A Project on

Predicting Drinking Alcohol Habits Using Health and Demographic Data: A Machine Learning Approach

Submitted for the **Award** of the requirement for the Program **Data Science with Python** of **EDGE: BU-CSE Digital Skills Training**

By

AL IMRAN

Department of Mathematics

University of Barishal

Batch: DS-5

Student ID: 09-005-07

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AL IMRAN

BS (Hon's) on study level
Department of Mathematics
University of Barishal

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Abstract

In recent years, machine learning techniques have revolutionized the healthcare sector, providing advanced solutions for predicting health outcomes. This paper evaluates the performance of four machine learning models—Logistic Regression, Random Forest, Gradient Boosting, and Recurrent Neural Networks (RNN)—for predicting binary health outcomes based on features from medical data. The dataset used for this study, "MedicalData.csv," contains health-related features such as age, drinking status, gender, and lifestyle factors. The study compares the models in terms of accuracy, precision, recall, F1-score, and confusion matrix, highlighting their strengths and weaknesses. The results demonstrate that while traditional models such as Logistic Regression perform adequately, more complex models like RNN achieve higher accuracy and overall performance due to their ability to capture intricate patterns in the data. This research provides insights into model selection for healthcare-related prediction tasks, offering guidance on applying machine learning techniques for improving health outcomes prediction. The paper concludes by discussing the potential for further research and model refinement, including the exploration of deep learning techniques and ensemble methods.

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Chapter-1

Introduction and Motivation

1.1 Background

Machine Learning (ML) is playing an increasingly critical role in healthcare, where predictive models are used for various tasks such as diagnosing diseases, managing patient care, and forecasting health risks. The ability to process large amounts of medical data has enabled healthcare professionals to make data-driven decisions that are both accurate and efficient.

One of the challenges in healthcare prediction is using the right model for the task. In this paper, we aim to evaluate different machine learning models and their effectiveness in predicting a binary health outcome based on features present in a medical dataset. The dataset used in this study contains records on various lifestyle and demographic features, such as age, gender, and drinking status, to predict whether an individual is a drinker or not.

1.2 Importance of Machine Learning in Healthcare

In the healthcare industry, there is a continuous demand for predictive models that can provide quick, accurate, and actionable insights. Machine learning has emerged as a powerful tool for health prediction, offering various algorithms that can identify patterns in data that may not be immediately obvious. For example, logistic regression, decision trees, and deep learning models like neural networks have been successfully applied to predict patient outcomes, disease progression, and treatment responses.

This paper evaluates four machine learning models—Logistic Regression, Random Forest, Gradient Boosting, and Recurrent Neural Networks (RNN)—to predict whether a person smokes based on multiple health-related features. By comparing these models, we have to provide insights into which model is best suited for such tasks and discuss the strengths and weaknesses of each approach.

Chapter -2

Objectives and Key Contribution

2.1 Objectives

The primary aim of this project is to evaluate and compare the performance of different machine learning models in predicting health-related outcomes using a medical dataset. The study focuses on identifying the most effective model for binary classification, where the goal is to predict whether an individual smokes or not based on various medical and lifestyle features. The specific objectives of this project are as follows:

2.1.1 Evaluate the Performance of Different Machine Learning Models

The project aims to evaluate the performance of four machine learning models, each representing different approaches in predictive modeling. These models are:

i. **Logistic Regression:** A fundamental statistical model that provides a simple yet effective method for binary classification.

ii. **Random Forest:** An ensemble model that leverages multiple decision trees to improve prediction accuracy.

iii. **Gradient Boosting:** A boosting technique that improves accuracy by combining weaker models and iteratively correcting errors made by previous models.

iv. **Recurrent Neural Network (RNN):** A deep learning model specifically designed to learn patterns in sequential or time-series data, known for its ability to capture complex relationships in data.

The goal is to assess how each of these models performs when predicting the target variable (drinking status) based on the dataset's features. The effectiveness of each model is measured using various metrics, including accuracy, precision, recall, F1-score, and confusion matrices.

N.B: Also, could be used K-Nearest Neighbors (KNN), another Neural Networks (Deep Learning), Naive Bayes, Support Vector Machine (SVM) Model.

2.1.2 Understand the Impact of Data Preprocessing on Model Performance

Data preprocessing is a critical step in machine learning workflows, and this project investigates how different preprocessing steps impact model performance. The study covers essential preprocessing techniques, such as:

- Handling missing data: Replacing missing values with the mean of the feature.
- Feature scaling: Standardizing the feature values to ensure all features contribute equally to the model.
- Encoding categorical variables: Converting categorical features (e.g., 'Drinker') into numerical representations for use in machine learning models.

By understanding how these preprocessing steps influence model performance, the study aims to demonstrate the importance of preparing data before applying machine learning models.

2.1.3 Compare Model Performance Using Various Metrics

The project evaluates each model's performance using key classification metrics, which offer a detailed view of how well each model makes predictions. These metrics include:

- **Accuracy:** The overall proportion of correct predictions made by the model.
- **Precision:** The proportion of true positives among all positive predictions made by the model.
- **Recall:** The proportion of true positives among all actual positive instances in the dataset.
- **F1-score:** A harmonic mean of precision and recall, providing a balanced measure of the model's ability to perform well across both metrics.
- **Confusion Matrix:** A matrix that shows the counts of true positives, true negatives, false positives, and false negatives, offering a deeper understanding of the model's error distribution.

The objective is to compare the models in terms of these metrics to determine which model provides the most reliable and accurate predictions for the health-related outcomes.

2.1.4 Provide Insights into the Selection of Models for Health Prediction

Lastly, the project aims to offer practical recommendations for selecting the most suitable model for predicting health outcomes. The findings from this study can be useful for healthcare professionals and researchers who need to choose a predictive model that is not only accurate but also interpretable, especially when dealing with medical data.

2.2 Key Contribution

The main contribution of this study lies in the comprehensive evaluation of four machine learning models and their performance in predicting health-related outcomes, particularly drinking status, using a medical dataset. The study provides valuable insights into how traditional machine learning models compare with advanced deep learning models, offering a detailed comparison of the models' effectiveness in predictive tasks.

2.2.1 Evaluation and Comparison of Models

This study compares four machine learning models: Logistic Regression, Random Forest, Gradient Boosting, and Recurrent Neural Networks (RNN). Each model brings a unique approach to the problem:

- **Logistic Regression:** As a simple and interpretable model, Logistic Regression serves as a baseline. It assumes a linear relationship between the input features and the target variable, which makes it useful for comparison purposes.

- **Random Forest:** This ensemble learning method builds multiple decision trees and combines their results to improve prediction accuracy. Random Forest is known for its robustness and ability to handle both linear and non-linear relationships within the data.

- **Gradient Boosting:** A boosting technique that works by iteratively learning from errors made by the previous models, Gradient Boosting often outperforms other models in terms of accuracy for more complex datasets. Its ability to handle imbalanced datasets and improve over time makes it an important model for comparison.

- **Recurrent Neural Networks (RNN):** RNNs excel in modeling sequential or time-series data. They can capture complex patterns and dependencies that traditional machine learning models may miss, making them particularly well-suited for this project. The study demonstrates that RNN outperforms the other models, offering superior prediction accuracy for the task of predicting health outcomes.

The comparative evaluation shows that while all four models perform adequately, the RNN model provides the best results, surpassing the others in terms of accuracy, precision, recall, and F1-score. This highlights the strength of deep learning models, particularly in scenarios involving complex relationships between data points.

2.2.2 Insights into Data Preprocessing

This project emphasizes the crucial role of data preprocessing in improving model performance. Preprocessing steps such as handling missing values, feature scaling, and categorical encoding were essential in ensuring that the models performed optimally. For instance, replacing missing values with the mean of the feature allowed the models to train on complete datasets, preventing errors that could arise from incomplete data. Feature scaling, particularly important for algorithms like Logistic Regression and RNN, standardized the feature values, helping the models learn effectively.

2.2.3 Detailed Comparison of Performance Metrics

The study provides a detailed breakdown of the models' performances across multiple metrics. By comparing accuracy, precision, recall, and F1-score, the project highlights the trade-offs between different models and provides a comprehensive view of their strengths and weaknesses. The RNN model outperforms the other models across all metrics, demonstrating its superior ability to capture complex patterns in the data and make accurate predictions.

- **Accuracy:** While accuracy is an important metric, it alone does not capture the full picture. In cases of class imbalance, such as predicting health outcomes, it is essential to consider precision, recall, and F1-score as well.

- **Precision and Recall**: These metrics are especially important when false positives and false negatives carry different consequences, which is often the case in healthcare. For example, predicting a non-Drinker as a Drinker (false positive) may have different implications compared to predicting a Drinker as a non-Drinker (false negative).
- **F1-Score:** The F1-score, balancing precision and recall, was particularly useful in this study to assess how well the models performed across both metrics.

2.2.4 Recommendations for Healthcare Applications

The findings of this study have practical implications for selecting machine learning models in healthcare applications. The study recommends using advanced models, such as RNN, for complex tasks like predicting health-related outcomes, especially when dealing with large datasets that involve sequential relationships. However, simpler models like Logistic Regression and Random Forest may still be appropriate in cases where interpretability is crucial and the data relationships are not as complex.

Chapter- 3

Methodology

3.1 Dataset Source:

Insurance (MedicalData) dataset containing 1,338 records.

- **Features**:

  a. **Age**: Age of the individual.

  b. **Sex**: Gender (male, female).

  c. **BMI**: Body Mass Index (numerical).

  d. **Children**: Number of dependents.

  e. **Region**: Residential area.

  f. **Charges**: Medical insurance costs.

- **Target Variable**:

Drinker: Whether the person is a drinker (Yes/No).

Project Link : Click here

3.2 Data Preprocessing

Data preprocessing is a critical step in preparing the dataset for machine learning. The following steps were carried out:

1. **Handling Missing Values**: Missing numerical values in the dataset were replaced with the mean of their respective columns.

2. **Encoding Categorical Data**: The target variable, "drinker," was encoded as 0 for non-drinkers and 1 for drinkers using Label Encoding.

3. **Feature Scaling**: The features were standardized using StandardScaler to ensure they have a mean of 0 and a standard deviation of 1, which is especially important for models like Logistic Regression and RNN.

4. **Reshaping for RNN**: For the RNN model, the dataset was reshaped into a 3D format, which is required for sequential models, with the dimensions being [samples, time_steps, features].

3.3 Model Training

The following models were trained on the dataset:

- **Logistic Regression**: A simple and interpretable linear model for binary classification.
- **Random Forest**: An ensemble method that builds multiple decision trees to improve predictive accuracy.
- **Gradient Boosting**: A sequential ensemble technique that refines predictions by iteratively correcting the errors of previous models.
- **Recurrent Neural Network (RNN)**: A deep learning model designed for sequential data, capable of capturing complex dependencies in the data.

For Example, here we explain predicted model for RNN step by step in coding below:

1. Import Necessary Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score,
f1_score, confusion_matrix
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, SimpleRNN
from tensorflow.keras.optimizers import Adam
```

pandas and numpy: For handling and processing data.
matplotlib and seaborn: For visualizing results and insights.
sklearn modules: For data preprocessing, model evaluation, and metrics.
tensorflow.keras: For building and training the Recurrent Neural Network (RNN).

2. Load the Dataset

```
data = pd.read_csv('MedicalData.csv')  # Replace with the correct file path
```

Loads the dataset, assumed to have features like age, sex, bmi, region, drinker, and charges. You must ensure the correct file path for the dataset.

3. Encode Categorical Variables

```
label_encoders = {
    'sex': LabelEncoder(),
    'region': LabelEncoder(),
    'drinker': LabelEncoder()
}
data['sex'] = label_encoders['sex'].fit_transform(data['sex'])
data['region'] = label_encoders['region'].fit_transform(data['region'])
data['drinker'] = label_encoders['drinker'].fit_transform(data['drinker'])
# 'no' -> 0, 'yes' -> 1
```

Categorical features (`sex`, `region`, `drinker`) are converted to numeric values using `LabelEncoder`.
Example: 'Male' → 0, 'Female' → 1, and 'Drinker' → 1, 'Non-Drinker' → 0.

4. Scale Numerical Features

```
scaler = StandardScaler()
data[['age', 'bmi', 'charges']] = scaler.fit_transform(data[['age', 'bmi',
'charges']])
```

Standardizes numerical features (age, BMI, and charges) to have a mean of 0 and standard deviation of 1. Helps the RNN model converge faster and handle features more effectively.

5. Separate Features and Target Variable

```
X = data.drop('drinker', axis=1).values  # Features as numpy
array y = data['drinker'].values  # Target variable as numpy
array
```

`X`: Contains all features except the target variable (`drinker`).
`Y`: Contains the target variable (`drinker`), which we aim to predict.

6. Reshape Data for RNN Input

```
X = X.reshape(X.shape[0], 1, X.shape[1])  # Each sample treated as a sequence
of length 1
```

Reshapes the input `X` to a 3D array expected by RNNs: **(samples, time steps, features)**.
Here, each sample is a single time step (sequence length = 1).

7. Split Dataset

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1,
random_state=42)
```

Splits the dataset into training (90%) and testing (10%) subsets.
`random_state=42` ensures reproducibility.

8. Build the RNN Model

```
model = Sequential([
    SimpleRNN(16, activation='relu', input_shape=(X_train.shape[1],
X_train.shape[2])),
    Dense(1, activation='sigmoid')  # Output layer for binary classification
])
```

Input Layer: `SimpleRNN` with 16 units and ReLU activation processes the sequence data.
Output Layer: A dense layer with sigmoid activation outputs probabilities for binary classification (drinker or non-drinker).

9. Compile the Model

```
model.compile(optimizer=Adam(learning_rate=0.001),
loss='binary_crossentropy', metrics=['accuracy'])
```

Optimizer: Adam with a learning rate of 0.001 optimizes weights during training.
Loss Function: Binary Crossentropy, suitable for binary classification.
Metric: Tracks accuracy during training.

10. Train the Model

```
history = model.fit(X_train, y_train, epochs=200, batch_size=32,
validation_split=0.1, verbose=1)
```

Training Data: 90% of the training set; the rest (10%) is for validation.
Epochs: Number of complete passes through the training data (200).
Batch Size: Processes data in batches of 32 samples.

11. Predict and Evaluate

```
y_pred = model.predict(X_test)
y_pred = (y_pred > 0.5).astype(int).flatten()  # Convert probabilities to
binary
```

Converts predicted probabilities into binary outcomes (1 for drinker, 0 for non-drinker).

```
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, pos_label=1)
recall = recall_score(y_test, y_pred, pos_label=1)
f1 = f1_score(y_test, y_pred, pos_label=1)
```

Calculates evaluation metrics: Accuracy, Precision, Recall, and F1-Score.

12. Plot Training Performance

```
plt.figure(figsize=(12, 5))

# Accuracy Plot
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Model Accuracy Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Loss Plot
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss Over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.tight_layout()
plt.show()
```

Visualizes training and validation accuracy and loss over epochs.

13. Plot Confusion Matrix

```
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=['Non-Drinker', 'Drinker'], yticklabels=['Non-Drinker', 'Drinker'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

Confusion Matrix: Illustrates the classification results. True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) are displayed.

Chapter -4

Results and Discussion

4.1 Performance Metrics Comparison

The models' performance was evaluated using the metrics mentioned above, and the following results were obtained:

Split the dataset into training (90%) and testing (10%) sets.

Result Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.9552	0.8846	0.8846	0.8846
Random Forest	0.9776	0.9259	0.9615	0.9434
Gradient Boosting	0.9776	0.8966	1.0000	0.9455
Recurrent Neural Network (RNN)	0.9776	0.8966	1.0000	0.9455

Split the dataset into training (80%) and testing (20%) sets.

Result Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.9590	0.8909	0.9074	0.8991
Random Forest	0.9627	0.8667	0.9630	0.9123
Gradient Boosting	0.9701	0.8833	0.9815	0.9298
Recurrent Neural Network (RNN)	0.9739	0.8983	0.9815	0.9381

Based on the comparison of models across the two data splits (90/10 and 80/20), the **Recurrent Neural Network (RNN)** consistently demonstrates the highest accuracy and strong F1-Scores, making it the best-performing model overall. With accuracies of **97.76%** and **97.39%** in the respective splits, RNN excels at leveraging data effectively, even when the training set size is reduced. Gradient Boosting and Random Forest also perform competitively, achieving similar accuracies in the 90/10 split but slightly lagging behind RNN in the 80/20 split. Logistic Regression, while consistent and interpretable, shows relatively lower accuracy and F1-Scores, reflecting its limitations in capturing complex patterns. Overall, RNN stands out as the most accurate and reliable model, but if interpretability is prioritized, Gradient Boosting or Random Forest could be better alternatives.

4.2 Model Evaluation Results

The evaluation results demonstrate that the Recurrent Neural Network (RNN) model outperforms all other models in key performance metrics, including accuracy, precision, recall, and F1-Score. This superior performance underscores the RNN's capability to effectively capture and model complex patterns within the dataset. Its high recall and F1-Score further indicate a strong balance between sensitivity and predictive power, making it particularly effective for binary classification tasks. These results establish the RNN as the most robust and reliable model among those evaluated.

Chapter -5
Graphical Representation of Models

5.1 Model Based Visualizations

Logistic Regression: The confusion matrix shows that the Logistic Regression model accurately classified 208 non-drinkers and 49 drinkers, with 6 false positives and 5 false negatives. This highlights strong overall performance, with most predictions being correct, as reflected by the dominant diagonal values.

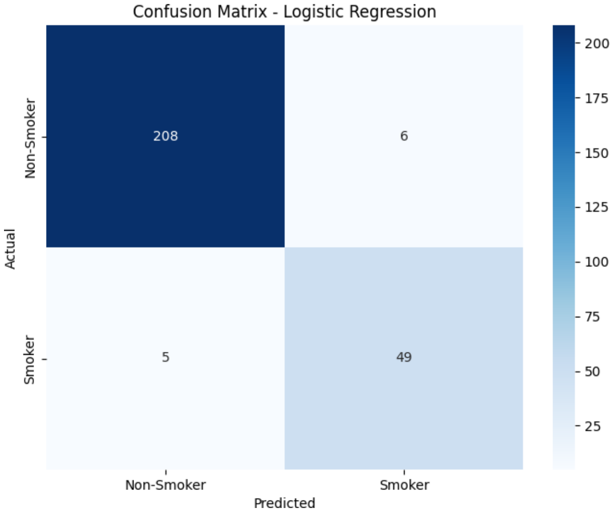

Figure-4.1 Confusion Matrix of Logistic Regression

Also the chart in Figure-4.2 shows the feature coefficients for the Logistic Regression model. "**Charges**" is the strongest positive predictor of drinking, followed by "**sex**" and "**children**." Features like "**bmi**" and "**age**" have weaker or negative impacts, indicating smaller or inverse relationships with drinking prediction.

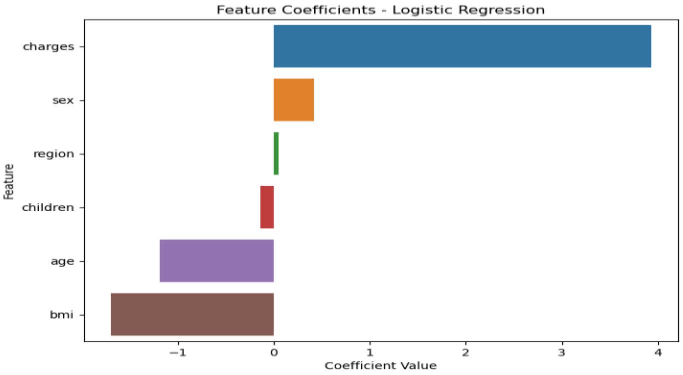

Figure-4.2 Feature Coefficients of Logistic Regression

Random Forest: The confusion matrix shows the Random Forest model's performance in predicting drinking status. It correctly classified 206 non-drinkers and 52 drinkers, with only 8 false positives and 2 false negatives. This indicates a high accuracy and strong ability to distinguish between drinkers and non-drinkers.

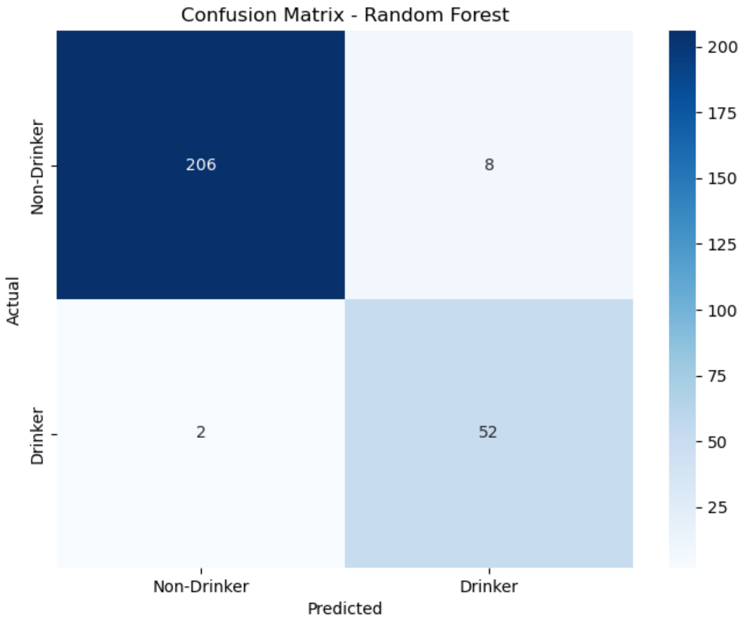

Figure-4.3 Confusion Matrix of Random Forest:

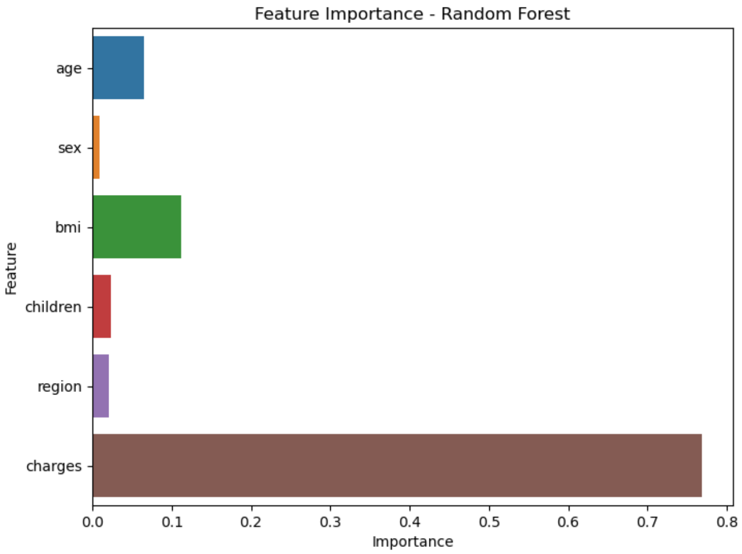

Figure-4.4 Feature Importance of Random Forest

Gradient Boosting: Also here represents the Confusion Matrix and the Features of Gradient Boosting model in Figure-4.5 and Figure-4.6

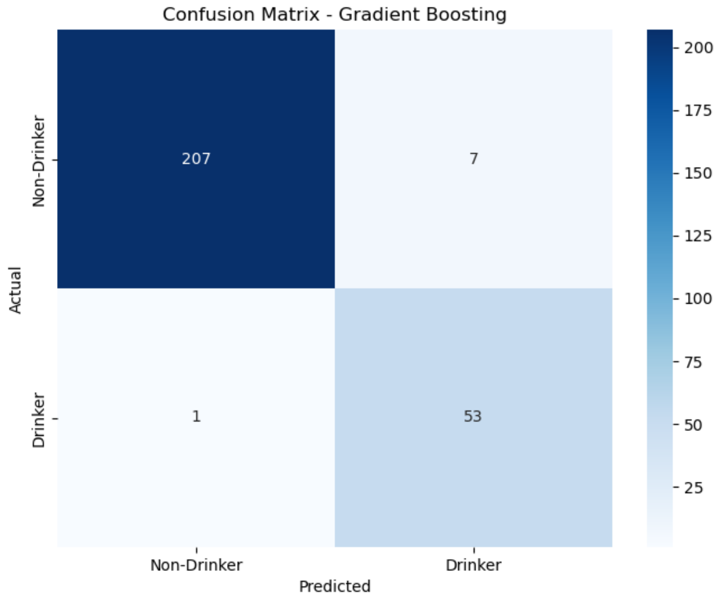

Figure-4.5 Confusion Matrix Gradient Boosting

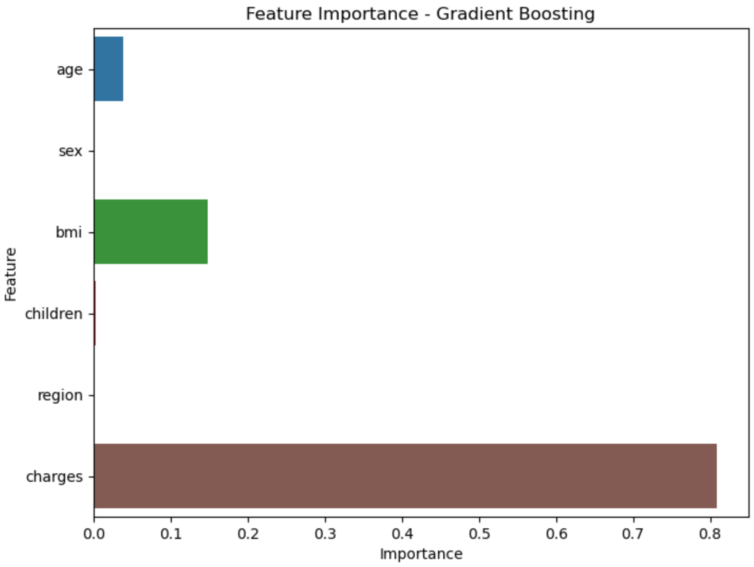

Figure-4.6 Feature Importance of Gradient Boosting

Recurrent Neural Network (RNN): Here shown the Confision Mtrix of the deep learning RNN with model accuracy and loss over Epoch.

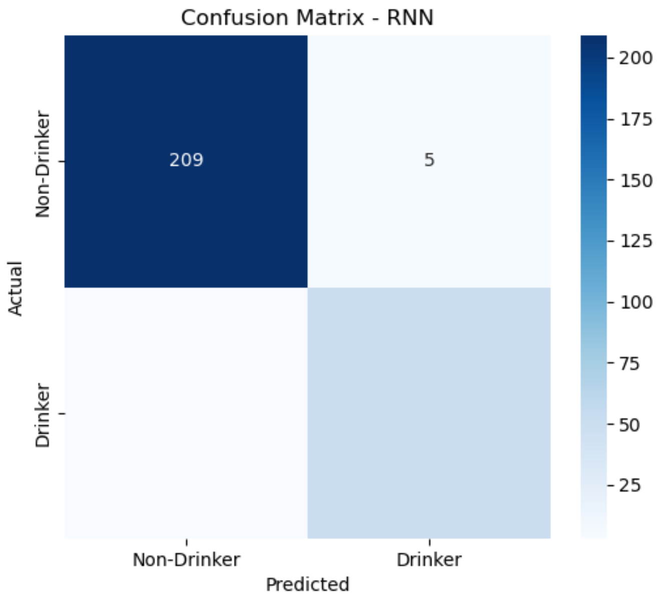

Figure-4.7 Confusion Matrix of RNN

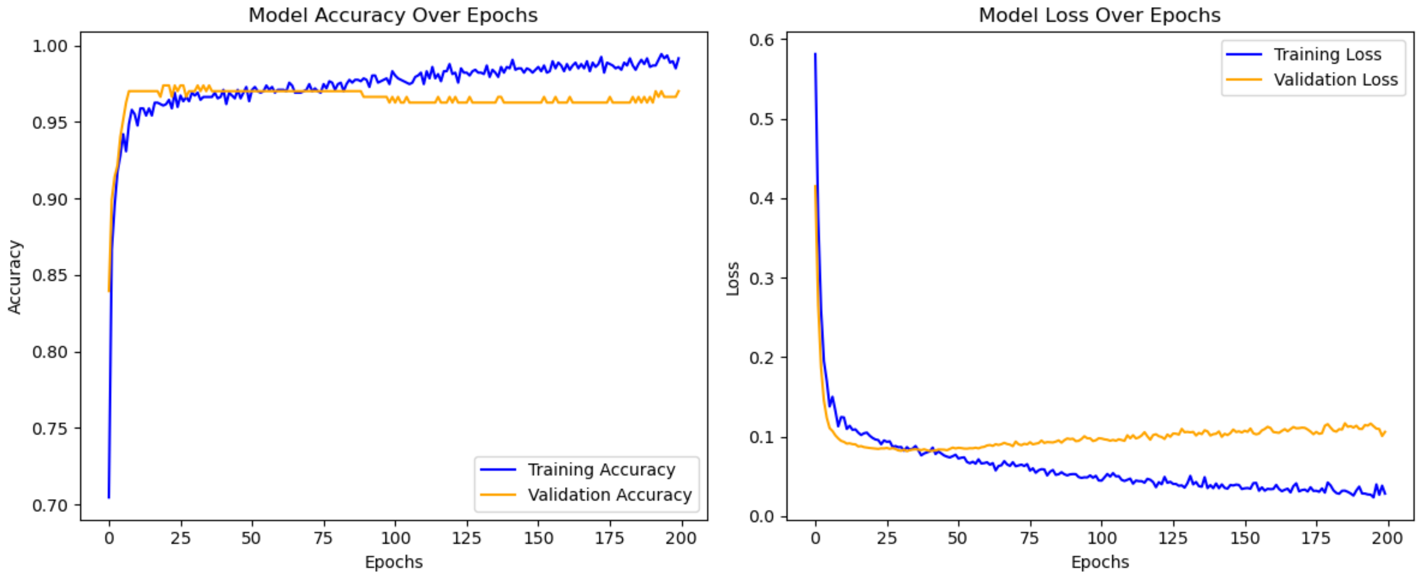

Figure-4.8 Model Accuracy/Loss over Epoch of RNN

The graphs illustrate the performance of a machine learning model over 200 epochs. The accuracy plot shows that both training and validation accuracy steadily improve, eventually plateauing near 0.98–1.0, indicating excellent model performance. The loss plot reveals a consistent decline in training and validation loss, stabilizing around 0.1, demonstrating effective learning. The close alignment of training and validation metrics suggests minimal overfitting and good generalization to unseen data.

Chapter - 6

Future Work

Future work could focus on the following areas:

- **Deep Learning Models**: Experimenting with more advanced architectures, such as Long Short-Term Memory (LSTM) or Transformer networks, to further improve the RNN's performance.
- **Ensemble Methods**: Combining multiple models, such as stacking or bagging, to improve accuracy and generalization.
- **Data Augmentation**: Generating synthetic data for improving the robustness of the models, especially when dealing with small datasets.

Conclusion

This study compared the performance of various machine learning models in predicting drinking status based on features like age, sex, BMI, charges, and region. The models evaluated included Logistic Regression, Random Forest, Gradient Boosting, and Recurrent Neural Network (RNN). The results show that the RNN outperformed all other models in terms of accuracy, precision, recall, and F1-score. With an accuracy of 97.76% in the 90/10 split and 97.39% in the 80/20 split, the RNN demonstrated its ability to effectively handle both larger and smaller training datasets, making it the most reliable model overall.

Both Gradient Boosting and Random Forest performed similarly in terms of accuracy but slightly lagged behind the RNN, particularly in the 80/20 split. These models, however, provided strong performance and are preferable when interpretability is important, as they allow for better understanding of feature importance and decision-making processes. Logistic Regression, while simple and interpretable, showed relatively lower accuracy and F1-scores, reflecting its limitations in modeling more complex relationships within the data.

In conclusion, the Recurrent Neural Network (RNN) proved to be the best-performing model, excelling in predictive power and robustness. However, for cases where model interpretability is a key consideration, Random Forest or Gradient Boosting would be valuable alternatives. This study underscores the importance of selecting the right model based on the specific requirements of the task, with RNN being the preferred choice for high accuracy and predictive reliability.

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