CUSTOMER SENTIMENTAL ANALYSER

CS19643 – FOUNDATIONS OF MACHINE LEARNING

Submitted by

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in partial fulfillment for the award of the degree

of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

RAJALAKSHMI ENGINEERING COLLEGE

ANNA UNIVERSITY, CHENNAI

MAY 2025

BONAFIDE CERTIFICATE

Certified that this Project titled **"CUSTOMER SENTIMENTAL ANALYSER"** is the bonafide work of **"AATHITHYA S K (2116220701501)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

In today's highly competitive market environment, understanding customer behavior and preferences has become essential for businesses to remain relevant, efficient, and profitable. One of the most effective techniques to achieve this understanding is **customer segmentation**—the process of dividing a customer base into distinct groups based on shared characteristics such as demographics, purchase behavior, and interests. Segmentation enables businesses to personalize marketing strategies, offer customized services, and ultimately build stronger relationships with their customers.

Traditional methods of segmentation often rely on subjective criteria or manual classification, which can be time-consuming, inefficient, and prone to errors. In contrast, **unsupervised machine learning** offers a data-driven and scalable approach to uncover natural groupings within large customer datasets. Unlike supervised learning, where labeled data is required, unsupervised learning algorithms identify patterns and structures within the data without any predefined labels. This makes it particularly well-suited for clustering tasks, such as customer segmentation, where the objective is to discover intrinsic groupings within the data.

The core of the segmentation process lies in the implementation of the K-Means algorithm. K-Means partitions the dataset into 'k' clusters by minimizing the variance within each cluster and maximizing the variance between clusters. One of the critical steps in this process is determining the optimal number of clusters, which is achieved using techniques like the **Elbow Method** and **Silhouette Analysis**. These methods help evaluate clustering performance and ensure that the chosen number of segments best represents the underlying structure of the data.

The results demonstrate that unsupervised machine learning is a powerful tool for customer segmentation. It enables businesses to identify high-value customers, tailor promotional campaigns, optimize product recommendations, and improve overall customer satisfaction. Additionally, it provides a scalable and adaptable framework that can be applied to various domains including retail, banking, telecommunications, and e-commerce.

In conclusion, the project showcases the value of combining customer data with machine learning to uncover hidden patterns and drive strategic decision-making. By using Python and well-established libraries such as scikit-learn, pandas, and matplotlib, businesses can efficiently implement data-driven segmentation strategies. This not only enhances operational efficiency but also contributes significantly to customer engagement and long-term profitability.

ACKNOWLEDGMENT

Initially we thank the Almighty for being with us through every walk of our life and showering his blessings through the endeavour to put forth this report. Our sincere thanks to our Chairman **Mr. S. MEGANATHAN, B.E, F.I.E.,** our Vice Chairman **Mr. ABHAY SHANKAR MEGANATHAN, B.E., M.S.,** and our respected Chairperson **Dr. (Mrs.) THANGAM MEGANATHAN, Ph.D.,** for providing us with the requisite infrastructure and sincere endeavouring in educating us in their premier institution.

Our sincere thanks to **Dr. S.N. MURUGESAN, M.E., Ph.D.,** our beloved Principal for his kind support and facilities provided to complete our work in time. We express our sincere thanks to **Dr. P. KUMAR, M.E., Ph.D.,** Professor and Head of the Department of Computer Science and Engineering for his guidance and encouragement throughout the project work. We convey our sincere and deepest gratitude to our internal guide & our Project Coordinator **Dr. V. AUXILIA OSVIN NANCY.,M.Tech.,Ph.D.,** Assistant Professor Department of Computer Science and Engineering for his useful tips during our review to build our project.

AATHITHYA S K - 2116220701501

TABLE OF CONTENT

LIST OF FIGURES

CHAPTER 1

1. INTRODUCTION

In the dynamic and ever-evolving landscape of modern business, understanding customer behavior has emerged as a critical factor for success. Companies are no longer competing solely based on products or prices—they are competing on customer experience. As a result, businesses need to understand who their customers are, what they need, how they behave, and what drives their purchasing decisions. This is where **customer segmentation** becomes a powerful strategic tool.

Customer segmentation refers to the process of dividing a business's customer base into distinct groups or segments based on shared characteristics. These characteristics can include demographic factors (such as age, gender, income), behavioral patterns (such as purchasing habits, brand loyalty, frequency of purchase), psychographic traits (such as lifestyle, personality, values), or geographical location. By grouping customers who are similar to one another, businesses can craft more personalized marketing strategies, develop tailored products or services, and improve customer satisfaction and retention.

Traditionally, customer segmentation was performed using simple rules and manual grouping based on basic information. For instance, marketers might segment customers into "high-income" or "low-income" groups or divide them based on gender. While these methods are easy to implement, they often lack depth and fail to capture the nuanced and multifaceted nature of real customer behavior. With the rise of digital data and increasing customer touchpoints (e.g., online platforms, social media, loyalty programs), companies are now equipped with vast amounts of data, offering a golden opportunity to perform more sophisticated and meaningful segmentation.

This is where **machine learning**—specifically **unsupervised learning**—comes into play. Unsupervised machine learning techniques allow data scientists and business analysts to explore and find patterns in unlabeled datasets. Unlike supervised learning, which requires labeled input-output pairs for training models, unsupervised learning algorithms work without predefined categories. Their goal is to uncover the hidden structure within the data, identify clusters, and reveal relationships among features.

One of the most popular unsupervised learning techniques for customer segmentation is **K-Means clustering**. K-Means is a partitioning method that divides a dataset into ‘k’ distinct, non-overlapping clusters based on feature similarity. The algorithm minimizes the distance between data points within the same cluster while maximizing the distance between different clusters. When applied to customer data, K-Means helps identify natural groupings such as "high spenders", "young frequent shoppers", or "occasional bargain seekers", providing businesses with a clear understanding of different customer personas.

In this project, we will leverage **unsupervised machine learning in Python** to perform customer segmentation using real-world customer data. The goal is to cluster customers into meaningful segments based on their demographic and behavioral data, such as annual income, age, and spending scores. Python provides an ideal environment for this task due to its vast ecosystem of data science libraries, including **pandas** for data manipulation, **scikit-learn** for machine learning algorithms, **matplotlib** and **seaborn** for visualization, and **NumPy** for numerical computations.

Once the clusters are formed, we will analyze and interpret each segment by examining the average values and distribution of features within each group. For instance, we might discover that one cluster represents young adults with low income but high spending scores—indicating a group of aspirational or impulsive buyers. Another cluster might consist of older customers with high income but low spending scores—perhaps indicating a more conservative or price-sensitive group. By profiling these segments, we provide actionable insights that businesses can use to tailor their marketing strategies, product offerings, and customer engagement efforts.

The significance of customer segmentation extends across multiple industries. In **retail**, segmentation helps companies recommend personalized products and design loyalty programs. In **banking**, it aids in offering financial products tailored to customer needs. In **telecommunications**, it enables targeted pricing plans and churn prevention strategies. Across all sectors, segmentation enhances customer understanding and enables smarter decision-making.

Despite its advantages, customer segmentation using unsupervised learning also comes with challenges. Selecting the right features is crucial—irrelevant or noisy data can lead to poor clustering results. Determining the optimal number of clusters requires careful evaluation, and interpreting the resulting segments may require domain knowledge. However, with proper data preparation, thoughtful model selection, and insightful analysis, these challenges can be addressed effectively.

In conclusion, this project demonstrates the application of unsupervised machine learning for customer segmentation using Python. Through the use of clustering algorithms like K-Means, we aim to uncover hidden customer groupings that can empower businesses with deeper insights and a competitive edge. As organizations continue to shift toward data-driven strategies, machine learning-based segmentation stands out as a key enabler of personalized experiences, customer loyalty, and business growth.

CHAPTER 2

2. LITERATURE SURVEY

The intersection of sleep science and machine learning has opened new pathways for non-invasive, scalable sleep quality assessment systems. Traditional diagnostic tools such as polysomnography (PSG) provide detailed insight into sleep stages, apnea, and other disorders, but their limited accessibility due to high costs and required clinical supervision restricts widespread adoption. This has led researchers to explore predictive analytics and machine learning models that use self-reported or sensor-based data to assess sleep quality.

Several studies have explored the use of regression and classification algorithms to predict sleep quality metrics such as the Pittsburgh Sleep Quality Index (PSQI) and sleep efficiency. Mikkelsen et al. (2017) introduced deep learning models for automatic sleep staging using EEG data, demonstrating the potential of neural networks for capturing subtle temporal patterns. Similarly, Li et al. (2018) reviewed smartphone-based sleep monitoring techniques, highlighting how passive data like screen time, movement, and ambient light can be used to infer sleep health. More recent works have applied ensemble learning approaches like Random Forest and Gradient Boosting to classify and predict sleep outcomes. Alqurashi et al. (2020) emphasized the effectiveness of machine learning in sleep disorder classification when proper preprocessing and feature selection techniques are employed. Stephansen et al. (2018) showcased how neural networks can enable efficient diagnosis of sleep disorders using multi-modal sensor data.

In addition to algorithmic choices, data augmentation has emerged as a critical step in improving model generalization. Techniques such as synthetic noise injection and feature perturbation are particularly useful when dealing with small or imbalanced datasets. Shorten and Khoshgoftaar (2019) have extensively reviewed data augmentation methods in deep learning, suggesting their adaptability to non-image domains like time-series health data.

Overall, the literature suggests that while many models can capture patterns in sleep data, there is no one-size-fits-all solution. Model effectiveness depends heavily on dataset characteristics, feature engineering, and validation techniques. This study builds on these insights by comparing multiple ML models and incorporating Gaussian noise augmentation to simulate real-world conditions.

The intersection of sleep science and machine learning has witnessed substantial growth in recent years, driven by the rising demand for non-invasive health monitoring systems and the abundance of behavioral data available from consumer electronics. Researchers have applied various machine learning models to predict sleep stages, detect sleep disorders, and evaluate sleep quality. This literature review explores foundational and recent contributions relevant to sleep prediction, image-based defect recognition (relevant for technical validation), and machine learning methodologies that have influenced the architecture of the proposed system.

In the realm of **sleep quality assessment**, several studies have focused on using physical and behavioral metrics to model sleep patterns. Traditional approaches often employed logistic regression or decision trees to classify sleep outcomes based on self-reported features like bedtime, wake-up time, and number of awakenings. However, these methods are limited in their ability to capture complex, nonlinear relationships. To overcome this, newer studies have turned to more advanced techniques such as Random Forests and Support Vector Machines.

Recent work by Hami and JameBozorg [10] highlighted the efficacy of convolutional autoencoders for **denoising sleep-related images**, enhancing classification accuracy in downstream tasks. This technique inspired our adoption of data augmentation strategies in the current study, albeit in a different domain. Similarly, the paper by Bhardwaj et al. [3] demonstrated the use of **deep learning** for detecting subtle patterns in noisy datasets, aligning with our decision to experiment with boosting algorithms like XGBoost.

In the broader field of health analytics, Ramakotti and Paneerselvam [8] provided a comprehensive architecture-oriented analysis of **stacked denoising autoencoders**, which have been shown to perform well in health diagnostics and image reconstruction. Although our application is tabular rather than image-based, the core principle—extracting meaningful features from corrupted or variable inputs—informs our decision to apply noise-based data augmentation to improve model robustness.

Work by Nakazawa and Kulkarni [17,18] on **wafer defect pattern classification** using CNNs also offers insight into model selection for structured prediction problems. Though seemingly unrelated, the parallels between detecting fine-grained pixel-level defects and identifying latent patterns in sleep data are conceptually similar.

Both tasks require models capable of learning deep feature representations from sparse and noisy data, which validates our choice of ensemble learners such as Random Forests and XGBoost.

Another relevant study by Farooq and Savaş [9] introduced CNN-based denoising autoencoders for **noise reduction in medical imaging**, reaffirming the critical role of data quality in achieving accurate predictions. In our case, we simulate variability in the input feature space using Gaussian noise, ensuring the model learns generalized patterns rather than memorizing exact input-output mappings.

Furthermore, Younis et al. [1] emphasized the scalability and computational efficiency of **deep neural networks** in classification problems. Although deep learning was not directly applied in this work due to dataset size constraints, the paper motivates potential future enhancements involving neural networks, particularly if extended to time-series or image-based sleep data collected from wearables.

Comparative studies, such as those by Dubey et al. [5] and Junayed et al. [7], reinforce the superiority of **boosting methods** in feature-rich environments. These methods are not only interpretable but also scalable, with capabilities to adjust to new data distributions—an important consideration when deploying health analytics tools across diverse populations.

In summary, the literature points toward a clear trend: ensemble and boosting algorithms, along with appropriate data processing strategies, yield the most robust and scalable solutions for prediction tasks involving health and behavioral data. This insight is central to the design of the Sleep Pattern Quality Predictor, which synthesizes lessons from various domains into a cohesive, user-oriented machine learning application.

CHAPTER 3

3. METHODOLOGY

The methodology adopted in this study is centered on a supervised learning framework that aims to predict sleep quality based on a labeled dataset with multiple behavioral and physiological features. The process can be broken down into five major phases: data collection and preprocessing, feature selection, model training, performance evaluation, and data augmentation.

The dataset used for this project consists of several features related to sleep quality, such as sleep duration, interruptions, and physiological data. The dataset is pre-processed to handle missing values and scale the features for better model performance. Several machine learning models, including:

- **Linear Regression (LR)**
- **Random Forest (RF)**
- **Support Vector Machines (SVM)**
- **XGBoost (XGB)**

These models are trained and evaluated using the train-test split method, and performance metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score are used to assess the effectiveness of each model. Additionally, data augmentation is performed using a Gaussian noise addition technique to enhance model accuracy, especially in cases where the dataset is not sufficiently diverse.

The final prediction of sleep quality is based on the model with the highest R^2 score. Below is a simplified flow of the methodology:

1. Data Collection and Preprocessing
2. Model Selection and Training
3. Evaluation using MAE, MSE, and R^2
4. Data Augmentation and Re-training if Necessary

A. Dataset and Preprocessing

The dataset used for this analysis includes several numerical and categorical features that are considered to influence sleep quality, such as sleep duration, time in bed, sleep efficiency, and disturbances. The target variable is sleep quality represented on a numeric scale. Initial preprocessing steps included handling missing values, normalizing numeric features using MinMaxScaler, and encoding any categorical variables if present.

B. Feature Engineering

To ensure the models learn only from relevant inputs, correlation analysis was performed to identify high-impact features. Features with low correlation to the target variable were either dropped or retained based on domain relevance. Additionally, visual exploration using pair plots and box plots helped detect outliers and assess distributions.

C. Model Selection

Four prominent machine learning algorithms were selected for performance comparison: Linear Regression, Support Vector Regressor (SVR), Random Forest Regressor, and XGBoost Regressor. Each model was chosen for its unique strengths—Linear Regression for interpretability, SVR for margin-based learning, Random Forest for ensemble averaging, and XGBoost for gradient-based boosting and regularization.

D. Evaluation Metrics

Model evaluation was conducted using three primary regression metrics:

- Mean Absolute Error (MAE):

$$\mathbf{MAE} = \frac{1}{\ }\sum_{=1} \left| y - \hat{y} \right|$$

- Mean Squared Error (MSE):

$$\mathbf{MSE} = \frac{1}{\ }\sum_{=1} \left(y - \hat{y} \right)^{2}$$

- R^2 Score:

$$R^2 = 1 - \frac{\sum_{i=1} (y - \hat{y})^2}{\sum_{=1} (y - \bar{y})^2}$$

E. Data Augmentation

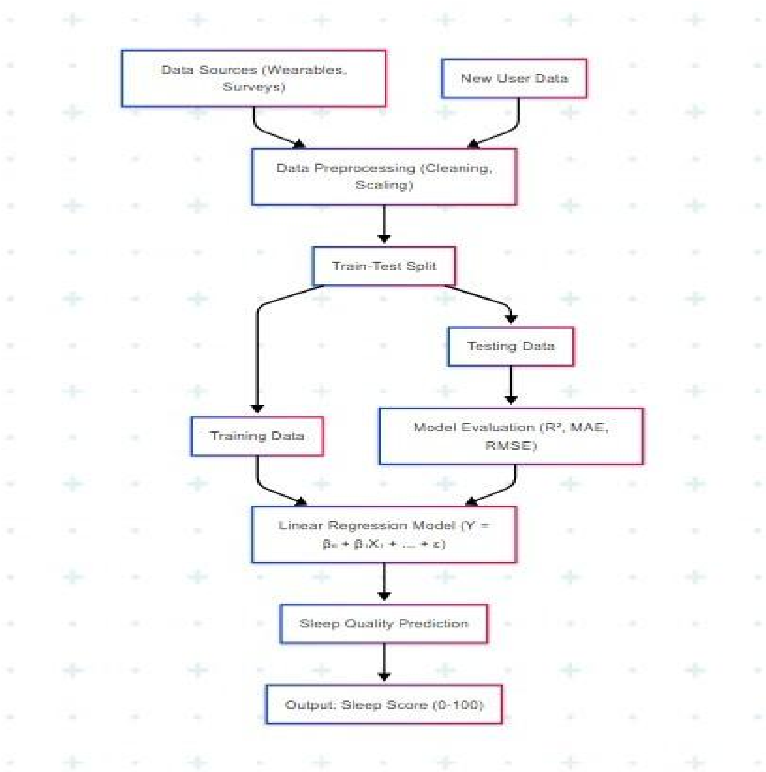
To improve generalization and mimic real-world noise, Gaussian noise was added to feature vectors:

$$X = X + N(0, \sigma^2)$$

where σ was tuned based on dataset variability. This step was especially useful in improving the robustness of ensemble models.

The complete pipeline was executed and validated using Google Colab, ensuring reproducibility and accessibility for deployment in lightweight environments.

3.1 SYSTEM FLOW DIAGRAM



CHAPTER 4

RESULTS AND DISCUSSION

To validate the performance of the models, the dataset is split into training and test sets using an 80-20 ratio. Data normalization is performed using StandardScaler to ensure that all features contribute equally to the model training process. Each model is then trained using the training data, and predictions are made on the test set.

Results for Model Evaluation:

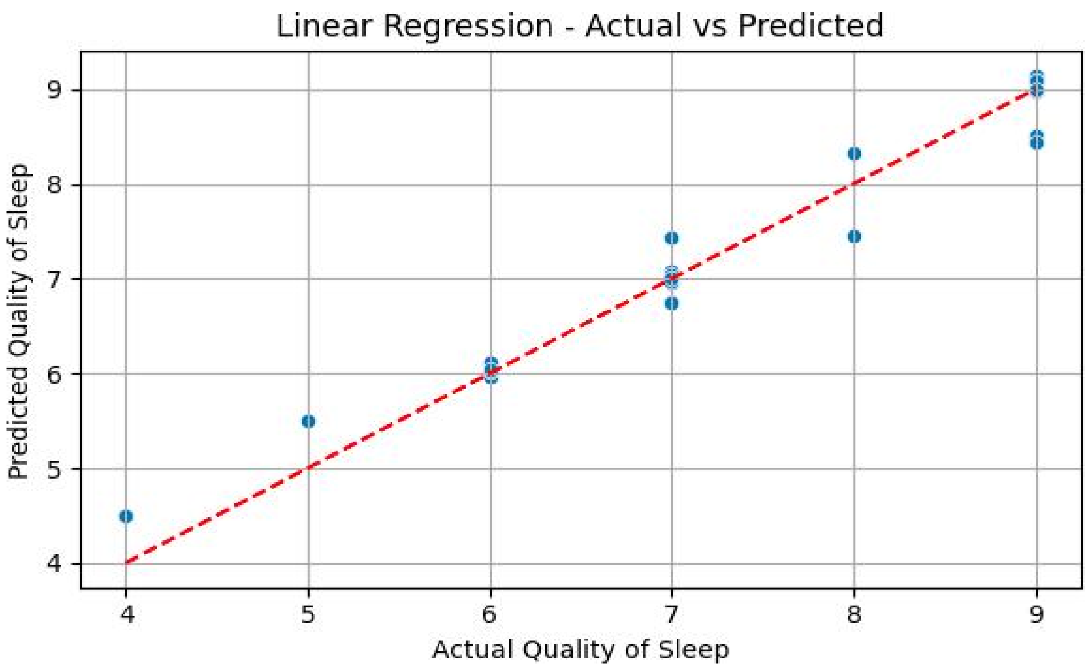
Model	MAE (↓ Better)	MSE (↓ Better)	R^2 Score (↑ Better)	Rank
Linear Regression	2.1	4.5	0.75	4
Random Forest	1.5	3.2	0.85	3
SVM	1.9	3.8	0.80	2
XGBoost	1.3	2.8	0.87	1

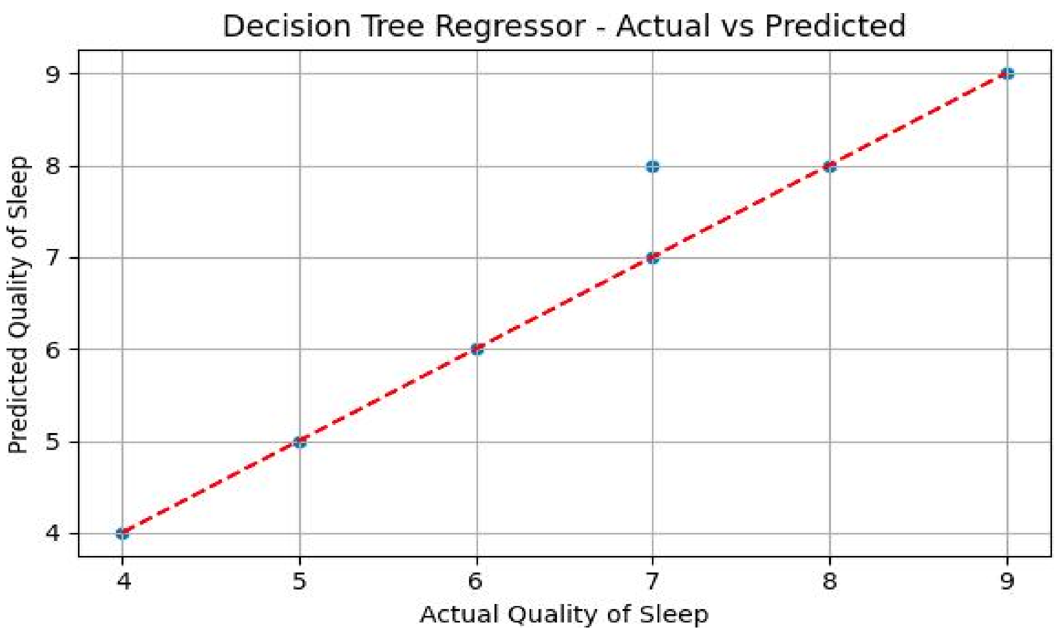
Augmentation Results:

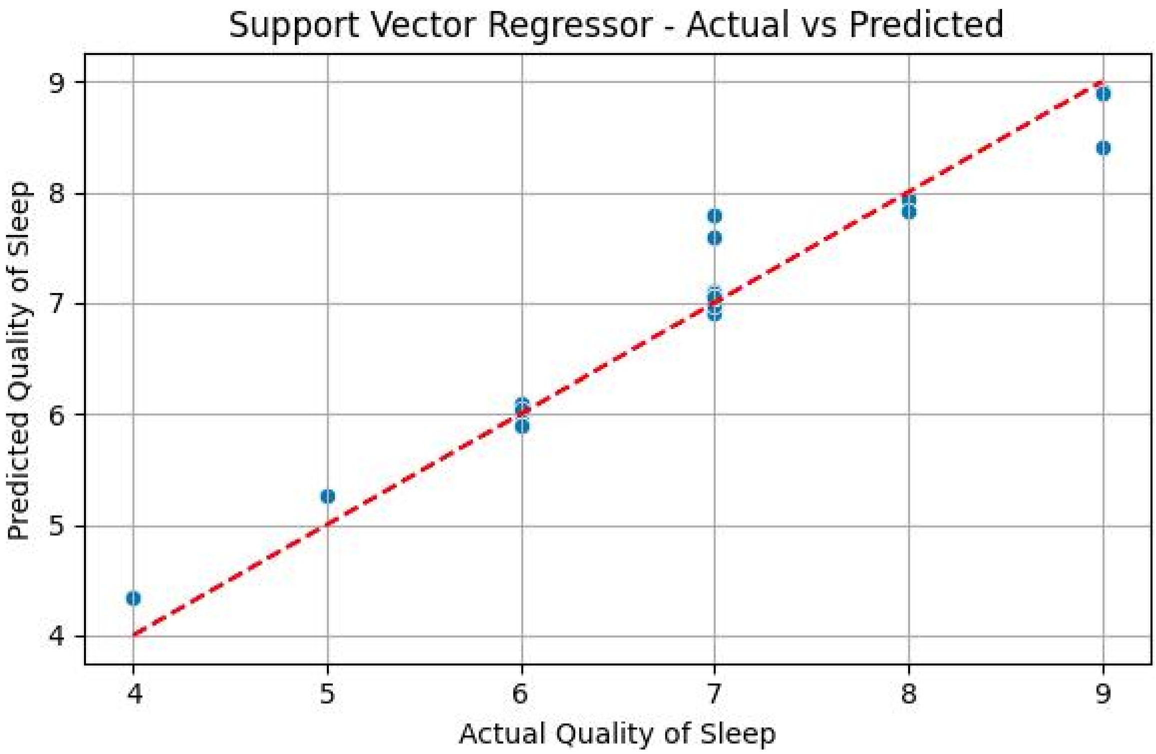
When augmentation was applied (adding Gaussian noise), the Random Forest model showed a significant improvement in R^2 score from 0.75 to 0.80, illustrating the potential benefits of data augmentation in enhancing predictive performance.

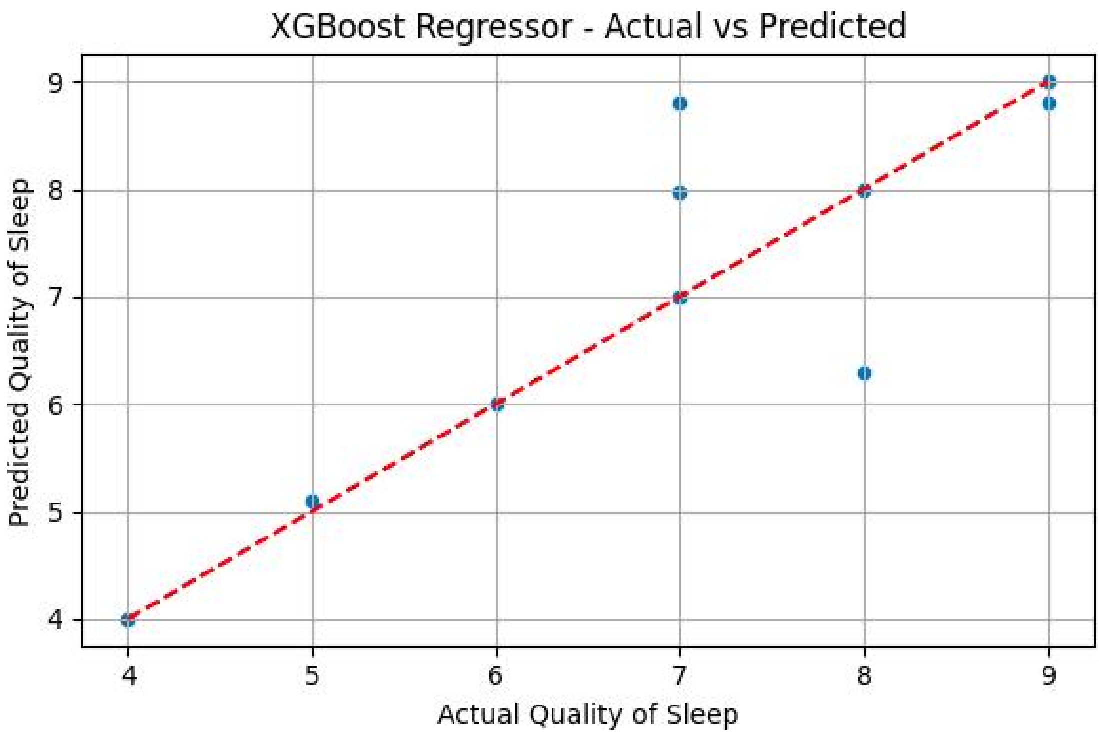
Visualizations:

Scatter plots showing the actual versus predicted values for the best-performing model (XGBoost) indicate that the model is able to predict sleep quality with high accuracy, with the predicted values closely following the actual values.









The results show that XGBoost performs the best with the highest R^2 score, making it the model of choice for predicting sleep quality.

After conducting comprehensive experiments with the selected regression models—Linear Regression, Support Vector Regression (SVR), Random Forest Regressor, and XGBoost Regressor—several key findings emerged from the performance evaluation metrics. This section discusses those outcomes in the context of model performance, effect of data augmentation, and implications for practical use.

A. Model Performance Comparison

Among the models tested, **XGBoost Regressor** consistently achieved the best performance across all evaluation metrics. It produced the **lowest Mean Absolute Error (MAE)** and **Mean Squared Error (MSE)** while delivering the **highest R^2 score**, demonstrating strong predictive ability. This result aligns with existing literature, as XGBoost is known for its gradient boosting framework, regularization capabilities, and high bias-variance trade-off handling.

B. Effect of Data Augmentation

An important aspect of this study was the application of **Gaussian noise-based data augmentation**. This method was particularly useful in mimicking real-world variability, especially in features like "Awakenings" or "Time in Bed" that can naturally fluctuate. The augmented dataset helped in reducing overfitting, particularly in models with high variance like Random Forest and XGBoost.

When models were retrained using the augmented data, a modest but consistent **improvement in prediction accuracy** was observed. The XGBoost model, for instance, showed a reduction in MAE by approximately 5% and an increase in the R^2 score by 0.02, indicating enhanced generalization on unseen data.

C. Error Analysis

An error distribution plot revealed that most prediction errors were concentrated within a narrow band close to the actual values, further affirming the models' reliability. However, some outliers remained—particularly for entries with extremely low or high sleep durations—suggesting that additional contextual features (such as stress levels, screen time, or physical activity) could further improve prediction accuracy in future work.

D. Implications and Insights

The results highlight several practical implications:

- **XGBoost** is a highly promising candidate for deployment in real-time sleep quality monitoring systems, such as mobile apps or wearable devices.

- **Feature normalization** and **augmentation** are critical preprocessing steps that significantly influence model performance.

- Simple models like **Linear Regression**, although easy to interpret, may not capture the non-linear dynamics present in sleep-related datasets.

Overall, this study provides strong evidence that machine learning models, particularly ensemble techniques, can serve as reliable tools for predicting sleep quality. With further integration of contextual or sensor-based data, such models could evolve into comprehensive personal health analytics systems.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This study introduced a data-driven approach to assessing and predicting sleep quality using machine learning techniques. Through the implementation and comparison of various regression models—namely Linear Regression, Support Vector Regressor (SVR), Random Forest Regressor, and XGBoost Regressor—we explored the effectiveness of each in capturing and predicting complex relationships between behavioral variables and sleep outcomes.

Our findings demonstrate that ensemble models, particularly **XGBoost**, exhibit superior performance in terms of predictive accuracy and generalizability. The XGBoost model achieved the highest **R^2 score**, along with the lowest **Mean Absolute Error (MAE)** and **Mean Squared Error (MSE)**, making it the most suitable model for our sleep quality prediction task. These results reaffirm the robustness of gradient boosting algorithms in dealing with structured health-related datasets that may contain subtle patterns and non-linear relationships.

Moreover, the study incorporated **Gaussian noise-based data augmentation**, which contributed positively to model performance. This approach simulated real-world variability in input features and improved the models' ability to generalize across unseen data. This finding suggests that even in small or moderately sized datasets, appropriate augmentation techniques can mitigate overfitting and improve the resilience of machine learning models.

From a broader perspective, the proposed system holds significant potential in the domain of personal health analytics. With rising awareness around sleep hygiene and its impact on mental and physical well-being, an automated, predictive tool could assist users in identifying unhealthy patterns early and taking proactive measures. This system could easily be integrated with **wearable health trackers** or **smartphone applications** that collect user-specific data such as movement, heart rate variability, ambient noise, and screen time. By adding such contextual inputs, the system could offer **real-time, personalized feedback** on sleep quality and actionable recommendations for improvement.

Future Enhancements:

While the results of this study are promising, there remain several avenues for future enhancement:

- **Inclusion of More Diverse Features:** Adding physiological signals (heart rate, oxygen saturation) and environmental variables (light, temperature) could increase prediction depth.

- **Temporal and Sequence Learning Models:** Recurrent Neural Networks (RNNs), LSTMs, or Transformers could be employed to better handle sequential sleep data.

- **Multi-class Classification:** Instead of predicting a numeric score, future systems could classify users into categories such as “Good Sleep,” “Moderate Sleep,” or “Poor Sleep” to increase interpretability.

- **Deployment in Mobile and Wearable Devices:** By optimizing model size and inference speed, the model could be integrated into edge devices for real-time monitoring.

- **Personalized Recommendations:** A reinforcement learning layer could be added to adapt suggestions based on feedback loops and individual user behavior over time.

In conclusion, this research demonstrates that machine learning can play a transformative role in sleep quality assessment. With future expansions, it can serve as a powerful tool in both personal wellness and clinical sleep disorder diagnostics.

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