities like playing games, watching movies or using social media will tend to poor sleep quality.

2.2 Problematic Smartphone Usage (PSU)

The major problem of PSU is the inability to control the smartphone usage, it is the behavior of frequently checking the mobile even when there is no need to check and when someone try to control it, they will fail to do so. This lack of control leads to anxiety, disrupted sleep and affects mental health. Not only students and adults are affected by PSU, nowadays even the kids are using phone while eating. This will affect the development of the kid's attention span and healthy eating habits.

The influence of smartphone usage among adolescent aged between 10 -24 years, *Chan et al (2023)* conducted research and classified smartphone usage as two types such as social and process. Social usage comprises of social media, chatting and phone calls and Process comprises of watching videos, movies, gaming music and educational purposes. The study revealed that chatting, calls, video, watching movies and listening to music are positively correlated with PSU. Usage of social media, gaming and educational purpose showed inconsistent results. He said more research is needed on music and calls since data is limited and concludes understanding these patterns will address PSU in young people.

According to *Nawaz (2024)* it is crucial to distinguish between productive and non-productive use, not all high usages are PSU. In his research he introduces Integrative Pathways Model (IPM) classified into effectual, ineffectual, and problematic use to find why people use smartphones and the motive behind it. He concludes there is a need for multi-dimensional approach to understand better about smartphone usage and pointing out that increased usage does not need to be always PSU.

2.3 Relationship Between Problematic Smartphone use and sleep disorder

The study conducted by *Zhang et al (2023)* explored the relationship between Problematic Smartphone Usage and Sleep disorders among the Chinese college Students during the COVID-19 pandemic. It is evident that both the PSU and Sleep disorders has doubled during the pandemic, and it has bidirectional relationship between both, implying one condition could worsen the other. The study used 1186 students to confirm the findings based on the advanced statistical methods and it was found that the relationship is less evident for male student who engage in more than one hour of daily physical activity. This study suggests that physical activity should be increased among the students to mitigate the effects of the PSU and sleep disorders.

2.4 Existing Approaches

Machine Learning models plays a significant in analysing the sleep quality data and smartphone usage metrics to predict PSU efficiently. Models like Support Vector Machine (SVM) and Logistic Regressions are used for the classification problems to predict a user is affected or not. The authors *Xiao et al. (2023)* has used machine learning to find how parameters like age, ethnicity, screen time, and Fear of Missing (FOMO) Out associated to smartphone usage a study conducted on Canadian adolescents during the COVID-19 pandemic. The data was collected from the participants via a questionnaire which ask details like screen time, excessive smartphone use, problems like depression, anxiety & stress and FOMO. They have built various machine learning model and only the Shrinkage algorithms (lasso, ridge, and elastic net regression) outperformed when compared to other models. He concluded that FOMO and emotional state plays a major role in contributing PSU. The limitations in the research are, it analyzed only the screen time and not considered the phone unlock pattern, so the model missed to analyze the pattern present in predicting PSU. Also, the data collected for the research is by asking the details from participants, so there might be some errors in the data collected. The author suggested the data used for the research should be collected from automated devices, since there is no human intervention the trustability of the data will be high. Finally, the author concluded that advanced deep learning techniques can be helping to identify the complex patterns present in the data, which predicts the PSU accurately.

The above research highlights the need for having accurate data for analysis. *Arora et al. (2022)* has conducted a study to analyze the sleep and behavioral health to predict PSU. They have used wearable device like smartwatches used to collect the user data which consists of physical activity, sleep metrics and phone metrics details from 24 participants and the data was collected for 7 days continuously. Also, they collected data on the behavioral health. To analyze the sleep quality and behavioral health they developed various machine learning model such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM) with polynomial kernel, SVM with RBF kernel, Multilayer Perceptron (MLP) and Naive Bayes (NB). For the sleep quality data, they have selected 14 features related to sleep and 21 features related to behavioral health are analyzed, the results indicate that SVM with polynomial achieved a higher accuracy compared to all the model build. Poor sleep quality based on the behavioral health is closely associated to mental disorders like depression, anxiety.

Achal et al. (2023) developed machine learning models to predict the PSU addiction levels based on smartphone usage. In their research they have framed 23 questions as survey and passed to people aged between 15 and 25 years to fill the details such as smartphone usage time, physical activity, stress, depression and other factors which contribute PSU. Using the data they build models (AdaBoost, Decision tree, KNN, LightGBM, Logistic Regression, Random Forest, SVM and XGBoost). The results have been evaluated based on the classification report, it is seen that SVM model has achieved higher accuracy of 82% and Decision tree with lower accuracy 60% in predicting PSU. The model demonstrate that PSU is associated with both physical and psychological disorders. He concludes due to the scarcity in the data they were not able to develop deep learning models.

From the existing research it is clearly evident that the models available to predict PSU are currently rely on the using the machine learning models. Using this model has been constraint like it can handle only less complex dataset and inability the find the complex pattern. Deep learning techniques must be used in the future research to find the complex hidden pattern present in the data.

2.5 Application of Deep Learning techniques to analyze sleep disorder

Deep Learning models are powerful technique for analysing the PSU, these models could perform more than the traditional machine learning models and capable of finding the hidden complex patterns present in the data. Li et al. (2021) developed a FNN model to analyze the sleep disorder, they collected the data from 148 sleep disorder patients and 33 unaffected patients. The FNN model achieved a high accuracy of 97.8% which outperformed the other machine learning models like SVM and Logistic Regression. The findings suggest that FNN model-based approach is reliable, and it acts as a baseline model developed which can be compare with the advanced model's performance.

Chaw et al. (2023) developed a CNN model to analyze the sleep apnea based on the oxygen saturation by collecting the real time patient's data and compare the results of the CNN model with other previous built traditional machine learning models. The accuracy of the CNN model has outperformed all the other models, and it achieved 91.30% of accuracy. *Sathyanarayana et al. (2016)* analyzed the relationship between physical activity and sleep quality, based on physical activity during the daytime and it directly help to get good sleep during the nighttime. In their research, they collected actigraphy data from 92 adults and build Logistics Regression model & deep learning techniques like Multilayer Perceptron (MLP), CNN, RNN and RNN-LSTM. The model's performance metrics shows the CNN and RNN-LSTM model has outperformed all the other models and highlights the effectiveness of the deep learning models in analysing the sleep quality.

Based on the literature it is clear that the PSU predictions models were developed only based on the traditional machine learning techniques. The various other research related to detect sleep quality has used deep learning models like FNN, CNN and RNN models by employing these methods the researchers has achieved higher performance models. So, in this research the author will use FNN, CNN, and RNN-LSTM models to predict the PSU based on the sleep and apps usage data.

3 Research Methodology

In this section, the research methodology has been discussed in detail on how PSU will be predicted based on apps usage and sleep quality. The methodology includes all the necessary steps to effectively identify the PSU patterns with a technical explanation.

To accomplish this, the author has used Knowledge Discovery in Databases (KDD) as shown in figure 1, a systematic approach that is suitable for analysing a large and complex dataset. It involves data selection, preprocessing, transforming data to capture meaningful, actionable and understandable patterns from a large dataset and make it suitable to predict PSU.

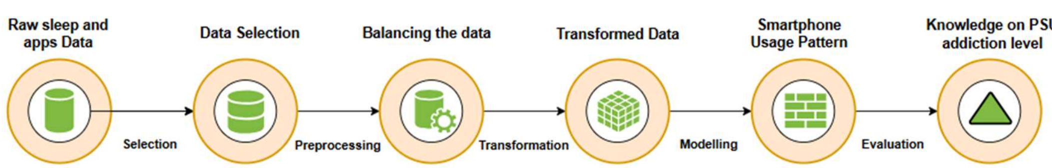


Figure 1. Knowledge Discovery in Databases (KDD)

3.1 Data Selection

It is important to thoroughly examine the data and acquire a deep knowledge on the field is an essential thing before selecting the data to analyze the issue related to PSU. Completely understanding the characteristics of PSU is crucial for accurately identify the problem and creating effective strategies to overcome it. In this study the data selected to predict PSU is by analysing the sleep and apps usage data. By examining the patterns in sleep and smartphone interaction like screen time or phone usage during the nighttime explains the level addiction towards PSU. The data should be collected using automated devices which provide continuous real time data and more accurate, since there is no manual intervention.

3.2 Exploration of the Data

In this stage, the relevant data must be found as per the requirement. Once the data is found, need to check whether it is feasible to load the data into a programming language for analysis. For this research the below two datasets has been used which is matching the requirement as mentioned.

- **Sleep data:** The data was collected from 24 undergraduate students for 7 continuous days using wearable smartwatches, to avoid any error in the data collection. It contains variables such as physical activities, sleep duration metrics, and phone usage metrics. Key metrics like sleep efficiency, night phone usage and phone unlock count help to identify patterns contributing PSU. The data was collected by *Arora et al. (2022).*

- **App Usage data:** The dataset contains 454018 rows of data contains information such as demographic, screen time, number of apps used and apps categories like social media, entertainment, and productivity to identify trends and possible indicators of PSU. The data was collected from global smartphone and electronics company during 2015 to 2019 by *Sapienza et al. (2023).*

3.3 Data Preprocessing

3.3.1 Data Cleaning

The first step in the preprocessing is to clean the data. Cleaning the data such as checking for missing values and removing the variables which are unnecessary. For this python inbuilt function has been used, there were no missing values in the datasets.

3.3.2 Feature Selection

The main idea of this research is to predict PSU based on the sleep and apps usage data, so from the sleep dataset only the variables which has the sleep metrics and phone usage metrics has been chosen. The apps usage dataset contains different categories of apps usage in that only the non-productive apps variables like social media, gamming, videos, shopping, etc are the variables considered as major contributors.

3.3.3 Feature Engineering

Feature engineering has been used to focus on the variables such as night phone usage and phone unlock count the most relevant phone usage metrics which are most influential parameter for PSU from sleep data. Non-productive apps like social media, entertainment, communication etc are grouped as major contributor for predicting PSU.

3.3.4 Exploratory Data Analysis:

The sleep data used for this research has used only the sleep metrics need to fulfil the research question. The sleep metrics like Sleep duration such as light sleep, deep sleep, Rapid Eye movement, Total sleep duration, sleep efficiency, awake percentage, sleep efficiency and sleep onset latency. Along, with this phone usage metrics like total screen time, night screen time and phone unlock counts has been used for analysing the sleep data. For the app's usage data, the list of apps usage categories like social, entertainment, TV/Movies, communication, Game, shopping and music will be considered as the major contributors for PSU and other productivity apps are also considered in the modelling.

3.3.5 Handling Class Imbalance

SMOTE (Synthetic Minority Over-sampling Technique) has been used in this research to handle the class imbalance present in the target variable 'label' and 'PSU_affected' of the dataset by generating synthetic samples for the minority class to balance the dataset. This technique improves the model's ability to find lower quantity classes and minimises the bias towards majority classes.

3.3.6 Encoding

One hot encoding is applied to the target variable to convert it from binary to categorial format, which is the understandable format for the neural networks to classify the data.

3.3.7 Normalization

StandardScaler is employed in this research to adjust the features to have mean 0 and standard deviation 1, which helps in reducing the influence of different feature scales on the model's performance. It will be fitted on both the training and test data to ensure consistent scaling across datasets. This technique helps in improving the accuracy and reliability of the machine learning model to predict PSU.

3.4 Model Training

In this research the author considered the alternate methodologies like Support Vector Machine (SVM), Logistic Regression, KNN, Decision tree, Random Forest, AdaBoost, XGBoost, LightGBM *Achal et al. (2023).* The listed techniques are for analysing the classification data, they struggle when the dataset is more complex and larger.

The author has chosen deep learning techniques like Feedforward Neural Networks (FNN), Convolutional Neural Networks (CNN) and Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) due to their ability to handle large datasets and identify the pattern present in the data. FNN is a simple and basic model which can be built for initial investigation, and it acts as a baseline for comparing with the models like CNN and RNN. CNN can be used for huge and complex dataset, it can find the hidden patterns present in the sleep and apps usage related data. RNN-LSTM are highly suitable for analysing data over a long period of time, which helps in capturing long term trends and effects. This model helps to track the sleep quality changes due to late night phone usage based on the impact over a long period.

Deep learning models are easy to use due to their Transfer Learning technique. In the context of analysing sleep and apps usage data to predict PSU, the model can be pre-trained on one task and can be reused with slight modification on a different task with improving accuracy and efficiency.

From the above, it is evident that deep learning models outperform traditional machine learning techniques by their ability to learn automatically allows for a deep understanding of how phone usage affects the sleep quality which leads to more accurate prediction of PSU.

3.5 Model Evaluation and Presentation

Model evaluation is the most critical part in the deep learning projects, where the performance of the models is assessed. The models are evaluated based on several metrics and techniques, such as classification report and confusion matrices which provides a detailed view of models' performance across the various classes.

Classification reports is used to evaluate the performance of the model which highlights the accuracy, precision, recall and F1-scores for each class, which provides the model strength and weakness by the ability to classify the classes correctly.

Confusion matrices is another tool to evaluate the performance of the classification models. It represents whether the classes are predicted correctly by plotting the values against the actual values. It also helps to find the model's strength and weakness in predicting the class.

Finally, all the model's output will be summarised in a clear and crisp manner using above-mentioned classification report and confusion matrices. Based on the results obtained from all the three models built, the accuracy, precision, recall and F1-Scores will be compared. The model which has higher accuracy and balanced precision, recall and F1-score will be considered as best model. This ensures the model are selected best not only based on accuracy but also maintains a good balance across other parameters. Then the selected model will be highlighted as the most effective model in predicting PSU and making it a tool for future use.

4 Design Specification

This section explains the techniques, architecture and frameworks used in the implementation of the models with the associated requirements. In this research, three models have been developed FNN, CNN and RNN-LSTM these models are chosen based on their capability to analyze sleep and apps usage data.

4.1 Modelling Techniques & Architectures

4.1.1 Feedforward Neural Networks (FNN)

Feedforward Neural Networks (FNN) is a simple base model to understand how the factors like phone usage metrics and sleep duration affects the sleep quality. They are useful for initial experiments and findings of this model helps to determine any complex models are needed to attain better performance.

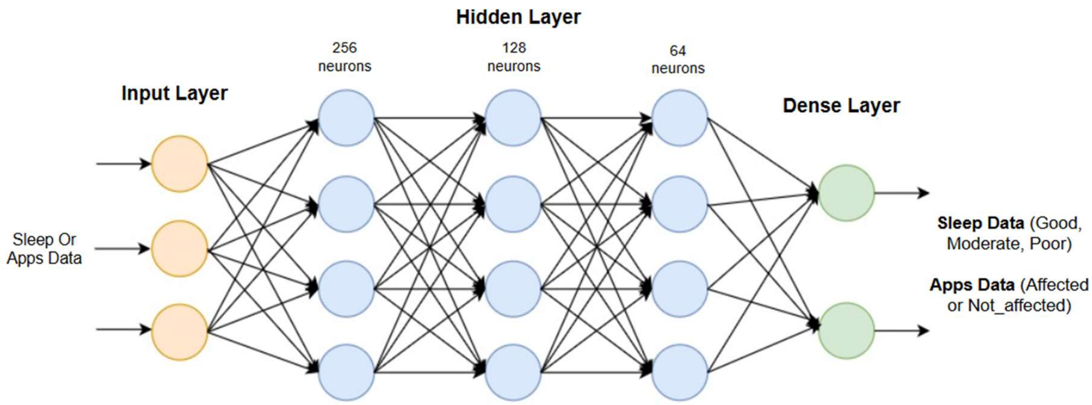


Figure 2. FNN Architecture

A FNN model designed for analysing sleep and app usage data will have the layers as shown in figure 2. The input layer accepts the processed data it will transform the data to format that is understandable by the neural networks. The transformed data is passed on the next layer called hidden layer, in this research the author has used 3 layers. Finally, the output layer will provide the output to predict the PSU based on sleep quality will be like 'Good', 'Moderate' or 'Poor" and apps usage like "Affected by PSU" or "Not Affected by PSU".

4.1.2 Convolutional Neural Networks (CNN)

CNN is used in this research because of its ability to identify sequential patterns present in the data. They help in identifying how the changes in sleep duration and app usage over the time affects the sleep quality.

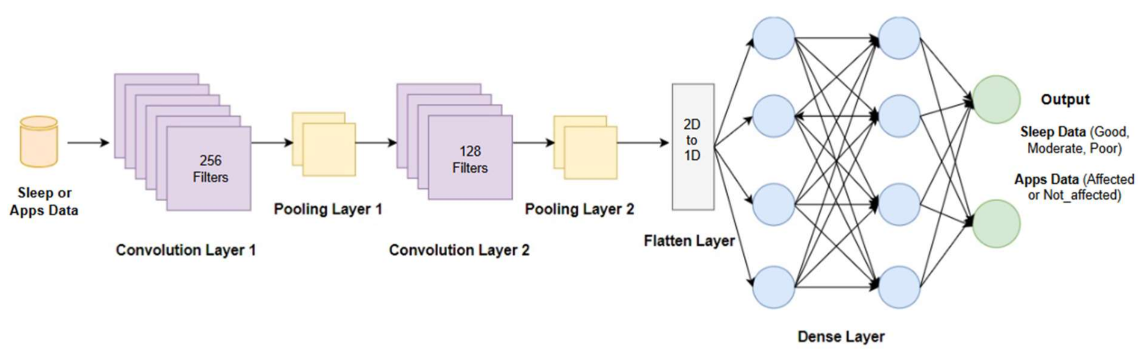


Figure 3. CNN Architecture

CNN model designed for analysing sleep and app usage data will have the layers as shown in figure 3. The input layer accepts the processed data and pass it on the next layer called convolutional layer it contains filters, in this design it has 2 layers to find the complex patterns present in the data and each layer is followed by pooling layer to reduce the dimensionality and dropout layers to prevent overfitting. Then the output from this layer sent to flatten layer to convert the 2D data to 1D and sent the dense layers to find the insights full patterns hidden in the data. Finally, the output layer will provide the output to predict the PSU based on sleep quality will be like 'Good', 'Moderate' or 'Poor" and apps usage like "Affected by PSU" or "Not Affected by PSU".

4.1.3 Recurrent Neural Networks Long-Short Term Memory (RNN-LSTM)

RNN-LSTM is designed to learn and remember long term dependencies in the sequential data. LSTM model is the advanced model of RNN, which helps to overcome the vanishing gradient problem and makes effective in capturing pattens over long sequences.

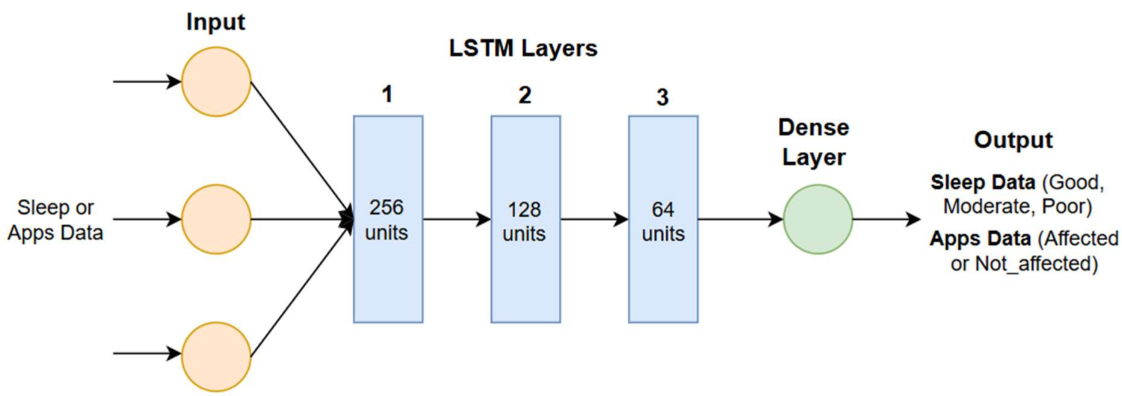


Figure 4. RNN-LSTM Architecture

RNN-LSTM model designed for analysing sleep and app usage data will have the layers as shown in figure 4. The input layer accepts the processed data and pass it on the next layer called LSTM layer, in this design it has 3 LSTM layer each layer is followed by normalization and a dropout layer. In this layer return_sequences are set to true, which ensures the output is sequenced and making it suitable for stacking the multiple LSTM layers. Then this data will be sent to dense layer where softmax activation function will be used to make the output in the form of classification. Finally, the output layer will provide the output to predict the PSU based on sleep quality will be like 'Good', 'Moderate' or 'Poor" and apps usage like "Affected by PSU" or "Not Affected by PSU".

4.2 Evaluation Technique

The models performance can be evaluated using the techniques such as accuracy measures the ratio of correctly classified instances among the total instances. It explains how well the model performs among all classes, this can be misleading if the dataset is imbalanced, due to its inability to differentiate the type of errors made. Precision measures all true positive predictions made by the models are actually positive predictions. Recall measures the number of true positive predictions made by the model among all actual true predictions. F1-Score is the harmonic mean of precision and recall used to achieve a balance between these two metrics. Confusion Matrices provides the detailed breakdown of model's predictions showing counts such as true positive & negative and false positive & negative for all classes.

5 Implementation

This is the final stage of developing a model which involves tools used, data selection, Exploratory Data Analysis, data cleaning, model building and hyperparameter tuning. This will produce various output to analyze the sleep patterns and apps usage patterns to predict PSU.

5.1 Tools & Language Used

Package	Description
Python	Language used for data preprocessing, modelling and evaluation
Jupyter Notebook	Used for interactive coding, visualization and Analysis.
Pandas	Used data manipulation and preprocessing
Numpy	Used for numerical operations and array handling
scikit-learn	Used for preprocessing and evaluation metrics
Imblearn	Uses SMOTE for handling data imbalance
Matplotlib & Seaborn	Used for building, training and evaluate the deep learning models.
Keras tuner	Used for hyperparameter tuning

5.2 Data Selection

In this research, the author has used two distinct datasets. One of the datasets is used to analyze the sleep quality and other dataset is used to analyze the apps usage. The author has built the deep learning models separately on each dataset and obtained the results. The variables are selected based on various criteria to make sure only the relevant and informative features are selected. The criteria include relevance to the research question, the features are selected to meet the novelty of the research which focus on analysing the sleep quality and app usage pattern to predict PSU.

- **Sleep data:** The dataset contains 24 variables such as physical activities, sleep duration metrics, and phone usage metric. For this research the author has selected only 12 variables related to sleep duration metrics and phone usage metrics to proceed further with the research as per the research question to analyze the sleep quality based on smartphone usage patterns particularly nighttime usage. Feature engineering has been used to create a composite feature called phone usage metrics by combining the night phone usage and phone unlock counts, which is relevant to analyze the impact of sleep due to phone usage before sleep.

- **App Usage data:** The dataset contains 25 variables such as demographic, screen time, number of apps used and apps categories like social media, entertainment, and productivity to identify trends and possible indicators of PSU. For this research the author has used only 20 variables such as different apps, median screen time and median number of apps to fulfill the research question to analyze the apps usage data to predict PSU. A feature called major contributor a variable helps the model to focus on important apps categories that are significant indicators of PSU.

The selection was also made based on the previous research as mentioned in Section 2 of Related works, variables that have been used in the established research are taken into consideration while doing this research. The selected variables were chosen to minimize the redundancy while ensuring the major aspects of sleep and app usage were represented.

5.3 Data Cleaning

In this stage, the data has been checked for any missing values, wrong data format. The dataset used for this research is a cleaned data without any errors. Normalization has been performed on the data to maintain the same scale for the all the variables used in this research.

5.4 Exploratory Data Analysis

EDA has been done to find whether there is any data imbalance present in the data, the training dataset of sleep data contains the class 0 (Good sleep quality) with count 81, class 1 (Moderate sleep quality) with count 47 and class 2 (Poor sleep quality) with count 6. Here the class 1 and class 2 are less in count compared to class 0. On the apps usage dataset Class 0 (Not affected by PSU) with count of 21474 and class 1 (Affected by PSU) with a count of 341740, difference is seen in the class distribution.

5.5 Data Balancing

The imbalance in the sleep and apps usage data has been handled using SMOTE (Synthetic Minority Over-sampling Technique) which applied to the training data to generate synthetic samples for the minority classes. The process involves selecting a random sample from the minority class and then finds its nearest neighbours to create synthetic samples. After applying SMOTE, the minority classes are upscaled to balance the number of instances to the majority class which makes all the classes to have same count of instances. Now, the sleep dataset contains Class 0,1 & 2 with count of 81 records for each class and apps usage data contains 341740 records for each class. Then the resampled training dataset was standardized using standardscaler to make consistent scale across the dataset. This helps the model to learn better about the minority classes which were previously underrepresented. This improved the model's ability to identify the classes correctly especially those related to affected by PSU.

Without SMOTE, the model would have been biased to the majority classes which leads to poor performance in identifying the minority classes. Application of SMOTE has mitigated the issue by making the imbalance dataset to more balanced training data which reduces the dominance of the majority class.

5.6 Model Building

This section explains about the different deep learning models developed such as FNN, CNN and RNN-LSTM and it explains about the implementation steps followed for this research.

5.6.1 Feedforward Neural Networks (FNN)

The model has been built with total of 10 layers, it contains 3 dense layers (256, 128, 64 respectively) and ReLU activation function to use non-linearity. There is a batch normalization layer after each dense layer to normalize the output of the previous layers. There is a dropout layer (0.5) after each batch normalization layer to prevent overfitting. The final dense layer is the output layer contains 3 units with a softmax function to provide classification output of 3 classes (Good, Moderate or Poor) for the sleep data and 2 classes (Affected or Not affected) for apps usage data. The model has been compiled with optimizer set as Adam and loss is set to sparse categorical crossentropy with metric is set to accuracy. Various callbacks have been used during the training process to optimize model's performance and accuracy. Callbacks like Early stopping is used to stop the training if there is no improvement for 10 continuous epochs to prevent overfitting and reduces unnecessary computation. Reduce Learning Rate on Plateau is used to adjust the learning rate, and it is reduced by a value of 0.2 with a threshold of 0.00001, this fine tune's learning rate when the model does not show any improvement while training.

The model has been trained with different epochs of 50,100 and 150 with early learning rate of 5 and 10. When training with epochs 50, the model resulted with lower accuracy, indicated that the model does not have sufficient training time. However, for the epochs 100 and more the results of the models were constant with more accuracy for both the patience level which indicates the model had enough time for training and it learned effectively in this range. The findings from the various trained models indicate that the model has reached its optimal performance by using 100 epochs. Therefore, increasing the epochs to higher value and stringent early stopping criteria did not provide any additional benefits. So, the model training was limited to 100 epochs to achieve a balance between sufficient training time and avoid overfitting. Cross validation with 5 folds is used to enhance the model's robustness by building the model on 4 fold's and validating the model on 5th fold. The dataset is divided into 5 parts with equal class distribution for training and validation to ensure proper performance metrics of the model.

5.6.2 Convolutional Neural Networks (CNN)

The model has been built with total of 11 layers, it contains 2 convolutional layers of 256 and 128 filter with kernel size of 3. The data will be passed to the 1st convolutional layer with ReLU activation function to find the sleep and apps usage patterns. Then the output from the 1st convolutional layer is sent to MaxPooling layer to reduce the dimensionality without affecting the features and then it is sent to a dropout layer to drop the 50% neurons to avoid overfitting. The same pattern is followed in the 2nd layers. Then the data from the convolutional, pooling and dropout layer is sent to flatten layer to convert the 2D to 1D and pass it to the next dense layers to find the complex patterns in the sleep and apps usage data. Then the output from these dense layers is sent to the fully connected layer which gives the output in the form of 3 classes (Good, Moderate or Poor) for the sleep data and 2 classes (Affected or Not affected) for apps usage data. The model has been compiled with optimizer as Adam and loss is set to sparse categorical crossentropy with metric is set to accuracy. Callbacks like Early stopping, Reduce Learning Rate on Plateau and Cross validation are implemented as same as FNN model and used 100 epochs for training the model.

5.6.3 Recurrent Neural Networks Long-Short Term Memory (RNN-LSTM)

RNN-LSTM model has been built with 12 layers, it contains 3 LSTM layers with 256, 128 and 64 units. Each LSTM layer has batch normalization function and dropout layer with dropout rate of 0.5 to prevent overfitting. The output from the 3 pairs of the layers is sent to the dense layers to provide the classification output in the form of 3 classes (Good, Moderate or Poor) for the sleep data and 2 classes (Affected or Not affected) for apps usage data. The model has been compiled with optimizer as Adam and loss is set to sparse categorical crossentropy with metric is set to accuracy. Callbacks like Early stopping, Reduce Learning Rate on Plateau and Cross validation are implemented as same as FNN model and used 100 epochs for training the model.

5.7 Hyperparameter Tuning

In this research, Hyperparameter tunning has been done for all the Deep learning models built for the sleep data to predict PSU. Keras Tuner is used to build the hyperparameter models, where the number of layers used for the model building are dynamically set based on the hyperparameter values provided by Keras tuner. The 'Hyperband' tuner is used to search for the best hyperparameter by building the model on the training data. Once the best hyperparameter is identified the model is built and trained on the test dataset.

6 Evaluation

This section explains about the results obtained from the models developed for the analysis of sleep and apps usage data to predict PSU. The author has assessed the metrics like accuracy, precision, recall and F1-score to evaluate the model's performance. This helps to compare the effectiveness of the various models built.

6.1 Sleep Data Analysis Using FNN

Table 1. Classification report for Sleep data analysis

Model	Accuracy	Class	Precision	Recall	F1
FNN	0.91	Good	0.95	0.95	0.95
		Moderate	0.91	0.83	0.87
		Poor	0.67	1	0.8
FNN (Tuning)	0.91	Good	1	0.95	0.97
		Moderate	0.91	0.83	0.87
		Poor	0.5	1	0.67
CNN	0.85	Good	0.91	1	0.95
		Moderate	1	0.58	0.74
		Poor	0.4	1	0.57
CNN (Tuning)	0.94	Good	1	1	1
		Moderate	1	0.83	0.91
		Poor	0.5	1	0.67
RNN-LSTM	0.94	Good	1	0.95	0.97
		Moderate	0.92	0.92	0.92
		Poor	0.67	1	0.8
RNN-LSTM (Tuning)	0.91	Good	0.95	0.95	0.95
		Moderate	0.91	0.83	0.87
		Poor	0.67	1	0.8

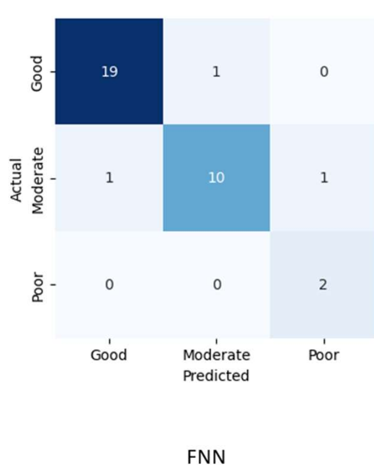
The model built for FNN with selected features on the sleep data has been evaluated, it achieved a test accuracy of 91% and with low loss of 0.17 which indicates the model has robust performance. The classification report in Table 1. shows high precision, recall and F1-score for the class good which represents the model's ability to find the class correctly. The moderate class also performs well, but the recall is slightly low. The model struggles for class poor, with low precision, perfect recall and high F1-score. This indicates the model will effectively identify the class good and moderate, with some challenges in predicting poor class correctly but sometimes it might misclassify poor as other classes, due to low support value for the class poor, as show in Table 3. for the subject 8 it misclassified moderate class as 'Poor'.

The below figure 5. shows the confusion matrix of the FNN model built using the selected features. It shows classes as 'Good', 'Moderate' and 'Poor'. Out of 34 samples, the model was able to predict sleep quality as good for 19 correctly, 1 misclassified as moderate and nothing was classified as poor. For the moderate class it classified 10 correctly and 2 misclassified as moderate & poor each. For the poor class, there is no misclassification and all classes are correctly classified.

6.2 Sleep Data Analysis Using FNN with Hyperparameter Tuning

The model built for FNN with hyperparameter tuning has been evaluated, it has achieved a test accuracy of 91% and with low loss of 0.28 which indicates the model has robust performance. The classification report in Table 1. shows higher precision, recall and F1-score for the class good which represents the model's ability to find the class correctly. The moderate class metrics remains the same as the model without hyperparameter tuning. For the class poor, it has low precision, perfect recall and F1-score of 0.67.

The below figure 5. shows the confusion matrix of the FNN model built using the selected features. It shows classes as 'Good', 'Moderate' and 'Poor'. Out of 34 samples, the model was able to predict sleep quality as good for 19 correctly, 1 misclassified as moderate and nothing was classified as poor. For the moderate class it classified 10 correctly and 2 misclassified as poor. For the poor class, there is no misclassification.



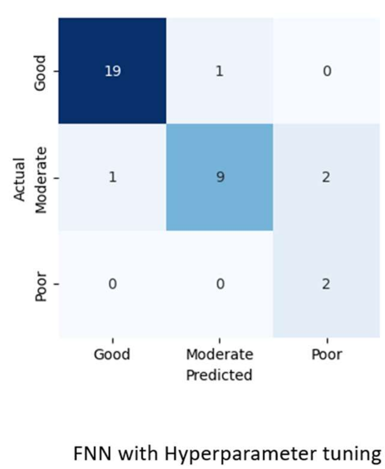
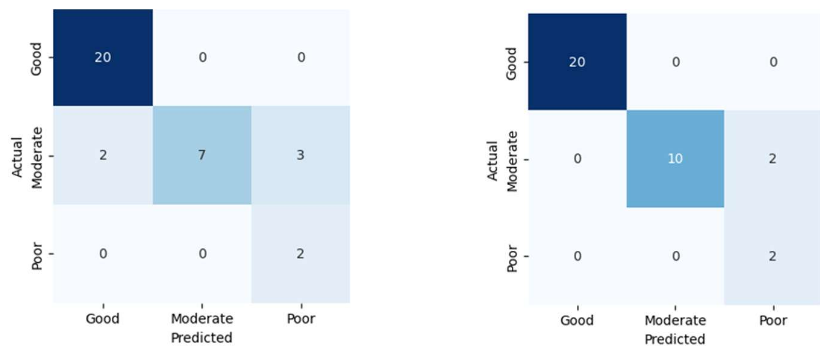


Figure 5. Confusion matrix for FNN model – Sleep data analysis

6.3 Sleep Data Analysis Using CNN

This model has achieved a test accuracy of 85% and with loss of 0.27 which indicates the model has good performance. The classification report in Table 1. shows the model has strong ability to classify the sleep class good in almost all instances and poor class remains same as previous model. For the ‘Moderate’ sleep class it has perfect precision and low recall, due to this model might misclassify some instances wrongly as shown in Table 3. for subject 2 & 8 is classified as ‘Poor’.

The below figure 6. shows the confusion matrix of the CNN model built using the selected features. There is no misclassification for the good and poor class. Out of 12 samples in moderate class, 2 misclassified as good and poor.



CNN

CNN with Hyperparameter tuning

Figure 6. Confusion matrix for CNN model – Sleep data analysis

6.4 Sleep Data Analysis Using CNN with Hyperparameter Tuning

This model optimized with hyperparameter tuning and achieved a test accuracy of 94% and with loss of 0.11 which indicates the model has strong performance. The classification report in Table 1. shows the models ability to classify the classes good and poor remains same as previous model. For the moderate sleep class, it has perfect precision and low recall, due to this model might misclassify some instances wrongly.

The below figure 6. shows the confusion matrix of the CNN model built using hyperparameter tuning. There is no misclassification for the good and poor class. Out of 12 samples in moderate class, 2 misclassified as poor.

6.5 Sleep Data Analysis Using RNN-LSTM

This model has achieved a test accuracy of 94% and with loss of 0.24 which indicates the model has strong performance. The classification report in Table 1. shows the model has strong ability to classify the sleep class good in almost all and poor class remains same as previous model. For the ‘Moderate’ sleep class it has perfect precision and low recall, due to this model might misclassify some instances wrongly as shown in Table 3. for subject 1 is classified as 'Good'.

The below figure 7. shows the confusion matrix of the CNN model built using hyperparameter tuning. There is no misclassification for the poor class. Out of 20 samples in good class, 1 misclassified as moderate and for the moderate 1 misclassified as poor.

6.6 Sleep Data Analysis Using RNN-LSTM with Hyperparameter Tuning

The RNN-LSTM model has been rebuilt with hyperparameter tuning, the results are not improved but in turn the accuracy has got decreased. Due to this, this model won't be suitable to predict PSU when compared to the RNN-LSTM model built previously.

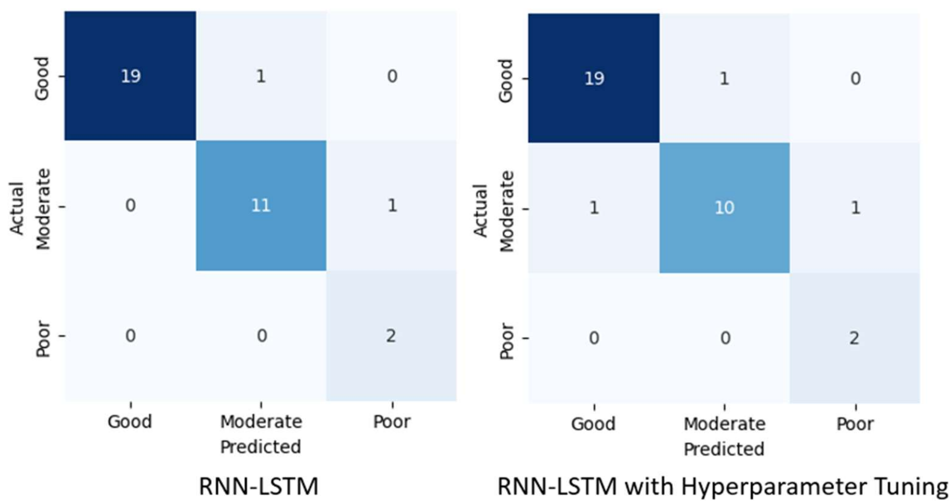


Figure 7. Confusion matrix for RNN-LSTM model – Sleep data analysis

6.7 Apps Usage Data Analysis Using FNN

Table 2. Classification report for Apps usage data analysis

Model	Accuracy	Class	Precision	Recall	F1
FNN	0.9987	Not Affected	0.98	1	0.99
		Affected	1	1	1
CNN	0.98	Not Affected	0.75	0.99	0.86
		Affected	1	0.98	0.99
RNN	0.998	Not Affected	0.97	1	0.98
		Affected	1	1	1

The FNN model built for analysing apps usage data has achieved a higher accuracy of 99.87% as shown in Table 2. With very low loss of 0.0043 and high precision, recall and F1-score for all the classes. The result shows the model is high reliable to predict the PSU.

The below figure 8. shows the confusion matrix of the FNN model built for the app's usage data. Out of 90804 records, the model correctly classified 5374 as not affected, 85308 as affected and misclassified 118 not affected class as affected and 4 affected class not as affected.

6.8 Apps Usage Data Analysis Using CNN

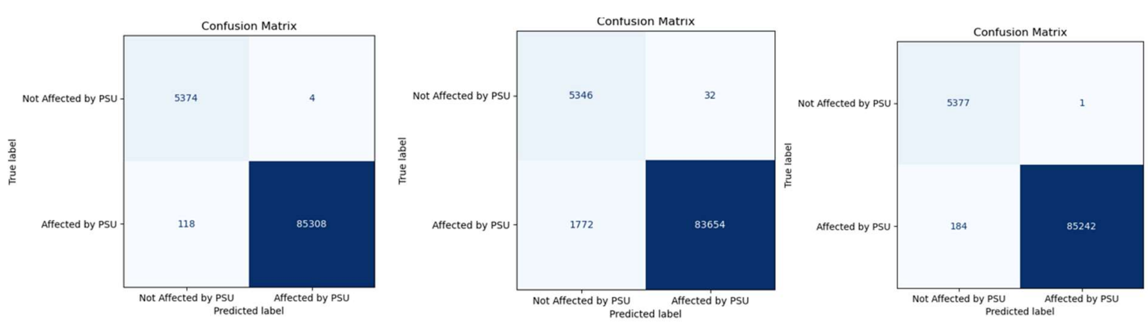
The below figure 8. shows the confusion matrix of the CNN model built for the app's usage data. Out of 90804 records, the model correctly classified 5346 as not affected, 83654 as affected and misclassified 1772 not affected class as affected and 32 affected class not as affected.

The classification report for CNN model has achieved a higher accuracy of 98.01% as shown in Table 2. And loss of 0.0545. The model has strong ability to predict the users affected by PSU than not affected by PSU.

6.9 Apps Usage Data Analysis Using RNN-LSTM

The below figure 8. shows the confusion matrix of the FNN model built for the app's usage data. Out of 90804 records, the model correctly classified 5377 as not affected, 85242 as affected and misclassified 184 not affected class as affected and 1 affected class not as affected.

The classification report for RNN-LSTM model has achieved a higher accuracy of 99.80% as shown in Table 2. The model has higher precision for both the classes and performs exceptionally well, with minimal error for the class not affected.



FNN CNN RNN-LSTM

Figure 8. Confusion matrix for Apps Usage Analysis

6.10 Predictions

Once the model has been trained and validated predictions can be done by passing the data on the trained model to make prediction. The table 3 & 4. shows predictions made by the models built in this research. For the sleep data all the 24 participants data was passed and predictions made in that 4 participants sleep quality was misclassified as highlighted. For the apps usage 11 random sample were passed and all the models predicted the same results.

Table 3. Predictions made Sleep Data

Subject	FNN	FNN (Tuning)	CNN	CNN (Tuning)	RNN-LSTM	RNN-LSTM (Tuning)
1	Moderate	Moderate	Moderate	Moderate	Good	Good
2	Moderate	Moderate	Poor	Moderate	Moderate	Moderate
8	Poor	Moderate	Poor	Moderate	Moderate	Moderate
21	Good	Moderate	Good	Moderate	Good	Good

Table 4. Predictions made for Apps Usage

Subject	FNN	CNN	RNN	Most used App
1	Affected	Affected	Affected	Communication
2	Not Affected	Not Affected	Not Affected	Communication
3	Affected	Affected	Affected	Social
4	Affected	Affected	Affected	Communication
5	Affected	Affected	Affected	Social
6	Affected	Affected	Affected	social
7	Affected	Affected	Affected	Game
8	Affected	Affected	Affected	Communication
9	Not Affected	Not Affected	Not Affected	Communication
10	Not Affected	Not Affected	Not Affected	Communication
11	Not Affected	Not Affected	Not Affected	Browsing

6.11 Discussion

In this research, the author has investigated the PSU using three deep learning models such as FNN, CNN and RNN-LSTM. Each model was evaluated based on their ability to classify the subject affected as PSU or not based on sleep quality as 'Good', 'Moderate' or 'Poor' with & without hyperparameter tuning and based on apps usage is classified as 'Affected' or 'Not Affected'.

The evaluation of this research involved comparing three distinct deep learning models built, based on their strength and weakness on classifying the categories and how it handles the different aspects of the data. The FNN model serves as a baseline for the research, but the data used for analysing the sleep quality contains smaller portion of samples labelled as 'Poor' this encourages to build the more sophisticated models like CNN and RNN-LSTM. The models build on the imbalanced data has provided more precision and shows the ability to identify the classes accurately.

To conclude, which model is the best model the author has not only considered the accuracy. Instead to obtain higher efficiency of the model, the author has decided to check the accuracy, precision and recall as the major evaluation metrices. The results obtained from this research showcase that CNN with Hyperparameter Tuning and RNN-LSTM tends to perform better in capturing complex patterns of the sleep data. FNN and RNN-LSTM are the more reliable models for analysing apps usage data. Since the research involved 2 datasets, the results suggest different models, in case if the research is conducted on the combined dataset which contains all the features in a single dataset RNN-LSTM would be the best model.

6.12 Limitations

While this study aims to analyze the relationship between smartphone usage and sleep quality, there are few limitations has been found:

1. **Limited Sample Size:** The dataset used for sleep analysis contains data of only 24 participants contains metrics like sleep duration and phone usage metrics collected for 7 days. Where the class categories are imbalanced, which leads to bias.
2. **Short Study Duration:** The data collection window of 7 days for the sleep data is relatively small, which has the limitation to capture long term patterns present in sleep behavior to predict problematic smartphone usage (PSU). Due to unavailability of the longer window dataset this 7 days window has been chosen. This shorter period helps in finding the short-term behavioral pattern which identifies the daily variations such as weekday vs weekends based on the excessive nighttime smartphone usage and changes in the sleep patterns.
3. **Data constraints:** The use of two different datasets, one for sleep quality analysis and one of app usage, may limit the ability to directly find the individual's sleep patterns with specific app usage behaviors. Integration of two datasets or collecting the combined dataset in future studies could provide a more complete understanding.

7 Conclusion and Future Work

The comparative analysis on deep learning model's such as FNN, CNN and RNN-LSTM for predicting PSU based on sleep quality and apps usage has provided valuable insights by informing whether a person is affected by PSU or not. The models build displayed their strength in predicting PSU, among all the models RNN_LSTM model has achieved the highest efficiency with minimal errors, intensive hyperparameter tuning on the model might enhance the model's performance.

Future work should focus on addressing the limitations encountered in this study, while collecting the data complete details should be collected in a single dataset like sleep quality, apps usage, physical activity and apps usage details for a longer window, the data should be collected from various age group, and it should be collected from various demographics. By collecting the data as mentioned it would help the researcher to identify the more complex patterns and predictions will be more accurate

In conclusion, this research has fulfilled the research question by providing a solid foundation for predicting PSU and based on the severity targeted interventions can be implemented. Suggestions like developing alternative habits like reading, exercise or times spending outdoor. To reduce the screen time usage limits should be set to the apps that contribute heavy PSU. Digital well-being features like usage of blue screen filters should be promoted, creating phone free zones to interact with people face to face, reducing the usage during meals and before bedtime. With the use of this deep learning models customised monitoring apps should be developed to analyze the behavior, usage and sleep patterns which could help in identifying the areas where intervention is needed.

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