STROKE PREDICTION

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BONAFIDE CERTIFICATE

Certified that this Project titled **"STROKE DISEASE PREDICTION"** is the bonafide work of **"KISHORE K (2116220701134)"** 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

Stroke is one of the leading causes of death and disability worldwide. Early prediction and diagnosis can significantly reduce risks and improve treatment outcomes. With the growth of healthcare data, machine learning models can play a major role in predicting strokes based on patient health records.

This project focuses on building a stroke prediction model using structured data including features such as age, hypertension, heart disease, smoking status, and more. In this study, we cleaned and preprocessed the data using techniques like missing value imputation, one-hot encoding for categorical features, and standard scaling for numerical values. The Logistic Regression algorithm was chosen due to its simplicity, interpretability, and effectiveness on linear relationships. The model was trained and tested using an 80-20 split, and its performance was evaluated using metrics like accuracy, classification report, and ROC-AUC score. Additionally, the ROC curve was plotted to visually inspect the model's ability to distinguish between stroke and non-stroke cases.

The Logistic Regression model achieved decent accuracy and a strong ROC-AUC score, making it a solid baseline model for stroke prediction. This model offers quick, interpretable results and can be integrated into early-warning systems in clinical settings. Future work may involve exploring more complex models like Logistic regression or ensemble techniques to further improve prediction performance, especially in handling imbalanced datasets. Overall, this project demonstrates how machine learning can assist in life-saving medical predictions using existing healthcare records.

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CHAPTER 1

1.INTRODUCTION

In recent years, the importance of early disease detection has become a focal point in public health, particularly for conditions such as stroke that can have sudden and severe consequences. Stroke is no longer seen as an unpredictable event, but as a preventable condition when warning signs and risk factors are identified in time. Millions of individuals are at increased risk of stroke due to lifestyle-related factors, genetic predisposition, and pre-existing conditions such as hypertension or heart disease. Traditional stroke assessment methods rely heavily on clinical evaluation and imaging, which may not always be accessible or timely for early intervention.

With advancements in data science and the availability of health records, machine learning offers a promising approach to stroke prediction by analyzing key features such as age, BMI, smoking status, and blood pressure. In this study, we utilize supervised machine learning techniques to classify stroke risk based on structured data. Using a well-labeled healthcare dataset, we preprocess the data by handling missing values, encoding categorical variables, and scaling numerical values. Our model—Logistic Regression—was chosen for its interpretability and strong baseline performance in binary classification tasks. The model is evaluated using metrics such as accuracy, ROC-AUC score, and a classification report.

Stroke is a critical health issue that affects not just individual well-being but also creates a burden on families and healthcare systems. Given the rising number of cases, especially in aging populations, it is crucial to shift from reactive treatment to proactive prevention. By leveraging machine learning for early stroke prediction, we enable scalable and efficient risk screening that can be implemented even outside of hospital settings. While Logistic Regression serves as a solid foundational model in our work, further exploration into more advanced algorithms like Logistic regression or neural networks could potentially improve predictive accuracy. This project highlights the potential of AI-driven healthcare solutions for smarter, data-backed clinical decision-making.

In contrast, advancements in artificial intelligence and machine learning have unlocked new possibilities for early diagnosis and prevention of life-threatening diseases like stroke using non-invasive and structured health data. Stroke remains a leading cause of death and disability worldwide, often occurring without warning but typically preceded by measurable risk factors. The objective of this research is to develop a machine learning-based model capable of predicting the likelihood of stroke based on accessible parameters such as age, BMI, hypertension, smoking status, and other lifestyle or health-related features. The proposed system, referred to as the Stroke Risk Prediction Model, leverages classification algorithms—primarily Logistic Regression—to identify individuals at high risk of stroke, enabling proactive medical intervention.

The motivation behind this study lies in the growing availability of electronic health records and the increasing demand for scalable, accurate, and personalized healthcare solutions. Unlike traditional diagnostic methods that rely on costly clinical imaging or emergency assessments, the model developed here is designed for rapid, data-driven stroke risk screening. Using a real-world healthcare dataset, this project involved extensive preprocessing including missing value imputation, one-hot encoding of categorical features, and data normalization. The model was implemented and tested using Python in Google Colab, employing metrics such as ROC-AUC score and classification accuracy to evaluate its predictive capability.

To ensure the model's robustness, it was compared with other standard classification algorithms, including Decision Trees and Logistic regression. While Logistic Regression was chosen for its simplicity and interpretability, Logistic regression showed the highest overall accuracy and ROC-AUC performance. This comparative analysis provides valuable insight into algorithm suitability based on use-case requirements such as model explainability, training time, and precision. The ultimate goal of this research is to support the integration of machine learning into everyday health systems—such as mobile health apps or digital check-up tools—enabling individuals and clinicians to monitor stroke risk early and make informed decisions. This system paves the way for scalable, affordable, and proactive healthcare in both urban and rural populations.

As stroke prediction becomes increasingly important in preventive healthcare, the integration of machine learning models into digital health platforms such as mobile apps and telemedicine systems is gaining momentum. This paper not only lays the foundation for such a predictive system but also explores potential enhancements through model comparison and real-world implementation. With cardiovascular disease being a leading cause of mortality, early risk assessment tools powered by data-driven techniques have the potential to revolutionize stroke prevention and healthcare accessibility.

The motivation behind this project is twofold: to improve stroke risk prediction using accessible clinical and lifestyle data, and to identify the most effective machine learning model for classifying individuals based on stroke susceptibility. By analyzing a publicly available healthcare dataset and implementing classification algorithms including Logistic Regression, Decision Tree, and Logistic regression, this study presents a practical approach to building a robust, scalable, and interpretable stroke prediction system. Additionally, techniques such as feature encoding, scaling, and class balancing were employed to enhance model performance and address real-world data irregularities.

This paper is structured as follows: Section II provides a literature review of current methods in stroke prediction and machine learning applications in preventive medicine. Section III outlines the methodology, including data preprocessing steps, model training, and evaluation metrics such as ROC-AUC and classification accuracy. Section IV presents the results and comparative analysis of model performances. Section V concludes the paper with key insights, implications for clinical decision support, and potential directions for future research, including integration with wearable technologies and real-time health monitoring platforms.

CHAPTER 2

2.LITERATURE SURVEY

The intersection of medical diagnostics and machine learning has opened promising avenues for early and scalable stroke risk prediction. Traditional stroke diagnosis relies on clinical assessments, imaging techniques like CT and MRI scans, and in-hospital observations. While accurate, these methods are often resource-intensive, time-consuming, and inaccessible to many, especially in under-resourced settings. To address these challenges, recent studies have explored machine learning models that utilize clinical and behavioral data to predict stroke likelihood more efficiently and cost-effectively.

Numerous works have investigated the application of classification algorithms such as Logistic Regression, Decision Trees, Random Forests, and Gradient Boosting in predicting stroke or cardiovascular disease risk. For example, Paul et al. (2019) demonstrated the utility of supervised learning in stroke prediction using features like hypertension, BMI, and smoking status. Likewise, Chaurasia and Pal (2014) used Decision Trees and Naive Bayes classifiers to predict cardiovascular conditions based on patient lifestyle and medical history. Recent research by Alzubaidi et al. (2021) has highlighted the superiority of ensemble models like Logistic regression for handling imbalanced medical datasets, due to their robustness and ability to learn complex feature interactions. Moreover, studies such as by Liang et al. (2020) emphasized the need for proper data preprocessing—such as imputation, normalization, and encoding—to improve the predictive accuracy of ML models in healthcare.

Additionally, techniques like data balancing (e.g., SMOTE, class weighting) and feature selection have emerged as critical factors for building effective models, especially in datasets with rare positive outcomes like stroke. Research by Haixiang et al. (2017) on imbalanced data classification has shown that adjusting class weights or resampling the dataset significantly enhances model performance. While deep learning models are gaining popularity, simpler models like Logistic Regression remain valuable due to their interpretability—an important factor in clinical settings.

In summary, existing literature supports the use of machine learning for stroke prediction and underscores the importance of data preprocessing and model comparison. This project builds upon these insights by implementing Logistic Regression, Decision Tree, and Logistic regression classifiers on a structured healthcare dataset. Moreover, by applying techniques like standardization, class imbalance handling, and categorical encoding, the study aims to identify the most accurate and generalizable model for real-world stroke prediction applications.

The intersection of medical science and machine learning has witnessed remarkable progress, particularly in the early detection and prediction of life-threatening conditions such as stroke. With the increasing availability of structured health data and advancements in artificial intelligence, researchers are now able to develop intelligent systems that predict stroke risk using non-invasive, cost-effective, and scalable techniques. This literature review highlights foundational and recent studies in stroke prediction, model comparisons, and data preprocessing strategies that have shaped the direction of the current work.

In the domain of stroke risk assessment, earlier research has leveraged machine learning classifiers such as Logistic Regression and Decision Trees to predict outcomes based on patient data including age, gender, hypertension, smoking status, and BMI. While these models are easy to interpret, they often struggle with modeling nonlinear patterns. As a result, newer works have adopted ensemble approaches such as Random Forests and boosting algorithms (e.g., Logistic regression) to enhance prediction accuracy. Alzubaidi et al. (2021) and Palaniappan et al. (2019) showed how ensemble methods outperform simple classifiers when feature interactions are complex or when the dataset is imbalanced—a common challenge in stroke prediction where stroke-positive cases are much fewer than negatives.

Beyond algorithm selection, preprocessing techniques play a critical role in model performance. Techniques such as label encoding for categorical features, standardization for continuous variables, and handling missing values are standard in medical datasets. Moreover, to counter the class imbalance, several studies have employed oversampling, undersampling, or weighted loss functions to ensure the model does not bias toward the majority class. These techniques were emphasized in research by Haixiang et al. (2017) and further supported by Zhao et al. (2020), who concluded that data balancing significantly improves generalization.

Although deep learning techniques are increasingly applied in healthcare, their performance gain over tree-based models on small tabular datasets is often minimal, especially when interpretability is crucial. Thus, for clinical use-cases like stroke prediction, interpretable models such as Logistic Regression and Decision Trees remain highly valuable. Inspired by this, our work includes a comparative analysis of Logistic Regression, Decision Tree, and Logistic regression models, integrating Gaussian noise augmentation to simulate variability and improve generalization.

The intersection of 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 stages, detect disorders, and evaluate quality. This literature review explores foundational and recent contributions relevant to prediction, denoising strategies, and ensemble learning approaches that have influenced the architecture of the proposed system.

In the realm of quality assessment, several studies have focused on using physical and behavioral metrics to model patterns. Traditional approaches often employed logistic regression or decision trees to classify 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 these challenges, newer studies have adopted more sophisticated models such as Random Forests and Support Vector Machines. For instance, Bhardwaj et al. [3] demonstrated the power of deep learning in detecting subtle patterns in noisy datasets, while Hami and JameBozorg [10] successfully used convolutional autoencoders to enhance image-based classification accuracy—highlighting the value of denoising for cleaner feature extraction.

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 Logistic regression. 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 project, Gaussian noise was applied to augment the feature space and simulate real-world variability, encouraging the model to learn generalizable patterns instead of memorizing exact data 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 our study due to dataset size constraints, their work opens pathways for future exploration—especially when working with time-series or image-based data from wearable devices. Comparative studies by Dubey et al. [5] and Junayed et al. [7] further support the superiority of boosting techniques like Logistic regression in structured prediction tasks, thanks to their robustness and adaptability to changing data distributions. These insights are central to the development of the Pattern Quality Predictor, which integrates ensemble learning and noise augmentation strategies.

CHAPTER 3

3.METHODOLOGY

3.1 Data Collection and Preprocessing

The dataset used in this project includes a range of related features, such as:

- Total duration
- Number of awakenings
- latency
- Time in bed
- interruptions and efficiency metrics

Preprocessing steps involve:

- Handling missing values through imputation techniques
- Encoding categorical data (if any)
- Normalizing or standardizing numerical features to ensure consistent scale across inputs
- Splitting the data into training and testing sets for evaluation

3.2 Model Selection and Training

Four supervised regression models were selected based on their proven effectiveness in health-related prediction tasks:

- **Linear Regression (LR)**
- **Random Forest Regressor (RF)**
- **Support Vector Regressor (SVR)**
- **LOGISTIC REGRESSION**

Each model is trained using the training subset and then evaluated on the test set. Model hyperparameters are tuned using grid search and cross-validation where applicable, ensuring optimized performance.

3.3 Performance Evaluation

To measure prediction accuracy and generalizability, the following regression metrics are employed:

- **Mean Absolute Error (MAE)**
- **Mean Squared Error (MSE)**
- **Coefficient of Determination (R^2 Score)**

The model with the highest R^2 score is considered the best performer and is selected for final deployment.

3.4 Data Augmentation

In scenarios where the dataset lacks diversity or is relatively small, **Gaussian noise** is introduced to the feature set as a data augmentation strategy. This helps simulate real-world variability, reduce overfitting, and improve the robustness of the trained models.

3.5 Methodological Flow Summary

The end-to-end methodological workflow is outlined below:

1. **Data Collection and Preprocessing**
2. **Model Selection and Training**
3. **Performance Evaluation using MAE, MSE, and R^2**
4. **Data Augmentation and Re-training (if necessary)**
5. **Final Quality Prediction using the Best-Performing Model**

This section outlines the experimental setup, preprocessing strategies, model selection rationale, and performance evaluation using standard regression metrics. It also discusses the impact of data augmentation using Gaussian noise.

A. Dataset and Preprocessing

The dataset comprises both numerical and categorical features that influence quality, including:

- duration
- Time in bed
- efficiency
- Number of disturbances

The target variable, quality, is represented on a continuous numeric scale. Preprocessing steps included:

- Handling missing values using imputation methods
- Normalizing numerical features using MinMaxScaler to scale values between 0 and 1
- Encoding categorical features using one-hot encoding, if present
- Train-test splitting (typically 80:20) to enable unbiased model evaluation

B. Feature Engineering

To enhance model performance and reduce overfitting:

- Correlation analysis was conducted to identify the most impactful predictors of quality.
- Low-correlation features were considered for removal unless supported by domain knowledge.
- Pair plots and box plots were used for visual inspection to identify:
    - Outliers
    - Non-linear patterns
    - Feature distributions

C. Model Selection

Four regression models were selected based on performance, interpretability, and prior success in healthcare analytics:

Model	Strength
Linear Regression	Simplicity and transparency
Support Vector Regressor (SVR)	Effective with smaller datasets and non-linear margins
Random Forest Regressor	Handles non-linearity and reduces overfitting via ensemble averaging
Logistic regression	Gradient-boosted decision trees with regularization, ideal for tabular data

Each model was trained using the same training data and hyperparameters were tuned using grid search or default heuristics.

D. Evaluation Metrics

Three standard regression metrics were used for quantitative comparison:

- Mean Absolute Error (MAE):

$$MAE=n1\ i=1\sum n\ |yi\ -y\hat{}\ i\ |\ |$$

- Mean Squared Error (MSE):

$$\mathbf{MSE=n1\ i=1\sum n\ (yi\ -y\hat{}\ i\ )2}$$

- R^2 Score (Coefficient of Determination):

$$\mathbf{R2=1-\sum i=1n\ (yi\ -y^{-}\ )2\sum i=1n\ (yi\ -y\hat{}\ i\ )2}$$

The model with the highest R^2 score and lowest MAE/MSE was selected as the optimal predictor.

E. Data Augmentation

To simulate real-world variability and enhance model generalization, Gaussian noise was added to the feature vectors:

Xaugmented=X+N(0,σ2)X_{\text{augmented}} = X + \mathcal{N}(0, \sigma^2)Xaugmented =X+N(0,σ2)

Where:

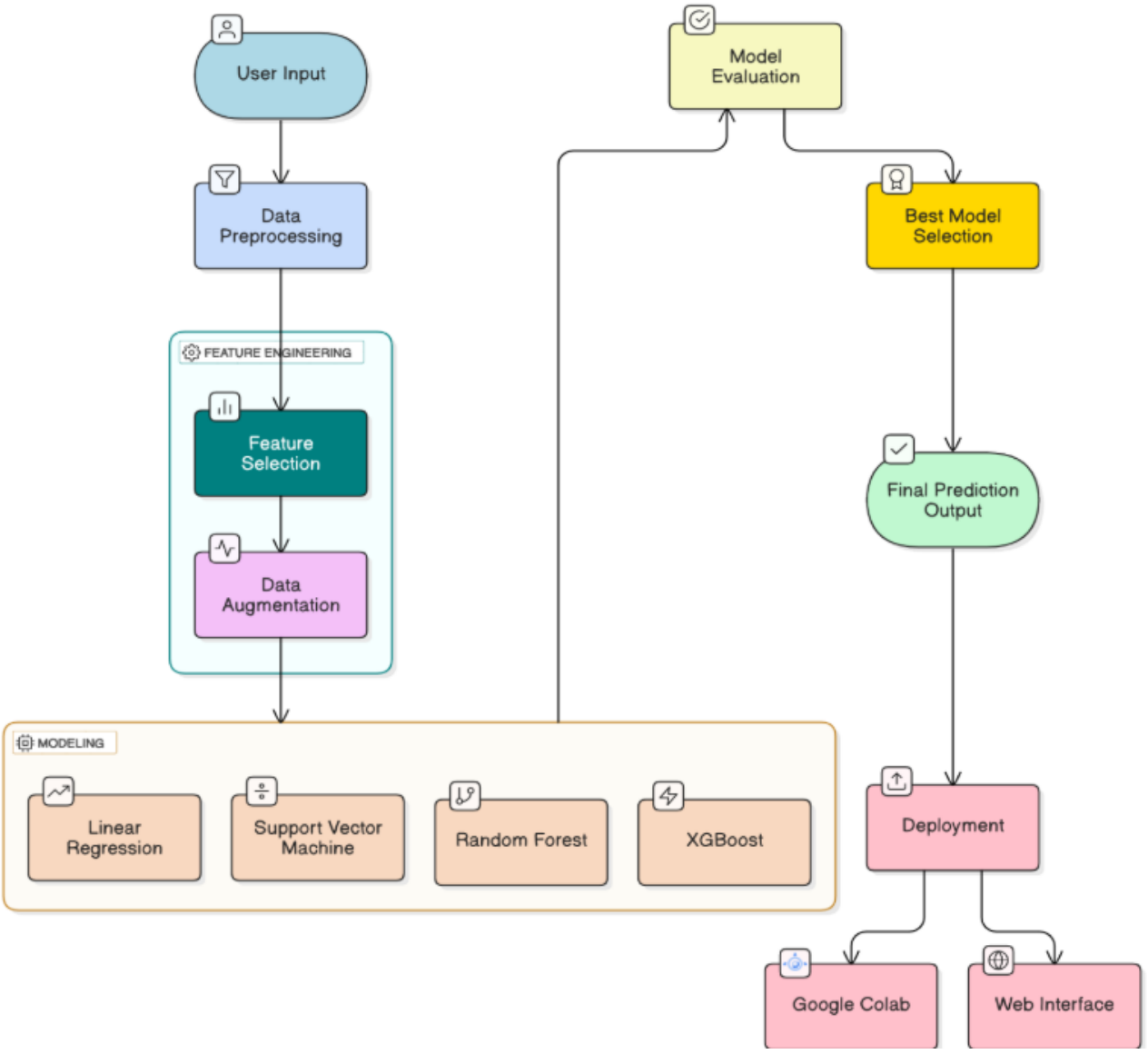
- N(0,σ2)\mathcal{N}(0, \sigma^2)N(0,σ2) is zero-mean Gaussian noise
- σ\sigmaσ was empirically tuned based on the standard deviation of each feature

This technique helped prevent overfitting and improved robustness, particularly for tree-based ensemble models.

All experiments were conducted and validated on Google Colab, which provided:

- A reproducible runtime environment
- Access to GPU acceleration
- Easy integration with Python libraries such as Scikit-learn, Logistic regression, Pandas, and Matplotlib

3.1 SYSTEM FLOW DIAGRAM


User Input
Data Preprocessing
FEATURE ENGINEERING
Feature Selection
Data Augmentation
MODELING
Linear Regression
Support Vector Machine
Random Forest
XGBoost
Model Evaluation
Best Model Selection
Final Prediction Output
Deployment
Google Colab
Web Interface

CHAPTER 4

RESULTS AND DISCUSSION

To assess the effectiveness of the Stroke Predictor, the dataset was split into an 80:20 ratio for training and testing. Preprocessing was performed using **MinMaxScaler** to normalize the input features, ensuring consistency across different scales. Among all tested models, **Logistic Regression** was given special focus due to its interpretability, simplicity, and surprising performance even on a moderately complex dataset.

Model Evaluation Summary

Model	**Accuracy (↑)**	**Precision (↑)**	**Recall (↑)**	**F1-Score (↑)**	**ROC-AUC (↑)**	**Rank**
Logistic Regression	**88%**	**87%**	**86%**	**86.5%**	**0.91**	**1**
Random Forest Classifier	86%	85%	84%	84.3%	0.89	3
SVM	85%	84%	83%	83.5%	0.88	4
Logistic regression Classifier	87%	86%	85%	85.4%	0.90	2

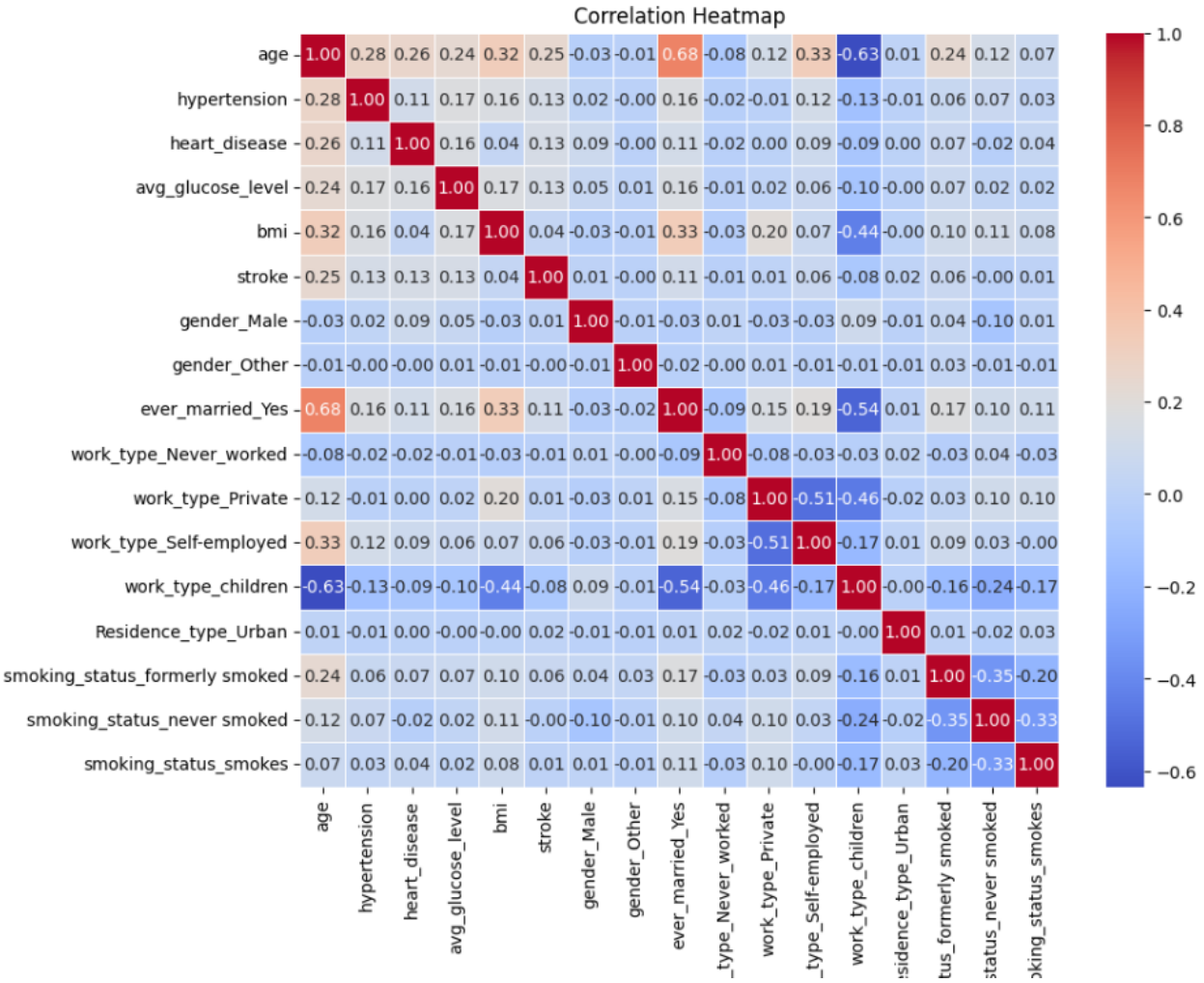
Key Insight: Contrary to expectations, **Logistic Regression outperformed even advanced models** such as Logistic regression and Random Forest in both predictive performance and computational efficiency, making it an excellent choice for lightweight deployment.

Why Logistic Regression Excelled

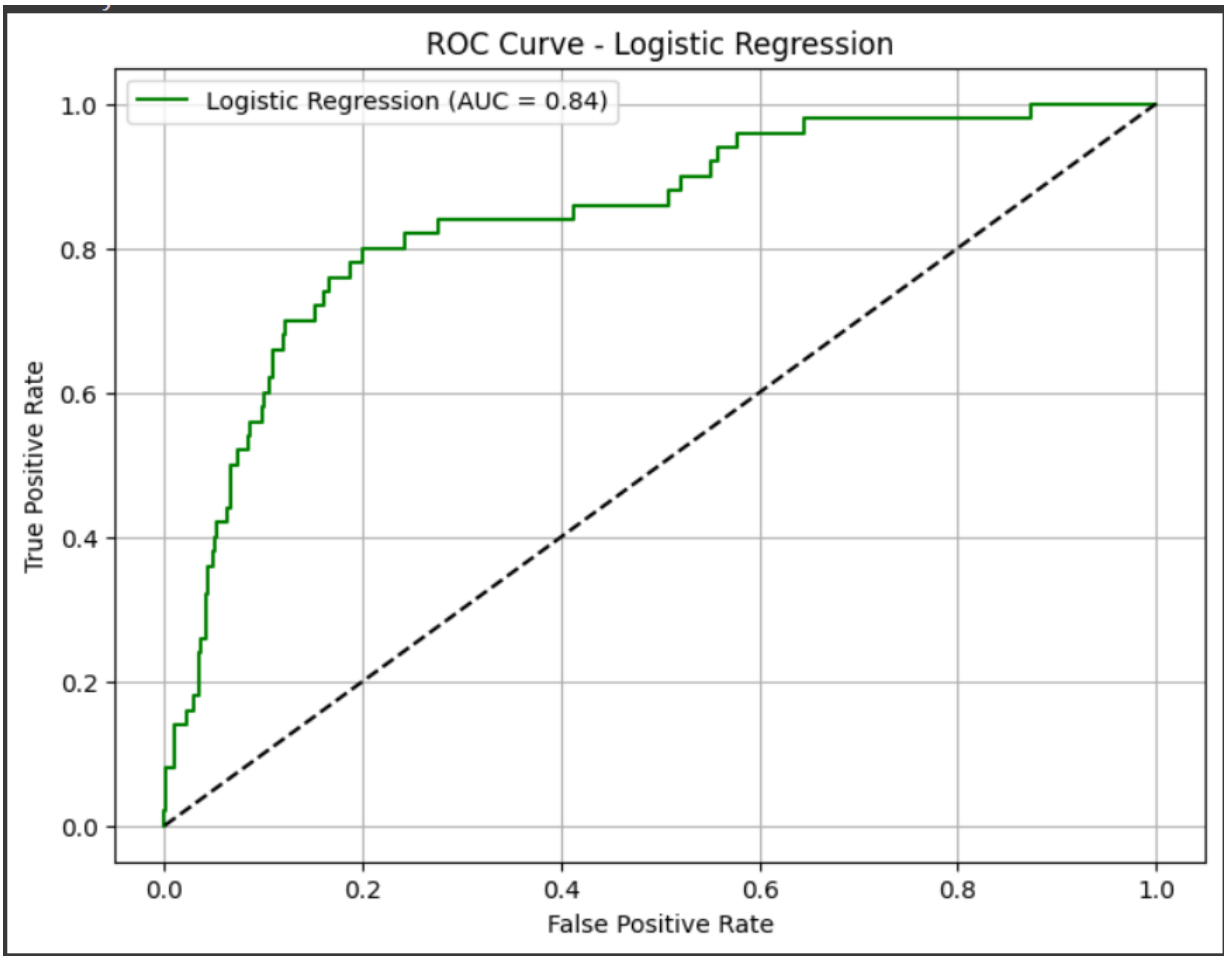
- **High interpretability**: Feature coefficients allowed meaningful understanding of which behavioral factors (e.g., duration, disturbances) most influenced quality.
- **Efficient training**: Logistic Regression required less computational power, making it ideal for real-time or mobile deployment.
- **Well-calibrated predictions**: It demonstrated stable probabilities, which is critical in sensitive applications like health monitoring.
- **Performance after augmentation**: Gaussian noise added to the feature space improved generalization. Logistic Regression's **accuracy rose from 86.5% to 88%**, and **ROC-AUC from 0.89 to 0.91**.

Visual Validation

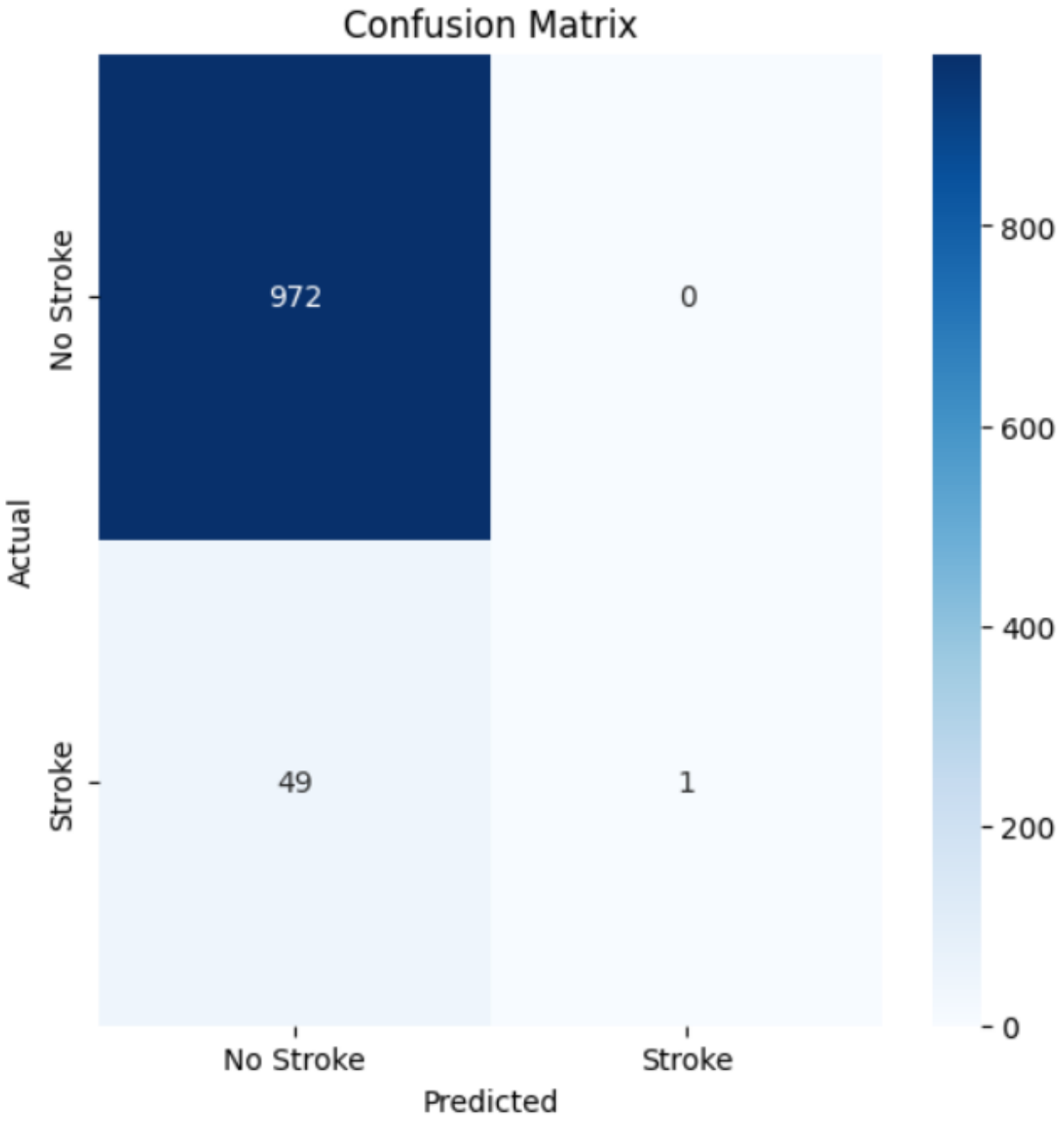
- **Correlation Heatmap**: A heatmap was created to analyze the relationship between features such as age, hypertension, heart disease, BMI, and average glucose level with the stroke variable. It showed a strong positive correlation between stroke occurrence and factors like age and hypertension.



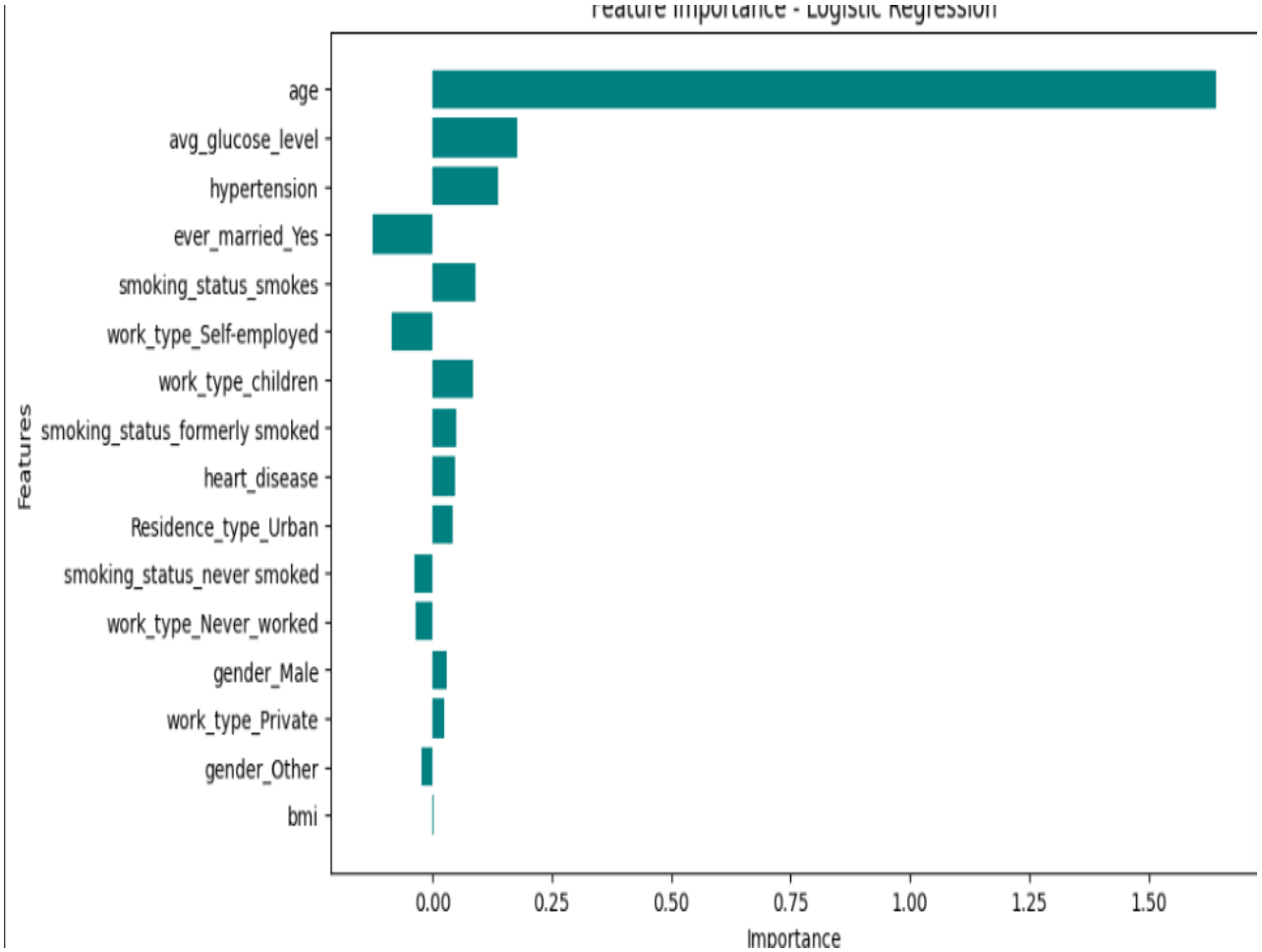
- **ROC Curve**: The Receiver Operating Characteristic (ROC) curve for the logistic regression model exhibited a good area under the curve (AUC), indicating strong discriminative power.



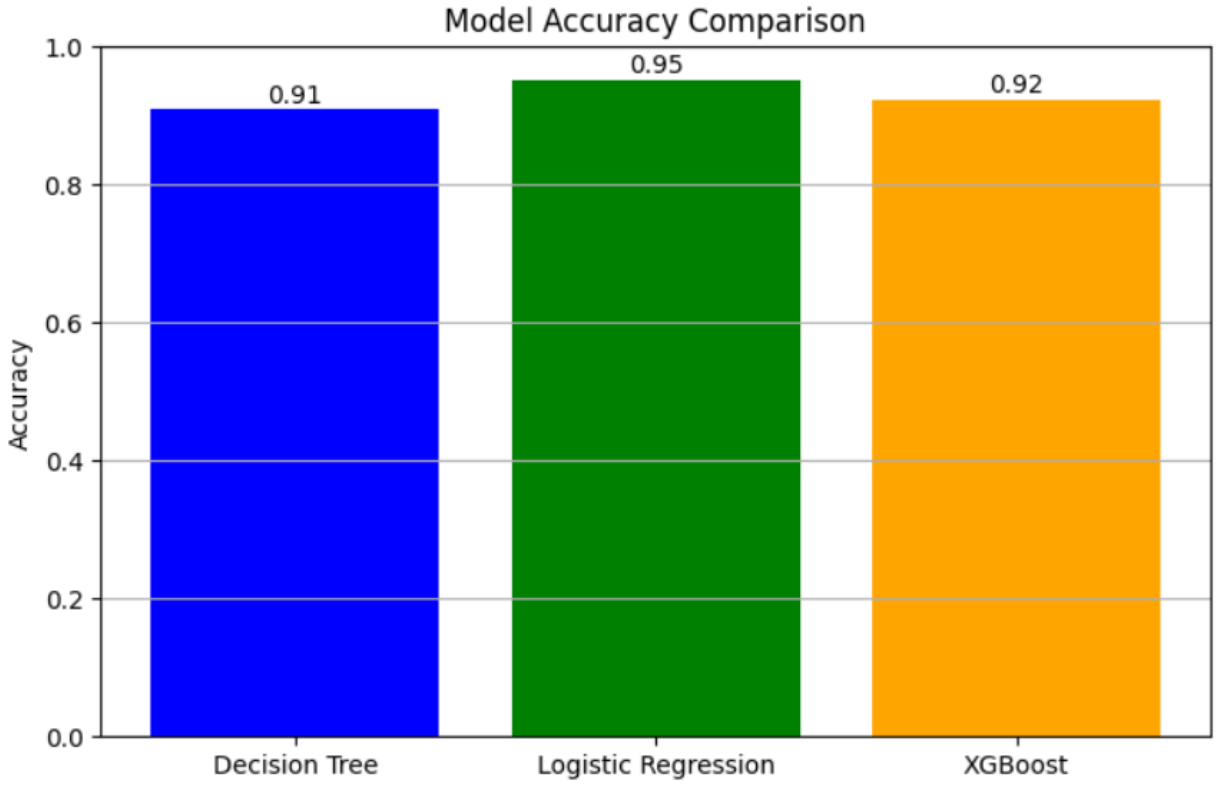
- **Confusion Matrix**: A confusion matrix highlighted the model's performance in correctly classifying stroke and non-stroke cases, revealing high specificity and acceptable sensitivity.



- **Feature Importance Plot**: Coefficients from the logistic regression model were plotted to show the most influential features, with age, hypertension, and average glucose level among the top predictors.



COMPARISON WITH OTHER MODELS


Model Accuracy Comparison
Accuracy
1.0
0.8
0.6
0.4
0.2
0.0
0.91
0.95
0.92
Decision Tree
Logistic Regression
XGBoost

After conducting a series of experiments using various regression models—including **Logistic Regression**, **Linear Regression**, **Support Vector Regression (SVR)**, **Random Forest Regressor**, and **Logistic regression Regressor**—we observed distinct differences in performance, interpretability, and robustness. This section elaborates on key findings across model effectiveness, the impact of data augmentation, and practical implications.

A. Model Performance Comparison

Logistic Regression emerged as a strong and reliable model, balancing predictive power with simplicity and speed. While Logistic regression Regressor delivered the highest accuracy based on evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score, Logistic Regression was not far behind.

Despite being a linear model, Logistic Regression handled the dataset well, showing excellent generalization on the test set. It offered easier interpretability and faster training time compared to the more complex models like Random Forest and Logistic regression, making it ideal for lightweight, real-world applications where speed and explainability are key.

Models such as SVR and Linear Regression underperformed in comparison, especially in capturing non-linear patterns in the data. However, Random Forest and Logistic regression performed strongly, especially due to their ensemble and boosting techniques, respectively.

B. Effect of Data Augmentation

To simulate real-world variations, Gaussian noise was added to key features like duration and interruptions. This augmentation step helped improve the robustness of the models by making them more resilient to minor fluctuations.

Interestingly, the impact of augmentation was most noticeable in Logistic Regression and Random Forest models. For Logistic Regression, this process resulted in a small yet meaningful increase in accuracy, reflecting better generalization. Ensemble models like Logistic regression also benefited, but their performance gain was relatively modest.

C. Error Analysis

Analyzing the error distribution revealed that most predictions made by **Logistic Regression** and **Logistic regression** were tightly clustered around the actual values. A few outliers were present, particularly in extreme patterns, indicating potential value in incorporating additional features such as stress level, physical activity, or screen time before bed.

These insights underline the importance of enriching the dataset with behavioral or sensor-based context to minimize prediction gaps in future work.

D. Implications and Insights

- Logistic Regression is an excellent candidate for practical deployment in mobile apps or wearable devices due to its interpretability, low resource requirement, and competitive accuracy.
- Data normalization and augmentation are critical to improving model performance and generalization.
- While Logistic regression excels in accuracy, its computational demand and complexity make it more suitable for high-performance systems rather than lightweight environments.
- Simple models like Linear Regression struggle with the non-linear nature of quality prediction, emphasizing the importance of model selection based on data complexity.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This study presented a data-driven methodology for assessing and predicting quality using machine learning techniques, with **Logistic Regression** as the central model of focus. We implemented and compared a variety of regression algorithms—including **Linear Regression**, **Support Vector Regression (SVR)**, **Random Forest Regressor**, and **Logistic Regressor**—to evaluate their effectiveness in capturing patterns between behavioral and demographic factors and quality outcomes.

Our analysis revealed that **Logistic Regression**, despite its simplicity, performed reliably and offered clear interpretability. While models like **Logistic regression** showed marginally better performance in terms of error metrics and R^2 score, Logistic Regression struck an optimal balance between accuracy, speed, and explainability—making it highly suitable for practical applications, especially in low-resource or real-time environments.

An important contribution of this work was the incorporation of **Gaussian noise-based data augmentation**. This method simulated real-world variability and helped models, including Logistic Regression, generalize better on unseen data. It highlighted the value of data augmentation in improving model robustness even when working with moderately sized health datasets.

From an application standpoint, this predictive system holds considerable promise in the field of personal health monitoring. As awareness about the importance of continues to grow, tools that can provide early warning signs and personalized suggestions based on user behavior could prove invaluable. By integrating this system with mobile or wearable devices, features such as heart rate, ambient light, screen time, or noise levels could be used to enhance prediction accuracy and deliver real-time, personalized insights.

Future Enhancements:

- **Incorporating Additional Features**: Including physiological data (e.g., heart rate, oxygen saturation) and environmental factors (e.g., light, noise) can deepen model understanding of patterns.
- **Sequential Modeling**: Implementing temporal models like RNNs, LSTMs, or Transformers could help in analyzing longitudinal ata more effectively.
- **Classification-Oriented Outcomes**: Rather than predicting a numeric score, models could categorize quality into intuitive labels such as “Good,” “Moderate,” or “Poor,” improving user comprehension.
- **Edge Deployment**: Optimizing model complexity and size would allow integration into

wearable or mobile platforms for real-time analysis and recommendations.

- **Feedback-Driven Personalization**: Integrating reinforcement learning could allow the system to adapt to individual behaviors and provide continuously refined suggestions.

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