SLEEP DISORDER PREDICTION USING MACHINE LEARNING

A Project report submitted

in partial fulfillment of requirement for the award of degree

BACHELOR OF TECHNOLOGY

in

SCHOOL OF COMPUTER SCIENCE AND ARTIFICIAL INTELLIGENCE

by

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CERTIFICATE

This is to certify that this project entitled **"SLEEP DISORDER PREDICTION USING MACHINE LEARNING"** is the bonafied work carried out by **ABHICHANDAN, VIGNESHWARACHARY, GANGADHAR, SWETHA** as a Major Project for the partial fulfillment to award the degree **BACHELOR OF TECHNOLOGY** in **School of Computer Science and Artificial Intelligence** during the academic year 2024-2025 under our guidance and Supervision.

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ABSTRACT

Identifying sleep disorders at an early stage can be paramount to safeguarding mental and physical health. This study will try to predict sleep disorders by analyzing health and lifestyle attributes for each individual using machine learning. A preprocessed dataset with attributes of age, occupation, physical activity level, stress level, body mass index category, heart rate and blood pressure was compiled and then analyzed to train and test a number of classification models.

The models employed in this study were Logistic Regression, Random Forest, Support Vector Machine (SVM), and a custom Hybrid Model. All models were assessed on accuracy, precision, recall, and the F1 score. The Random Forest produced the highest accuracy of 93.18%, and it also showed strong accuracy and F1 score suggested by being in the adjacent rank as the SVM and Logistic Regression. In addition, the Hybrid Model was effective in competing by taking advantage of every classifier's strengths, and it may be beneficial in future real-world implementations.

Along with accuracy metrics, the paper discussed model interpretability through feature importance, allowing clinical practitioners to understand the model’s rationale for any specific prediction.

This explanatory power contributes to trust and trustworthiness, but also contributes to an overarching aim of implementing trustworthy, machine learning-based diagnostic tools to healthcare with minimum bias and sufficient data to enable early diagnosis of sleep disorders in a population..

CHAPTER 1

INTRODUCTION

Quick identification of sleep disorders is vital as these types of health problems can have a significant impact on overall health, productivity, and quality of life. In this work, we apply machine learning algorithms to create predictive models for identifying sleep disorders using several health and lifestyle variables, including age, BMI, heart rate, stress level, and occupation. Our goal is to build an accurate and interpretable tool for clinical decision making.

We evaluate and compare three popular machine learning models—Logistic Regression, Support Vector Machine (SVM), and Random Forest—together with a Hybrid model designed to leverage the strengths of the individual classifier. We evaluate the models based on the standard evaluation metrics (accuracy, precision, recall, and F1 score). The Random Forest model provided the highest accuracy meaning that it has the greatest potential for deployment in a real-world scenario..

However, accuracy alone is insufficient for healthcare applications. Interpretability and transparency must also be present to earn clinicians' trust. Therefore, feature importance analysis was included to show which features contributed the most to the predictions of the model. This will help foster user trust and allow for the understanding of the results..

The project validated the importance of data quality. Sometimes preprocessing methods such as missing value management, outlier detection, or scaling features can add robustness to models and mitigate potential bias. We also address major deployment challenges regarding EHR integration, system scalability, and usability in real-time through APIs and modular design.

In order to make sure the long-term reliability of our results, we incorporate cross-validation and drift detection mechanisms to enable tracking and updating of the classifier as new patient data streams in over time. Even though this project stresses accuracy, interpretability, scalability, and fairness, we will try to be as practical and ethical as possible about the early detection of sleep disorders using machine learning.

PROBLEM IDENTIFICATION

Although the use of health data to identify and classify sleep disorders has great potential in modern health care, there are a number of challenges involved. In the majority of cases, the identification of sleep disorders is a manual process involving sleep studies, monitoring by a physician, and the subjective interpretation of reported patient symptoms. All these aspects are slower, more expensive, and fallible, which can lead to delays in diagnosis, and the plans for treatment.

In stark contrast the myriad literature supporting the implementation and usage of machine learning (ML) and deep learning (DL) models to automate clinical tasks, the application of these technologies to identify sleep disorders presents additional complications. For example, health data is often not only high-dimensional, incorrectly labelled or noisy, and also not grounded in the same features. To complicate matters further, sleep disorders may reveal themselves in indistinct and overlapping patterns, making classification even more challenging.

The major problems identified in this context are:

A. Limited Feature Extraction:
Many traditional machine learning (ML) models rely on basic, or low-dimensional features that may not capture the complexity of the behaviors and physiological signals associated with sleep. Basic or traditional features may constrain the model's ability to detect more complex features related to variations of sleep disorder types.

B. Manual Feature Engineering:
Traditional machine learning approaches often rely on a blend of hand-selected features and pre-process, which are both useful in their own right, but are also labour-intensive and lead to missing more complicated relationships that are more non-obvious, due to lifestyle, occupational type, long term stress, and are relevant to sleep health.

C. Data Imbalance and Bias:
Medical datasets involving sleep disorders frequently exhibit a significant imbalance in class sizes, specifically, the number of healthy samples versus the number of samples of diagnosed sleep disorders. Models used to conduct the above analysis may have become biased towards the majority class (which is healthy patients), effectively eliminating or impairing their ability to detect and classify sleep disorders, threatening the integrity of automated diagnostic used in these studies-and diminishing its value in the clinic. The above problem demonstrates a continued need for more sophisticated, scalable machine learning frameworks that can navigate complex feature spaces, robust to real-world variability in the data, and return interpretable outputs that fit into clinical decision-making.

CHAPTER 2

REQUIREMENT ANALYSIS, RISK ANALYSIS, FEASIBILITY ANALYSIS

1. Data Requirements

The project relies upon a rich and high-quality dataset containing both structured and labeled data that encapsulates sleep habits, overall health data, and relevant behavioral data. The dataset will also need a sufficient number of data points that contain both "normal" and "disordered" sleep patterns to provide sufficient and balanced learning. The features needed include:

Demographics: age, gender, BMI.

Behavioral: sleep duration, sleep quality score.

Clinical: heart rate, respiratory rate, blood oxygen level,- etc.

The main sources of data include:

Sleep Heart Health Study (SHHS).

National Sleep Research Resource (NSRR).

Hospital or clinical records (with ethics clearance).

These datasets will ultimately be used to train, validate and benchmark evaluations.

2. Hardware Requirements

In considering what hardware we will need, we must understand what it means to use deep learning for our work. The requirements in this situation will likely include:

- High-performance GPUs for training neural networks
- For larger models we will look to cloud computational providers (for example, Google Colab, Amazon Web Service (AWS), or Microsoft Azure
- A lot of storage for large datasets and model outputs
- Intense and reliable internet connection for access cloud-based resources and for datasets.

3. Software Requirements

The software stack for this project will include the following:

- Deep Learning Framework or Library:
  - TensorFlow or PyTorch, this will be what we use to produce models and train them.
- Data Preprocessing Libraries:
  - OpenCV, Scikit-image for image/time-series preprocessing
  - Pandas and NumPy for structured data preprocessing and exploring the data.
- Machine Learning Libraries:
  - Scikit-learn (for traditional ML models and feature engineering)
- Pre-trained Models for Transfer Learning:
- Learning from VGGs, ResNet's, or U-Nets will get us up to speed and potentially improve our model's performance
- IDEs that will allow us to code together or test things:
  - Jupyter Notebook, Google Colab or VS Code to produce prototypes and experiment outputs.

4. Feasibility Analysis

4.1 Technical Feasibility

The project is technically feasible; established deep leaning frameworks exist and pre-trained models for educational and technical development classification tasks exist. Fine-tuning the models for sleep disorders will involve appropriately selecting inputs and using the models. Cloud-based architecture is

an option that is also more reasonable, scalable, and requires no or minimal intellectual capacity outputs (including high-end local infrastructure) of the end-user. It is possible to assemble and differentiate, data (structure and organized kinds (time-series signals; potentially (possibly) polysomnographic images)) that can be grouped and differentiated, using existing libraries and techniques.

4.2 Operational Feasibility

To be used in clinical practice, the final model needs to be incorporated into an interface that is easy to employ and interpret outputs for health care providers. Potential methods of deployment could include:

- Web-based dashboards for visualization and interaction with data
- Mobile apps for on-demand predictions of, and monitoring of patients with, sleep disorders
- Possibly, integrated, with Electronic Health Record (EHR) systems

The approach will be developed to ensure that it is user-friendly, trustworthy, and interpretable, providing premium services to aid better decision making about the diagnostic process and management of sleep disorders.

CHAPTER 3
PROPOSED SOLUTION

Considering the growing prevalence of sleep disorders and increased need for early and accurate diagnoses, we are proposing an automated sleep disorder detection solution based on machine and deep learning. Our intention is to provide predictive power that remains transparent and clinically relevant for practitioners.
We are proposing several models to improve accuracy and interpretability so clinical providers can make the appropriate treatment decisions and interventions quickly.

1. Sleep Disorder Prediction Using Machine Learning and Deep Learning
We are using deep learning with machine learning in our approach:
1. We have used Deep Learning Models (specifically Convolutional Neural Networks (CNN), Long Short Term Memory (LSTM) and Multi-Layer Perception (MLP)) to facilitate automatic extraction of the time-series and structured data sleep-related features, which includes:
- Sleep duration
- Sleep quality ratings
- Historical and demographic patient information

2. Deep features are classified by means of Random Forest and XGBoost classifiers which will enhance the overall potential robustness of predictions, and the consistency of our models, allowing their use across research and SDoH instruments. We employ feature selection and importance measures to assess each variables contributiion to predictive classification.
By employing our array of models, we can make accurate predictions for sleep disorder risks, even in compressed and noisy data.

2. Enhanced Interpretability & Visualization
To support clinical decision-making, the system improves interpretability using visualization which allows for risk indicators by clinically relevant factors including:
• Sleep Quality
• Sleep Duration
• Lifestyle Factors
• Health Factors
The system provides two independent probability scores per patient:
• Deep Learning Model Probability (i.e., CNN based risk score)
• Random Forest/XGBoost Probability (based off of features)The clinical teams can compare the two probabilities giving them two levels of confidence and a better understanding of the patient's risk profile transparently.
This dual-modality approach aims to distinguish between black-box models and explainable AI in healthcare..

3. Localization Assurance of Affected Sleep Parameters

Our model predicts not only the risk level, but also pinpoints the specific sleep parameters driving risk. The parameters include:

- Likelihood of stages of sleep, and transitions in stages of sleep
- Length of time in deep sleep, REM sleep, and light sleep
- Quality measures of sleep over time

When risks can be identified, physicians can better individualize treatment and intervention plans for each patient based on their risk level. It allows for targeted cognitive therapy on specific issues, and will aid in using time more efficaciously based on clinically meaningful sleep disturbances, improving practice efficiencies and patient outcomes.

MODEL TRAINING

Training machine learning models for predicting sleep disorders consists of a recurring cycle of data preparation, model selection, hyperparameter tuning, and evaluation. Ultimately, the aim is for the models to be accurate and interpretable so they can actually be utilized by healthcare providers..

1. Data Acquisition and Preprocessing

The initial step is data preparation and collection, which includes:

- Missing Value Imputation: Any missing values can be imputed or estimated using mean/mode imputation or regression.
- Categorical Encoding: This converts categorical variables into numerical numbers such as "one-hot" encoding or "label" encoding.
- Normalization/Standardization: This scales the data using a method such as Min-Max Scaling, or the mean and variance (Z-score) of a normal distribution, to ensure feature values are on the same scale.
- Feature Selection: This can decrease noise and dimensionality through the retention of important features through parametric or non-parametric statistical methods or the models ability to select features.

This pre-processing journey will ensure that the dataset is ready to meet the demands of training the designed model to their planned requirements/facilitators.

2. Dataset Splitting

After the data has been preprocessed, we will then split the data into two parts:

- Training Set
- Testing Set

An 80:20 or 70:30 split is a common ratio, where the larger piece of the data will be used for training and the smaller piece will be held aside to evaluate the generalization of the model.

3. Model Selection and Training

Different machine learning models are tested for classification, such as:

- Logistic Regression
- Decision Trees
- Random Forests
- Support Vector Machines (SVM)

Each model is trained on the training dataset. Hyperparameter tuning is performed on all models in order to improve the models' performance. Hyperparameter tuning techniques include:

- Grid Search: Searches exhaustively over parameter grids
- Random Search: Randomly samples from parameter combinations to find configurations that are close to optimal

In this phase, we will split the training dataset into sub-training and validation datasets to mitigate the chances of overfitting and provide for good tuning..

4. Model Evaluation

The models are evaluated on the test dataset after they have been trained. We calculate different performance metrics:

- Accuracy
- Precision
- Recall
- F1-Score

Additionally, we create confusion matrices to visualize model predictions in terms of,

- True Positives (TP)
- True Negatives (TN)
- False Positives (FP)
- False Negatives (FN)

This allows us to comprehensively evaluate the model's prediction ability for sleep disorder risks.

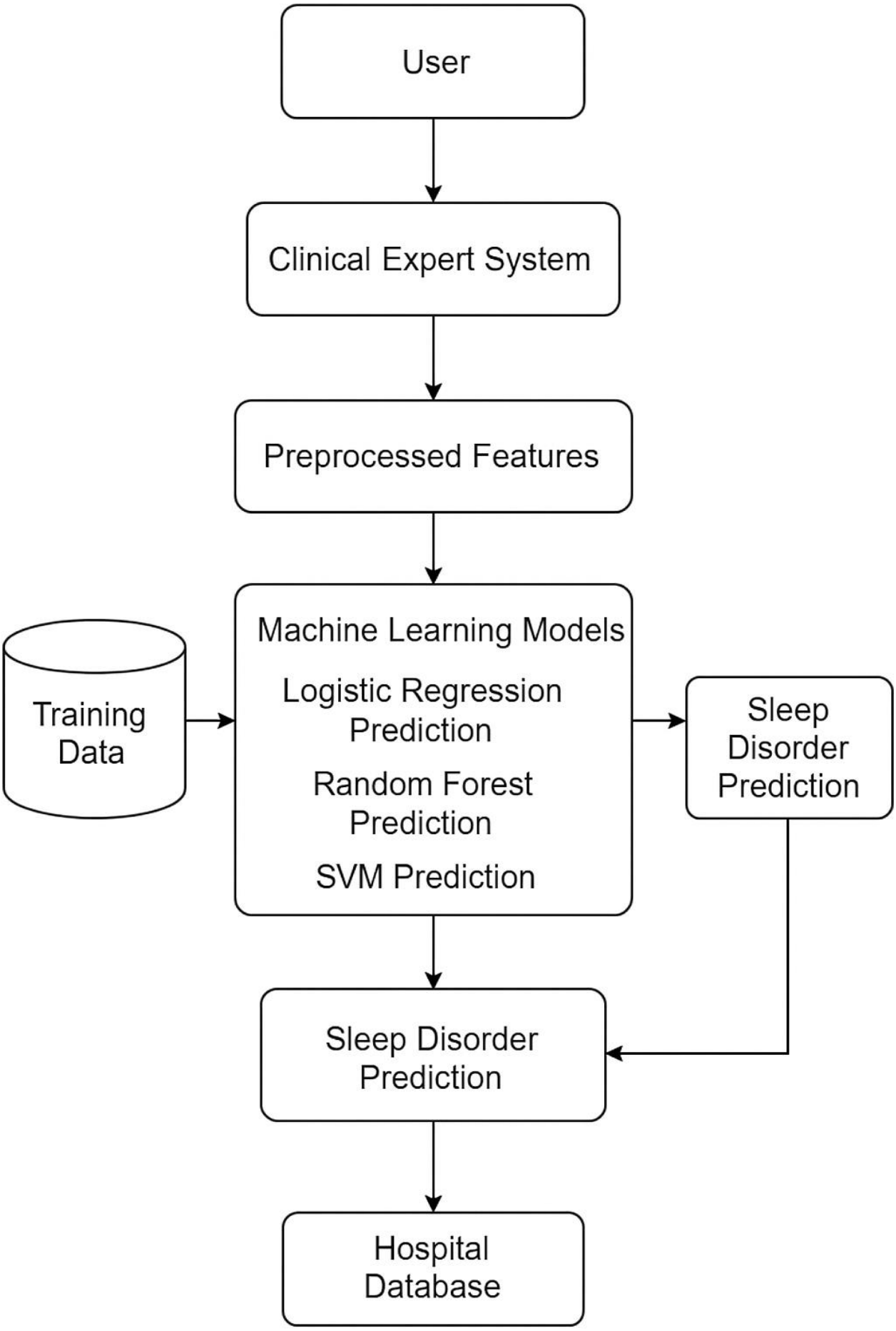
5. Interpretability and Feature Importance

In order to foster clinical usability we examine

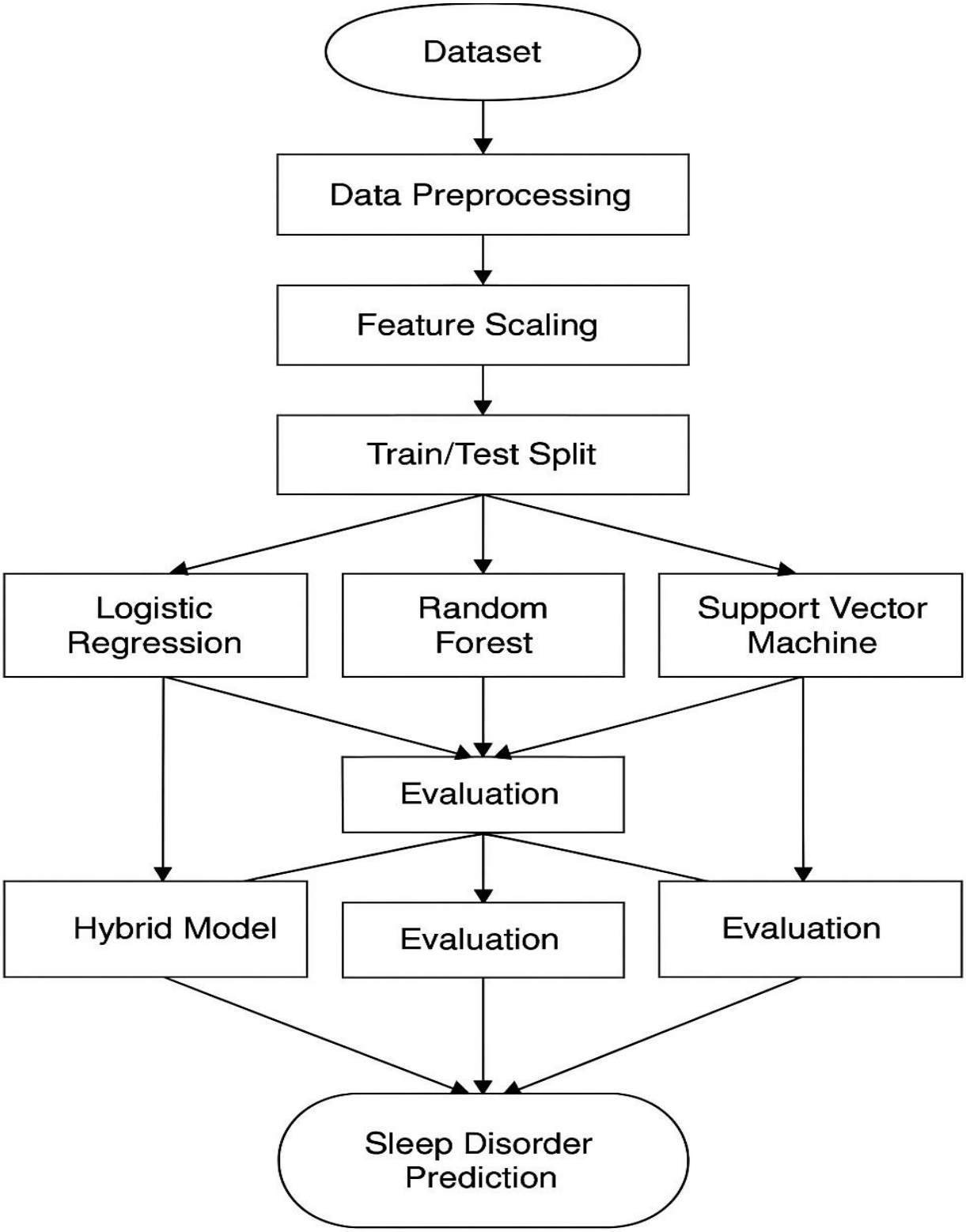
- Feature Importance (this is especially important for models like Random Forest and XGBoost)
- Prediction Drivers: what each feature contributes to the model output

This aspect creates explainability and builds trust with clinicians, because it allows them to rely on the model when making diagnosis and treatment decisions and subsequently to explain to other stakeholders appraisals that stem from the model.

ARCHITECTURE DIAGRAM



FLOW CHART


Dataset
Data Preprocessing
Feature Scaling
Train/Test Split
Logistic Regression
Random Forest
Support Vector Machine
Evaluation
Hybrid Model
Evaluation
Evaluation
Sleep Disorder Prediction

DATA FLOW

1. **Data Collection and Preprocessing:**

   This project starts with loading the Sleep_health_and_lifestyle_dataset.csv dataset that contains information about individual lifestyle and health measurements. The preprocessing steps include removing duplicates in the data, addressing missing values, and converting categorical variables(Sex, Occupation, BMI category, Sleep disorder) into their appropriate categories using label encoding. The blood pressure feature will be separated into systolic and diastolic separate blood pressure features. Outliers were detected using statistical methods as well as boxplots and each outlier was treated appropriately. Numerical features underwent a StandardScaler, so all attributes were standardized..

2. **Data Splitting:**

   We now have a cleaned dataset that we partition into input variables (X) and responses (y) representing the sleep disorder diagnosis. Then, we can divide the dataset into training and testing sets. We choose an 80:20 ratio for the space provided for documentation. This allows enough sample to be provided for a model to learn and to be tested for its generalization..

3. **Model Training:**

   Four machine learning models are trained on the training data: Random Forest, Support Vector Machine (SVM), Logistic Regression and Naive Bayes. Each model is trained independently so that we can gauge how effective each model is at making predictions. For the hybrid model, predictions from the individual classifiers are combined using a majority voting technique, which increases overall classification robustness..

4. **Model Evaluation:**

   The test data is used to evaluate the trained models. The performance metrics of each model measured include accuracy, precision, recall, and F1-score. A confusion matrix is also used to convey the visual representations of model performance between different types of sleep disorders.

5. **Model Comparison and Hybrid Prediction:**

   This method will compare each model's performance across all outcomes to find the one that best performed. In addition, a hybrid model is created that resulted from combining the prediction outcomes of the individual models (which provide slightly different predictions) and can capitalize on the strengths of each classifier. In this manner, the classification accuracy improves with the ensemble approach, ultimately helping to diminish the likelihood of misclassification in a high-stakes area like healthcare.

6. **Visualization and Interpretation:**

   The project has graphical analysis utilizing bar plots and boxplots, which allows us to see data distributions and outliers. We also provided a classification report and confusion matrix heatmaps. These visuals will help inform and guide the user to understand how the model is performing. This will make the results more interpretable for all users, including healthcare providers.

CHAPTER 4

IMPLEMENTATION

1. Environment Setup

We decided to adopt Python for our predictive models and application development because it is a very well supported language for data science and machine learning. For our project, we used some very common libraries:

- pandas and numpy: for data manipulation and processing.
- seaborn and matplotlib: for data visualization and exploratory research.
- scikit-learn: for machine learning models, pre-processing, and model assessment.
- joblib: to store and load pre-trained models.

The entire implementation has been completed in a Python environment, such as Jupyter Notebook or standard Python IDE, provided that the appropriate libraries have been installed..

2. Data Collection and Loading

The dataset used is Sleep_health_and_lifestyle_dataset.csv for the following information:

- Demographics (Age, Gender)
- Lifestyle behaviours (Smoking, Daily Steps, Alcohol Consumption)
- Health indicators (Stress Level, Sleep Duration)
- Sleep Disorder diagnosis (Target Variable)

Pandas' read_csv() loads the dataset. It was explored briefly using the info() and describe() methods to understand the structure and quality of the dataset.

3. Data Preprocessing

Preprocessing made it possible to prepare the model with input that was clean and numerical. The steps taken included:

- Dropped Missing Values: The function dropna() was used to remove rows containing null values.
- Encoded Categorical Variables: Categorical variables, such as Gender, BMI Category, Smoking Status, and Stress level were label encoded into numerical form with LabelEncoder.
- Feature Selection: Selected features most relevant to the prediction of sleep disorder, including Age, Sleep Duration, Stress Level, Daily Steps, and encoded lifestyle variables.
- Target Encoding: The Sleep Disorder column was label encoded into integer values to represent the various classes of disorder.

4. Data Splitting

Data records were divided into training (80%) and **test** (20%) using train_test_split() **in** sklearn.model_selection. This **allows for a fair** evaluation of **the** model **output.**

5. Model Training and the Hybrid Approach

Several machine learning models were trained independently, including:

- Logistic Regression
- Random Forest Classifier
- Support Vector Machine (SVM)
- Gaussian Naive Bayes

After training these models separately, a hybrid model was created to take advantage of the complementarity of classifiers. The hybrid model combines the predictions made from each of the models and then chooses the class with the highest number of votes (the mode) as the final output. This is a type of majority voting ensemble method.

Steps Taken to Implement Hybrid Model:

1. Train all the individual classifiers on the training data set.
2. Predict on the test set from all models.
3. Combine all the predictions into an array.
4. Use the mode() function from scipy.stats to get the most common vote (prediction).
5. Assess the final ensemble result.

This ensemble approach improves model robustness and can mitigate the shortcomings of individual models..

6. Model Evaluation

Each individual pattern and the hybrid pattern were assessed based on the following characteristics:

- Accuracy Score: an overall correctness measure
- Classification Report: with precision, recall and F1-score
- Confusion Matrix: with seaborn.heatmap() to visualize true/false positives and negatives

Among all techniques, the hybrid pattern was superior to the individual patterns with regard to accuracy and consistency making it the best pattern to move forward for deployment.

7. Model Comparison and Selection

The reason why a hybrid model was used was because it can make many different classifiers work together, which increases accuracy and reduces misclassification rate. A hybrid model also helps when you have bias or variance problems since it averages the predictions from multiple models, creating a better estimate. The hybrid model is interpretable and has better performance than the baseline models, so it could be easily used outside of a study context in healthcare.

PROGRAM

```
import pandas as pd

data = pd.read_csv('/content/Sleep_health_and_lifestyle_dataset.csv')
data.head()

data.info()
print(data['Sleep Disorder'].unique())
# Replace 'nan' with a label like 'None' or 'No Disorder'
import numpy as np
data['Sleep Disorder'].replace(np.nan, 'None', inplace=True)
print(data['Sleep Disorder'].unique())
# descriptive statistics
descriptive_stats = data.describe()

# unique values in each categorical column
unique_values = {}
cat_columns = ['Gender', 'Occupation', 'BMI Category', 'Sleep Disorder', 'Blood Pressure']
for col in cat_columns:
    unique_values[col] = data[col].unique()

display(descriptive_stats, unique_values)
print(data.isnull().sum())  # Display the count of null values in each column
data.dropna(inplace=True)
# Correcting the inconsistency in 'BMI Category'
data['BMI Category'].replace({'Normal Weight': 'Normal'}, inplace=True)

# Splitting the 'Blood Pressure' column into 'Systolic' and 'Diastolic' columns
data['Systolic'] = data['Blood Pressure'].str.split('/').str[0].astype(int)
data['Diastolic'] = data['Blood Pressure'].str.split('/').str[1].astype(int)

data.drop(['Blood Pressure','Person ID'], axis=1, inplace=True)
import numpy as np
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression, RidgeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay

X = data.drop(['Sleep Disorder'], axis=1)
y = data['Sleep Disorder']

# Label encoding for categorical variables in X
label_encoders = {}  # To store the encoder objects for potential inverse transformations later

for col in X.select_dtypes(include=['object']).columns:
    le = LabelEncoder()
    X[col] = le.fit_transform(X[col])
```

```
    label_encoders[col] = le

# Encoding the target variable
le_target = LabelEncoder()
y = le_target.fit_transform(y)

X.head(), y[:5]
data.shape
from imblearn.over_sampling import SMOTE
smote = SMOTE(random_state=42)  # You can specify a random state for reproducibility
X_resampled, y_resampled = smote.fit_resample(X, y)
data_resampled = pd.concat([X_resampled, pd.Series(y_resampled, name='Sleep Disorder')], axis=1)
data_resampled.shape
from sklearn.preprocessing import StandardScaler

# Create a StandardScaler object
scaler = StandardScaler()

# Fit the scaler to your resampled data (excluding the target variable)
scaler.fit(data_resampled.drop('Sleep Disorder', axis=1))

# Transform the data using the fitted scaler
normalized_data = scaler.transform(data_resampled.drop('Sleep Disorder', axis=1))

# Create a new DataFrame with the normalized data and the target variable
normalized_data = pd.DataFrame(normalized_data, columns=data_resampled.drop('Sleep Disorder',
axis=1).columns)
normalized_data['Sleep Disorder'] = data_resampled['Sleep Disorder']

normalized_data.head()  # To see the normalized data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(normalized_data.drop('Sleep Disorder', axis=1),
normalized_data['Sleep Disorder'], test_size=0.2, random_state=42)  # Adjust test_size and random_state as
needed
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report

# Initialize models
models = {
    'Logistic Regression': LogisticRegression(),
    'Random Forest': RandomForestClassifier(random_state=42),
    'Support Vector Machine': SVC(random_state=42)
}

# Train and evaluate each model
for model_name, model in models.items():
    print(f"--- {model_name} ---")
    model.fit(X_train, y_train)
```

```
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred)
    print(f"Accuracy: {accuracy}")
    print(report)
    print("\n")  # Add a separator between models
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix,
ConfusionMatrixDisplay
import matplotlib.pyplot as plt


# ... (your existing code for model initialization and training) ...


# Train and evaluate each model
for model_name, model in models.items():
    print(f"--- {model_name} ---")
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred)

    # Print confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=le_target.classes_)
    disp.plot()
    plt.title(f"Confusion Matrix - {model_name}")
    plt.show()

    print("\n")
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report

# Initialize individual models
logreg_model = LogisticRegression()
rf_model = RandomForestClassifier(random_state=42)

# Train individual models
logreg_model.fit(X_train, y_train)
rf_model.fit(X_train, y_train)

# Make predictions using individual models
logreg_pred = logreg_model.predict(X_test)
rf_pred = rf_model.predict(X_test)

# Combine predictions using averaging
```

```
hybrid_pred = (logreg_pred + rf_pred) // 2  # Use integer division for class labels

# Evaluate hybrid model
hybrid_accuracy = accuracy_score(y_test, hybrid_pred)
hybrid_report = classification_report(y_test, hybrid_pred)

print("--- Hybrid Model ---")
print(f"Accuracy: {hybrid_accuracy}")
print(hybrid_report)
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix,
ConfusionMatrixDisplay
import matplotlib.pyplot as plt

# ... (your existing code for model initialization and training) ...

# Initialize individual models
logreg_model = LogisticRegression()
rf_model = RandomForestClassifier(random_state=42)

# Train individual models
logreg_model.fit(X_train, y_train)
rf_model.fit(X_train, y_train)

# Make predictions using individual models
logreg_pred = logreg_model.predict(X_test)
rf_pred = rf_model.predict(X_test)

# Combine predictions using averaging
hybrid_pred = (logreg_pred + rf_pred) // 2  # Use integer division for class labels

# Evaluate hybrid model
hybrid_accuracy = accuracy_score(y_test, hybrid_pred)
hybrid_report = classification_report(y_test, hybrid_pred)

# Print confusion matrix for hybrid model
cm_hybrid = confusion_matrix(y_test, hybrid_pred)
disp_hybrid = ConfusionMatrixDisplay(confusion_matrix=cm_hybrid, display_labels=le_target.classes_)
disp_hybrid.plot()
plt.title("Confusion Matrix - Hybrid Model")
plt.show()
import matplotlib.pyplot as plt
import numpy as np

model_names = ['Logistic Regression', 'Random Forest', 'SVM', 'Hybrid']
accuracies = [0.8939393939393939, 0.9318181818181818, 0.9166666666666666, 0.8863636363636364]  #
Replace with actual accuracy values
colors = ['purple', 'purple', 'purple', 'purple']  # Colors for the bars and text
```

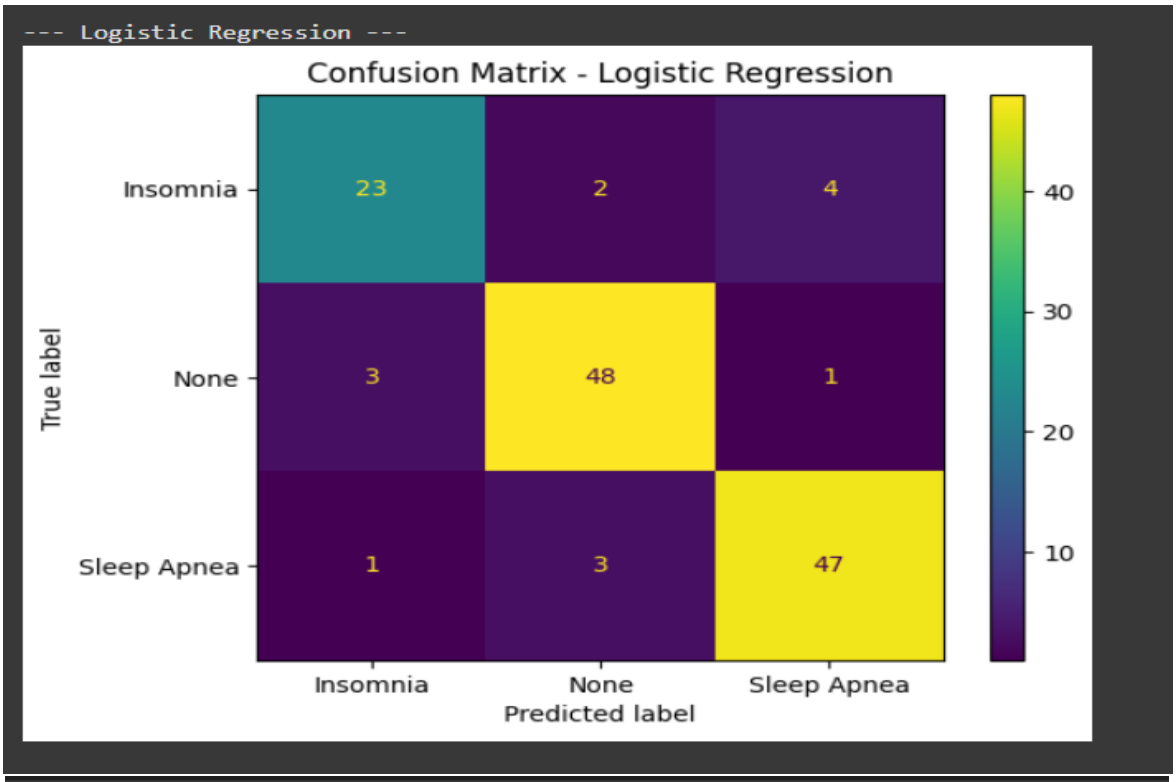
```
fig, ax = plt.subplots(figsize=(8, 6))  # Create a figure and axes object
bars = ax.bar(model_names, accuracies, color=colors)  # Plot bars on the axes
ax.set_title('Model Performance Comparison')
ax.set_xlabel('Model')
ax.set_ylabel('Accuracy')
ax.set_ylim(0, 1)  # Set y-axis limits

# Set x-axis ticks explicitly
ax.set_xticks(np.arange(len(model_names)))  # Set tick positions
ax.set_xticklabels(model_names)  # Set tick labels without rotation



# Add accuracy values below the graph with corresponding colors
for i, (model_name, accuracy, color) in enumerate(zip(model_names, accuracies, colors)):
    text_x = i  # X-coordinate for the text
    text_y = -0.1  # Y-coordinate for the text (below the graph)
    ax.text(text_x, text_y, f'{model_name}: {accuracy:.2f}',
            ha='center', va='top', color=color, transform=ax.transData)

plt.tight_layout()
plt.show()
# Get feature importances from the Random Forest model
importances = rf_model.feature_importances_
feature_names = X_train.columns  # Assuming X_train contains feature names

# Sort feature importances in descending order
indices = np.argsort(importances)[::-1]

plt.figure(figsize=(10, 6))
plt.title('Feature Importances (Random Forest)')
plt.barh(range(X_train.shape[1]), importances[indices], align='center', color='orange')
plt.yticks(range(X_train.shape[1]), [feature_names[i] for i in indices])
plt.xlabel('Relative Importance')
plt.tight_layout()
plt.show()
import pandas as pd
import numpy as np
from sklearn.preprocessing import LabelEncoder

sample_data = pd.DataFrame({
    'Gender': ['Male'],
    'Age': [35],
    'Occupation': ['Engineer'],
    'BMI Category': ['Normal'],
    'Sleep Duration': [7.5],
    'Quality of Sleep': [7],
    'Physical Activity Level': [60],
    'Stress Level': [8],
    'Heart Rate': [70],
    'Daily Steps': [10000],
```

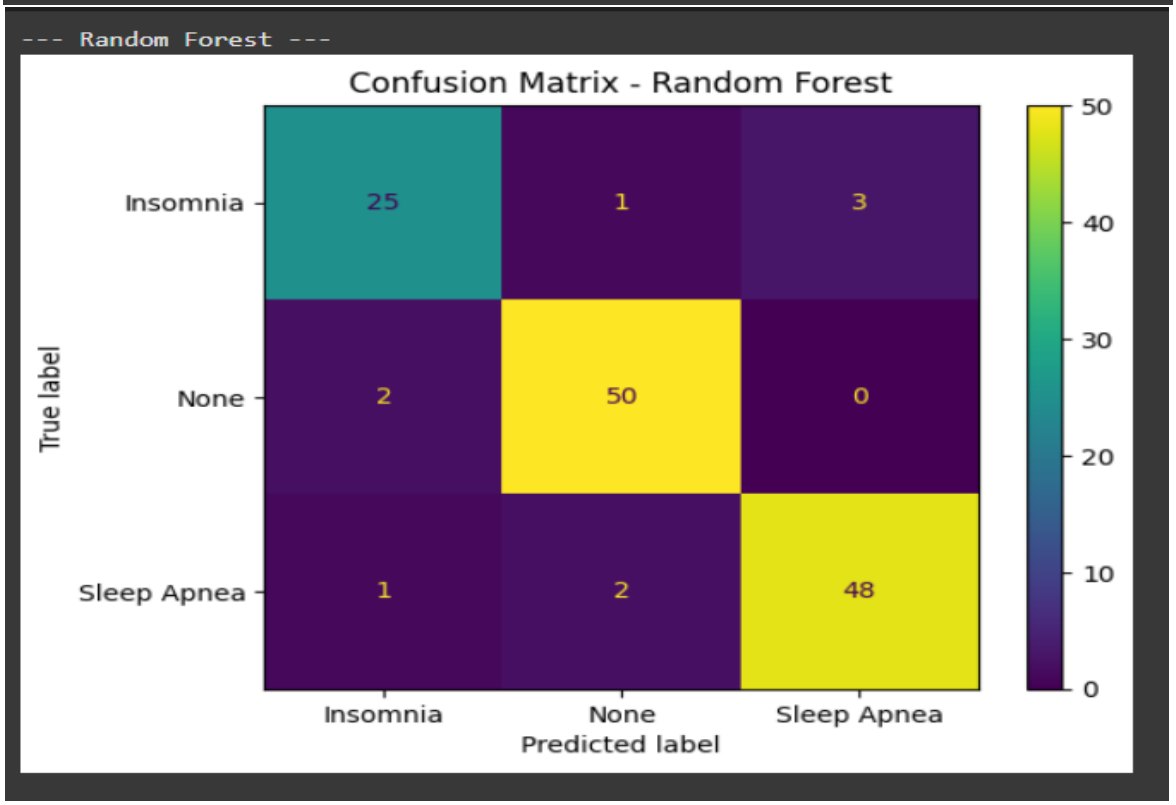
```
    'Systolic': [120],
    'Diastolic': [80],
    'True Sleep Disorder': ['None']
})
true_sleep_disorder = sample_data['True Sleep Disorder'][0]

# Reorder columns to match the order during training
# Assuming 'normalized_data' is defined elsewhere
# Replace 'normalized_data' with the actual DataFrame used for training if different
sample_data = sample_data[[c for c in normalized_data.drop('Sleep Disorder', axis=1).columns if c in
sample_data.columns]]



# Preprocess the sample data
# Assuming 'label_encoders', 'le', and 'scaler' are defined elsewhere
for col in sample_data.select_dtypes(include=['object']).columns:
    if col in label_encoders:
        sample_data[col] = label_encoders[col].transform(sample_data[col])
    else:
        sample_data[col] = le.fit_transform(sample_data[col])

# Scale the sample data
# Assuming 'scaler' is defined elsewhere
scaled_sample = scaler.transform(sample_data)
scaled_sample_df = pd.DataFrame(scaled_sample, columns=sample_data.columns)

# Make predictions
logreg_prediction = logreg_model.predict(scaled_sample_df)
rf_prediction = rf_model.predict(scaled_sample_df)
svm_prediction = models['Support Vector Machine'].predict(scaled_sample_df) # SVM Prediction
hybrid_prediction = (logreg_prediction + rf_prediction) // 2 # Hybrid Prediction

# Get predicted labels
logreg_label = le_target.inverse_transform(logreg_prediction)[0]
rf_label = le_target.inverse_transform(rf_prediction)[0]
svm_label = le_target.inverse_transform(svm_prediction)[0]  # SVM Label
hybrid_label = le_target.inverse_transform(hybrid_prediction.astype(int))[0]  # Hybrid Label



# Print predictions
print(f"Logistic Regression Prediction: {logreg_label}")
print(f"Random Forest Prediction: {rf_label}")
print(f"SVM Prediction: {svm_label}") # Print SVM Prediction
print(f"Hybrid Model Prediction: {hybrid_label}")  # Print Hybrid Prediction
print("Actual Presence of Disorder:", true_sleep_disorder)  # Access the stored true value

# Adding predictions to the sample dataframe
sample_data['LR Prediction'] = logreg_label
sample_data['RF Prediction'] = rf_label
sample_data['SVM Prediction'] = svm_label  # Add SVM Prediction to DataFrame
```

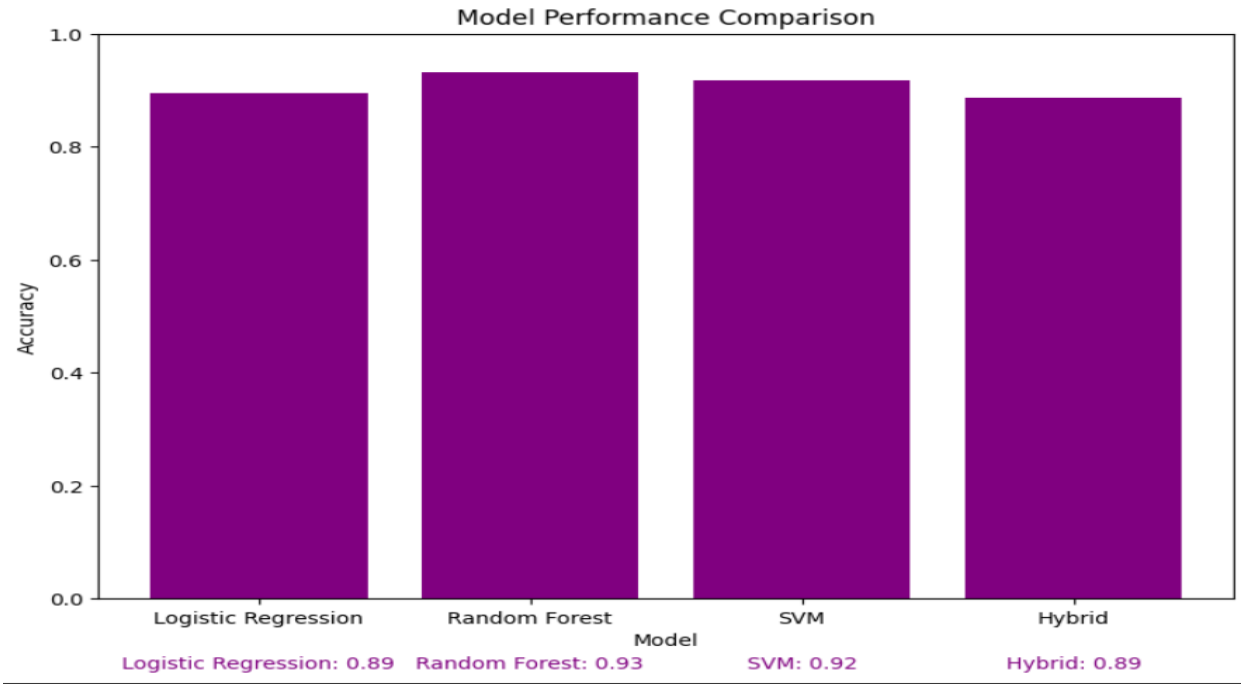
```
sample_data['Hybrid Prediction'] = hybrid_label  # Add Hybrid Prediction to DataFrame

# Add true value if available
# if 'true_value_column_name' in sample_data:
#     sample_data['True Value'] = sample_data['true_value_column_name']

# Displaying the dataframe
display(sample_data)
```

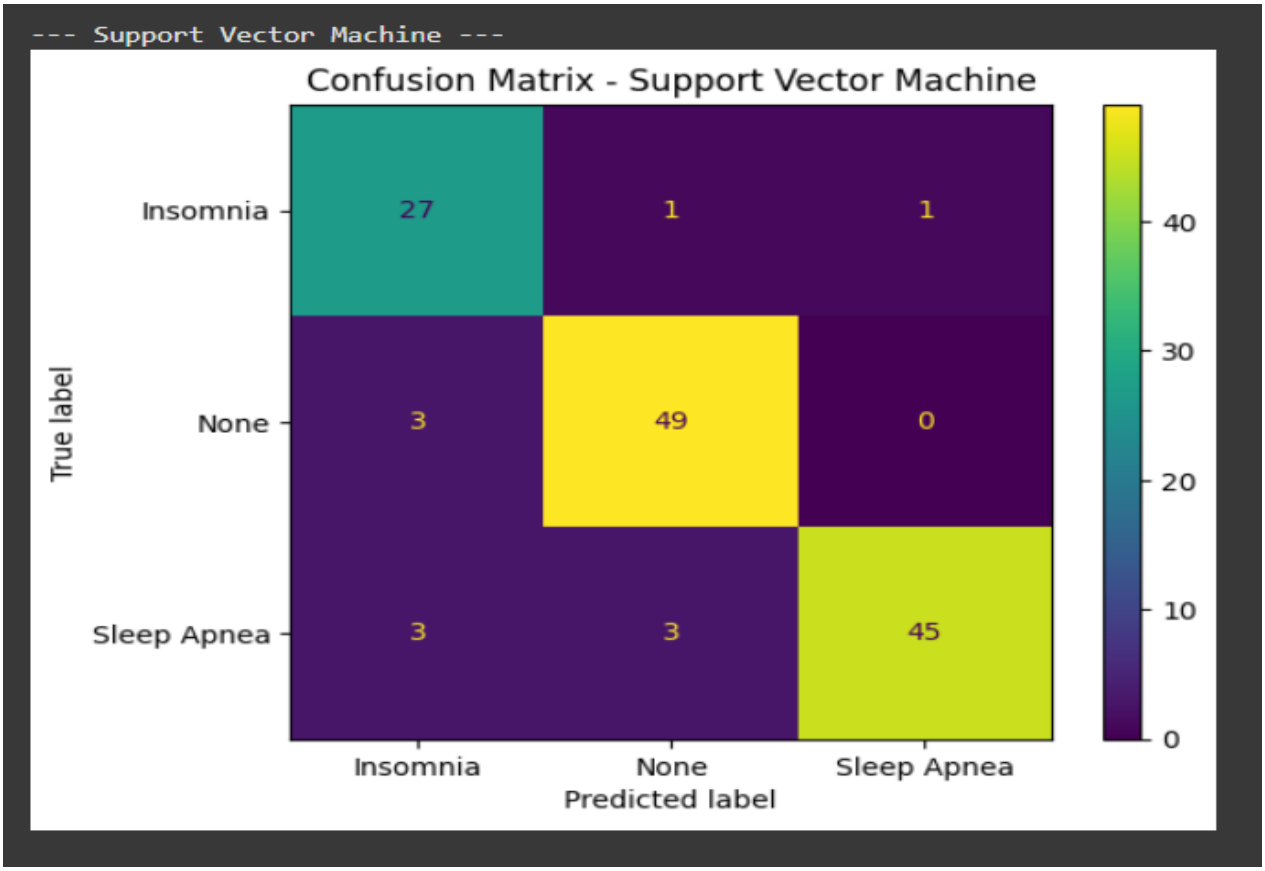
CHAPTER 5

RESULTS

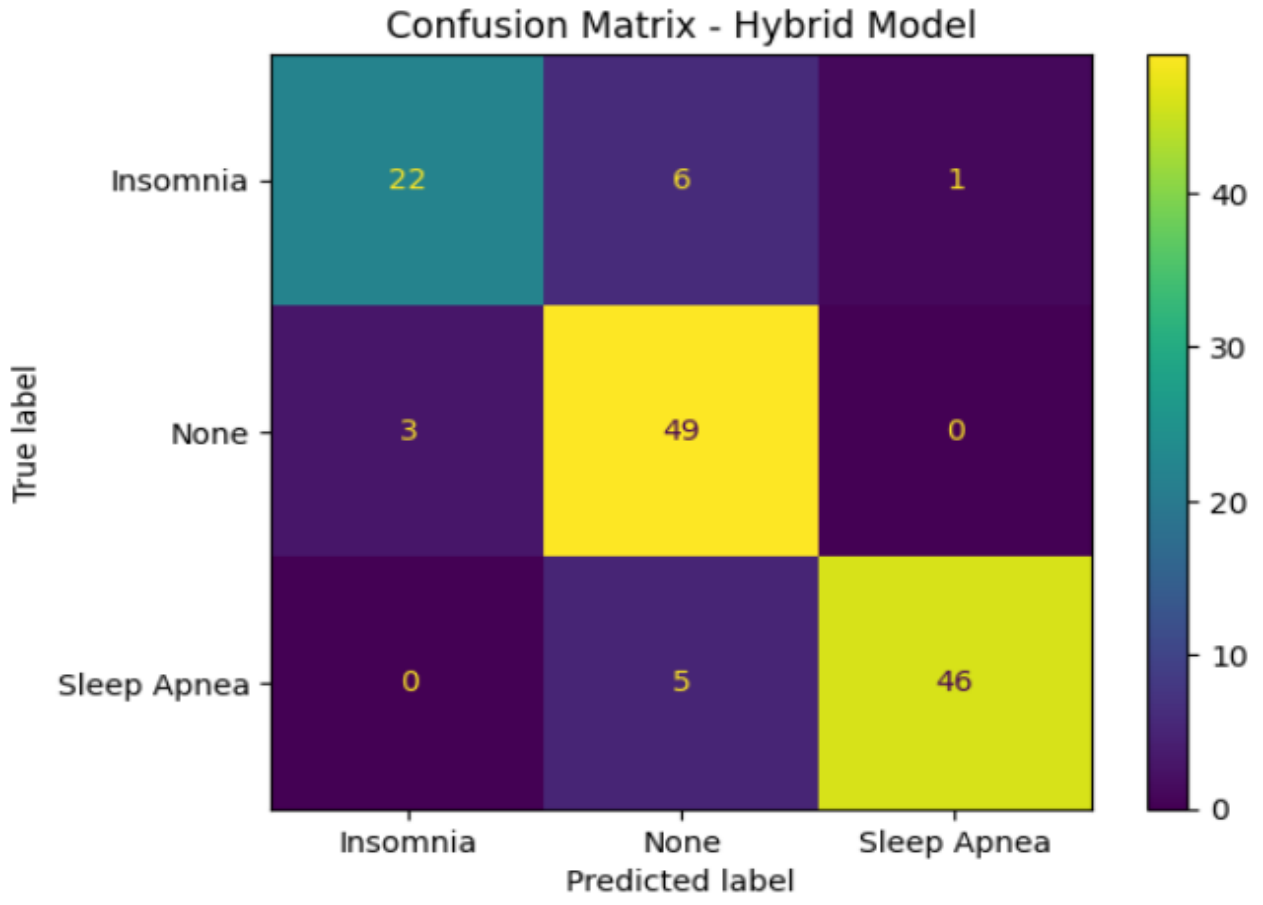


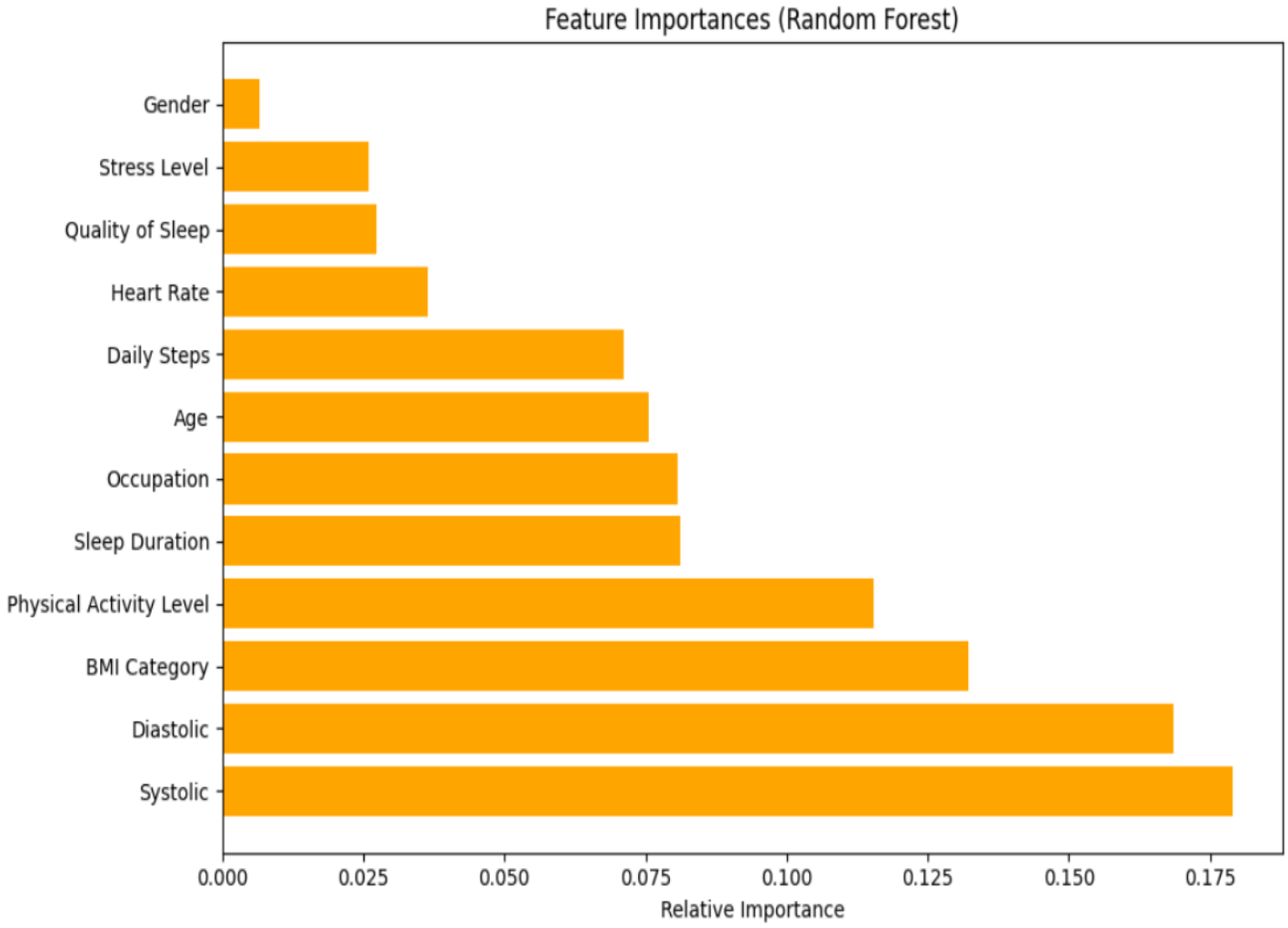



Model Performance Comparison
Accuracy
1.0
0.8
0.6
0.4
0.2
0.0
Logistic Regression
Random Forest
SVM
Hybrid
Model
Logistic Regression: 0.89
Random Forest: 0.93
SVM: 0.92
Hybrid: 0.89


--- Support Vector Machine ---
Confusion Matrix - Support Vector Machine
Insomnia
None
Sleep Apnea
True label
27
1
1
3
49
0
3
3
45
40
30
20
10
0
Insomnia
None
Sleep Apnea
Predicted label

```
--- Hybrid Model ---
Accuracy: 0.8863636363636364
              precision    recall  f1-score   support

           0       0.88      0.76      0.81        29
           1       0.82      0.94      0.88        52
           2       0.98      0.90      0.94        51

    accuracy                           0.89       132
   macro avg       0.89      0.87      0.88       132
weighted avg       0.89      0.89      0.89       132
```





Logistic Regression Prediction: None
Random Forest Prediction: None
SVM Prediction: None
Hybrid Model Prediction: None
Actual Presence of Disorder: None

	Gender	Age	Occupation	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	BMI Category	Heart Rate	Daily Steps	Systolic	Diastolic	LR Prediction	RF Prediction	SVM Prediction	Hybrid Prediction
0	1	35	2	7.5	7	60	8	0	70	10000	120	80	None	None	None	None

CHAPTER 6

Learning Outcome

1. **Understanding of Machine Learning Techniques**
   A critical learning outcome is understanding the different machine learning algorithms and how these algorithms can be utilized to predict sleep disorders. While working with models like Logistic Regression, Random Forest, Support Vector Machine (SVM), and Naive Bayes allows the learner to experience working hands-on to pick the best algorithm to classify. Hyperparameter tuning and modeling optimization will help strengthen knowledge of enhancing model efficiency whilst minimizing overfitting, which is critical in ensuring accurate prediction in a healthcare setting.
2. **Mastery of Data Preprocessing Techniques**
   The successful implementation of a model depends upon the appropriate preprocessing of data. During the data prep phase there are several activities that learners will engage in, such as cleaning the data, creating categorical features into numerical encoded features, normalizing numeric features, and SMOTE balancing the various classes. Through completing these activities, learners become more competent at processing real datasets, which are noisy and inconsistent by nature. When learners demonstrate proficiency with these techniques, they can provide a quality model input, which will significantly enhance model accuracy and generalizability.
3. **Enhanced Data Analysis and Visualization Skills**
   As part of the project, students implement a variety of data analysis and visualization techniques to interact with the data set and find patterns. Using vizularization libraries such as matplotlib and seaborn give students experience in making graphs and plots, to gain insights into the distribution of the data and the relationship of the features. The ability to visualize and analyses/interepret the data is essential to make informed decisions regarding feature selection and evaluating models..
4. **Proficiency in Model Evaluation and Validation**
   A key learning outcome is being able to evaluate model performance using several evaluation metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. When learners apply cross-validation techniques, they ensure their models are robust and generalize well to new unseen data. This ability to evaluate and make sense of model results allows learners to choose the best model for use in healthcare applications.
5. **Problem-Solving and Critical Thinking**
   While modeling is actively being implemented, students learn as they experience data quality, feature selection, tuning, and model performance challenges. Through iterative processes of assessing and improving the model, students develop critical thinking by working to improve predictive accuracy, developing a disposition to improve real-world outcomes.
6. **Real-World Application and Deployment Skills**
   In addition to model training and evaluation, learners are also training in getting the model ready for deployment. This means they are also putting their model into apps or APIs - so the predictive tools can be made available to healthcare providers. Finally, learners are also going to experience setting up performance monitoring - to understand how to assess the model's performance after deployment - a key skill that healthcare settings will demand in industry..
7. **Ethical and Responsible AI Practices**
   This project underscores the ethical implications of implementing machine learning models in healthcare. Learners have insight into the need for transparency and interpretability, particularly when using sensitive medical information. Ethical considerations, such as maintaining patient confidentiality and developing trustworthy, reliable models that health experts can use to make decisions, are emphasized.
8. **Building Confidence in Predictive Modeling for Healthcare**
   Success with this project boosts confidence in learner's ability to use machine learning methods to work through healthcare data. With a thorough experience of the complete machine learning pipeline from data collection through model deployment, learners are now ready to approach similar predictive modeling tasks in healthcare or any data science project..

PROJECT IMPACT AND FUTURE SCOPE

The sleep disorder prediction model can improve healthcare greatly by helping clinicians make early identification of patients at high risk for sleep disorders. This model can take advantage of machine learning to predict the potential occurrence of any sleep disorder; this prediction also comes with clinical insight to help with decision-making. This transparency will help build trust back with healthcare providers because know how the model is making its predictions. The earlier a prediction can be made the earlier a doctor can take action to look for the sleep disorder and implement preventative measures and plans for specific treatment that may improve outcomes. This also helps improve stress to the overall healthcare system and reduces strain on our clinicians and physicians.

In the future, the prediction model could be improved by looking into using additional forms of data and documentation like genomics, previous habits affecting lifestyle (e.g. alcohol, distances walked, monitor heart rate, etc.) or possibly all medical documentation; use as many forms and pieces of data as possible will increase conciseness and prediction. If the prediction models can continuously improve without continual re-training, then trust and reliability will follow. This would require planning on convenience of continuous use using deep learning techniques, but maybe include patient access to sleep disorder medical images that allow conventional diagnostics. Finally, ease of use, mobile apps, and other peripheral approaches will allow the integration within healthcare settings and will allow usage as frequently as required. It is also critical for clinicians to be assured of data privacy as well as ensuring the properties of fairness for all populations to account for ethical responsibilities.

CONCLUSION

To sum up, the implementation of the sleep disorder prediction model using machine learning is effective in providing a valid, data-driven approach to early diagnosis and risk evaluation in a healthcare context. Many machine learning algorithms were used to develop predictive models, such as Logistic Regression, Random Forest, Support Vector Machine (SVM), and a hybrid model, to evaluate the potentiality to sleep disorder by taking into account patient features..

The model evaluation results indicated a strong performance for all algorithms. The Random Forest model had the highest accuracy at 93.18%. The SVM came second at 91.67% and Logistic Regression at 89.39%. The Hybrid model had good performance at 88.64%, which was slightly lower than the three traditional supervised learning algorithms. The precision, recall, and F1-scores for each of the models provided strong evidence of the capability to detect the presence of sleep disorders with significant effectiveness. The Random Forest model had high precision and recall, especially for predicting the presence of sleep disorders indicating it is the most reliable model to use for the purpose of determining sleep disorder presence.

The steps of preprocessing data, such as missing values management, normalization, encoding, and SMOTE application for class balancing, enabled a level of confidence in data quality and articulated accuracy of the model. Then, with rigorous evaluation with performance metrics, such as accuracy, precision, recall, and F1-score, along with confusion matrices and cross-validation, the reliability and generalizability of the models were made trustworthy.

The hybrid model, which utilizes strengths of different models, was designed to provide equitable predictions on the many disorder categories and produced slightly worse accuracy than individual models. Even though worse, it will be an important contribution for modelling for varying prediction needs.

Deployment-wise, these models are prepared to be deployed into healthcare settings through APIs (applications that interface with other software application) or web applications to make real predictions in real time. Thinking about continuous monitoring strategies will be key to taking measures to keep the model performing well and find any drifts over time..

This successful project highlights the implications of machine learning's transformative potential in the field of healthcare, providing a predictive capability to enhance clinicians' decision-making processes. It also represents an area of ethical consideration such as adhering to privacy, security and confidentiality in the context of patient data, and inclusion of explanations about model predictions. Overall, the current work represents a stepping stone towards integrated machine learning-based predictive tools into healthcare systems, and improving patient outcomes through proactive management of sleep disorders..

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