CardioVision AI: TensorFlow Cardiac Risk Predictor

AI for Healthier Hearts

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Abstract

Cardiovascular diseases remain a predominant cause of morbidity and mortality globally, necessitating early and accurate prediction to enhance patient outcomes. This study aims to develop a robust machine learning model using TensorFlow for predicting heart disease in patients. The model analyzes critical medical parameters such as age, gender, chest pain type, resting blood pressure, cholesterol levels, and other relevant features to achieve a predictive accuracy exceeding 84.61%. Through meticulous data preprocessing, feature engineering, and hyperparameter optimization, various neural network architectures were evaluated to determine the most effective approach. The final model, which incorporates regularization and learning rate refinement, demonstrated superior generalization capabilities with a test accuracy of 85.33% and a recall rate of 0.90. This predictive tool is designed to support healthcare professionals in making informed decisions, ultimately improving patient care and reducing the incidence of undiagnosed heart disease. Future research will explore additional features and datasets to further enhance the model's predictive power and applicability in diverse clinical settings.

Introduction

Cardiovascular diseases (CVD) remain a leading cause of morbidity and mortality globally, accounting for millions of deaths annually. Early detection and intervention are critical in reducing the adverse outcomes associated with heart disease. With the advent of advanced machine learning techniques, it has become increasingly feasible to develop predictive models that can aid healthcare professionals in identifying at-risk individuals with greater accuracy and efficiency.

This paper presents a comprehensive approach to developing a machine learning model for predicting heart disease using TensorFlow. The primary objective of this study is to achieve a model accuracy exceeding 84.61%, thereby enhancing the reliability of predictions and contributing to better patient outcomes. This target is motivated by the performance benchmark established by Al Bataineh and Manacek in their study, which achieved an accuracy of 84.61% [1].

The dataset utilized in this study comprises various medical parameters, including age, gender, chest pain type, resting blood pressure, cholesterol levels, fasting blood sugar, resting electrocardiographic results, maximum heart rate, exercise-induced angina, oldpeak (ST depression induced by exercise), and the slope of the peak exercise ST segment. These features are critical indicators of cardiovascular health and are used to train and evaluate the predictive model.

The methodology adopted in this study involves several key steps:

1. **Data Preprocessing**:
    - **Removal of Duplicates**: Ensured the dataset's integrity by eliminating duplicate entries.
    - **Feature Scaling**: Applied standard scaling to normalize the feature values, which is essential for the convergence of gradient-based algorithms.
    - **Train-Validation-Test Split**: Divide the dataset into training (60%), validation (20%), and test (20%) sets to enable robust model evaluation and hyperparameter tuning.
2. **Initial Model Development**:
    - Developed multiple feedforward neural network architectures using TensorFlow, each with varying layers and neurons.
    - Compiled the models with the Adam optimizer and binary cross-entropy loss function, chosen for their efficacy in binary classification tasks.
3. **Hyperparameter Optimization**:
    - **Regularization and Learning Rate Tuning**: Conducted extensive parametric studies to refine the regularization parameters and learning rates. This involved a systematic grid search and manual adjustments to identify the optimal values that minimize overfitting while ensuring model robustness.
    - **Model Evaluation**: Evaluated each model based on F1-scores and accuracy metrics on the validation set, selecting the configurations that demonstrated superior performance.

4. **Final Model Selection and Testing**:
    - The best-performing models were subjected to rigorous testing on the held-out test set to evaluate their generalization capabilities. The model achieving the highest accuracy and F1-score was selected as the final predictive tool.

Through these systematic and iterative optimization steps, the study aims to develop a robust and reliable heart disease prediction model. The results and insights derived from this research have the potential to significantly contribute to the field of predictive healthcare, enabling early diagnosis and better management of cardiovascular diseases.

Dataset

The heart disease dataset used in this study includes a range of medical parameters critical for predicting cardiovascular health outcomes. The dataset comprises the following attributes, found in Table 1.1 below:

Heart Disease Dataset Attribute Description			
Attribute	Code Given	Unit	Data Type
Age	Age	in years	Numeric
Sex	Sex	1, 0	Binary
Chest Pain Type	chest pain type	1, 2, 3, 4	Nominal
Resting Blood Pressure	resting bp s	in mm Hg	Numeric
Serum Cholesterol	cholesterol	in mg/dl	Numeric
Fasting Blood Sugar	fasting blood sugar	1, 0 > 120 mg/dl	Binary
Resting Electrocardiogram Results	resting ecg	0, 1, 2	Nominal
Maximum Heart Rate Achieved	max heart rate	71 - 202	Numeric
Exercise Induced Angina	exercise angina	0, 1	Binary
Oldpeak = ST	oldpeak	depression	Numeric
The Slope of the Peak Exercise ST Segment	ST Slope	0, 1, 2	Nominal
Class	target	0, 1	Binary

Table 1.1 – Heart Disease Dataset Attribute Description

The following is a description of the attributes that can be found in Table 1.1.

1. **Age**: The age of the patient in years (numerical).
2. **Sex**: The gender of the patient, where 1 represents male and 0 represents female (Binary).
3. **Chest Pain Type**: Categorized into four types:
    - 1: Typical angina
    - 2: Atypical angina
    - 3: Non-anginal pain
    - 4: Asymptomatic (Nominal)
4. **Resting Blood Pressure**: The patient's resting blood pressure in mm Hg (numerical).
5. **Serum Cholesterol**: The serum cholesterol level in mg/dl (numerical).
6. **Fasting Blood Sugar**: Indicates if the fasting blood sugar level is greater than 120 mg/dl, where 1 represents true and 0 represents false (Binary).
7. **Resting Electrocardiogram Results**: Categorized into three types:
    - 0: Normal
    - 1: Having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV)

    - 2: Showing probable or definite left ventricular hypertrophy by Estes' criteria (Nominal)

8. **Maximum Heart Rate Achieved**: The maximum heart rate achieved during exercise (numerical).
9. **Exercise Induced Angina**: Indicates if the patient experiences' angina induced by exercise, where 1 represents yes and 0 represents no (Binary).
10. **Oldpeak**: ST depression induced by exercise relative to rest (numerical).
11. **The Slope of the Peak Exercise ST Segment**: Categorized into three types:

    - 1: Upsloping
    - 2: Flat
    - 3: Downsloping (Nominal)

12. **Class (Target)**: Indicates the presence of heart disease, where 1 represents heart disease and 0 represents no heart disease (Binary).

Table 1.2 below summarizes the descriptions of the nominal attributes above.

Description of Nominal Attributes	
Attribute	Description
Sex	1 = male, 0= female
Chest Pain Type	Value 1: typical angina Value 2: atypical angina Value 3: non-anginal pain Value 4: asymptomatic
Fasting Blood Sugar	(fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)
Resting Electrocardiogram Results	Value 0: normal Value 1: having ST-T wave abnormality (T wave inversions and/or ST elevation or depression of > 0.05 mV) Value 2: showing probable or definite left ventricular hypertrophy by Estes' criteria
Exercise Induced Angina	1 = yes; 0 = no
The Slope of the Peak Exercise ST Segment	Value 1: upsloping Value 2: flat Value 3: downsloping
Class	1 = heart disease, 0 = Normal

Table 1.2: Description of Nominal Attributes

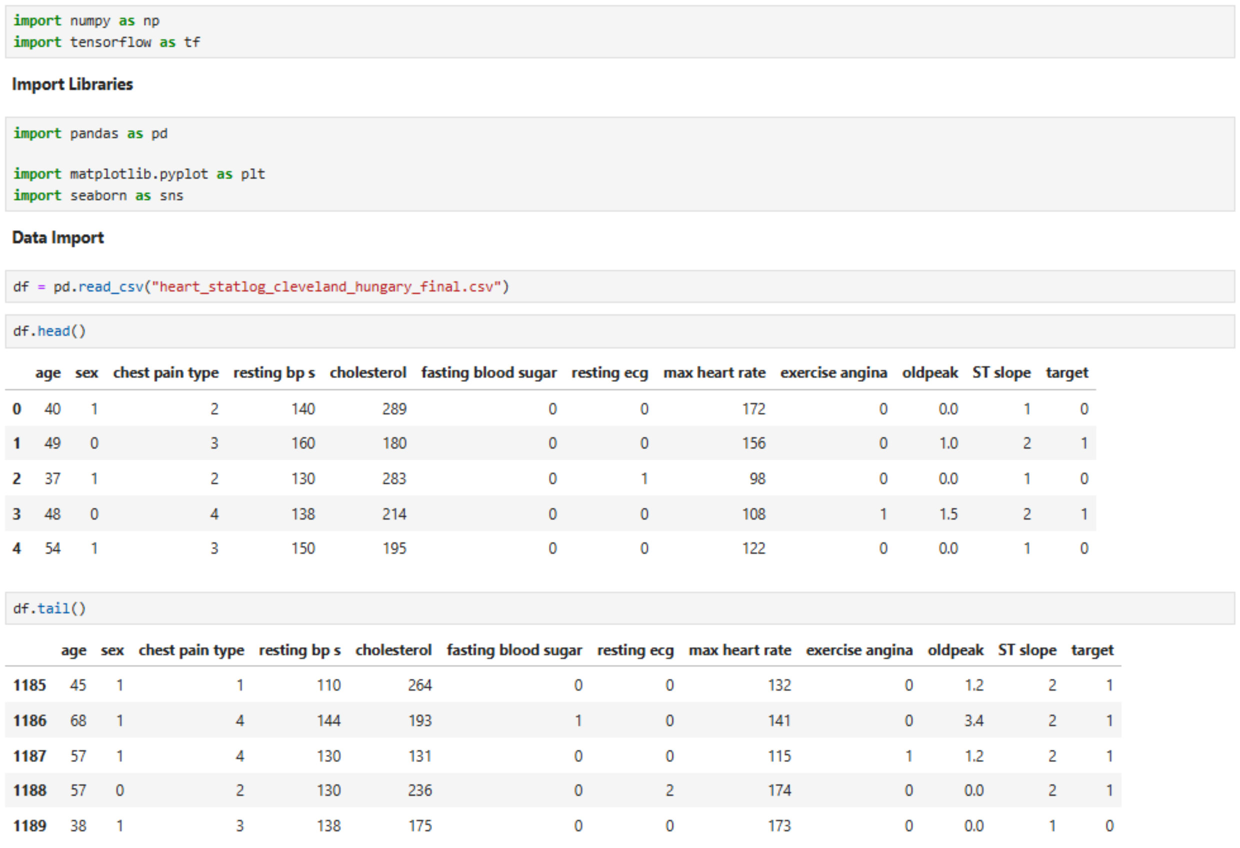
In the following section, to better understand our data we will conduct an Exploratory Data Analysis on the Heart Disease Dataset.

Exploratory Data Analysis

Exploratory Data Analysis (EDA) is a crucial step in understanding the underlying patterns and characteristics of a dataset before applying any machine learning algorithms or statistical models. This process involves summarizing the main features of the dataset, often using visual methods, to identify trends, patterns, and potential anomalies.

In this section, we will conduct a comprehensive analysis of the dataset, focusing on key variables such as sex and chest pain types, among others. By visualizing the distribution and relationships of these variables, we aim to uncover insights that will inform the subsequent stages of our analysis.

The following plots were created using Python in Jupyter Notebook. We utilized libraries such as Matplotlib and Seaborn to generate insightful visualizations, while Pandas was instrumental in importing and filtering the data to highlight key parameters of interest. The code block below shows how we imported the necessary libraries and dataset.



```
import numpy as np
import tensorflow as tf
```

Import Libraries

```
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns
```

Data Import

```
df = pd.read_csv("heart_statlog_cleveland_hungary_final.csv")
```

```
df.head()
```

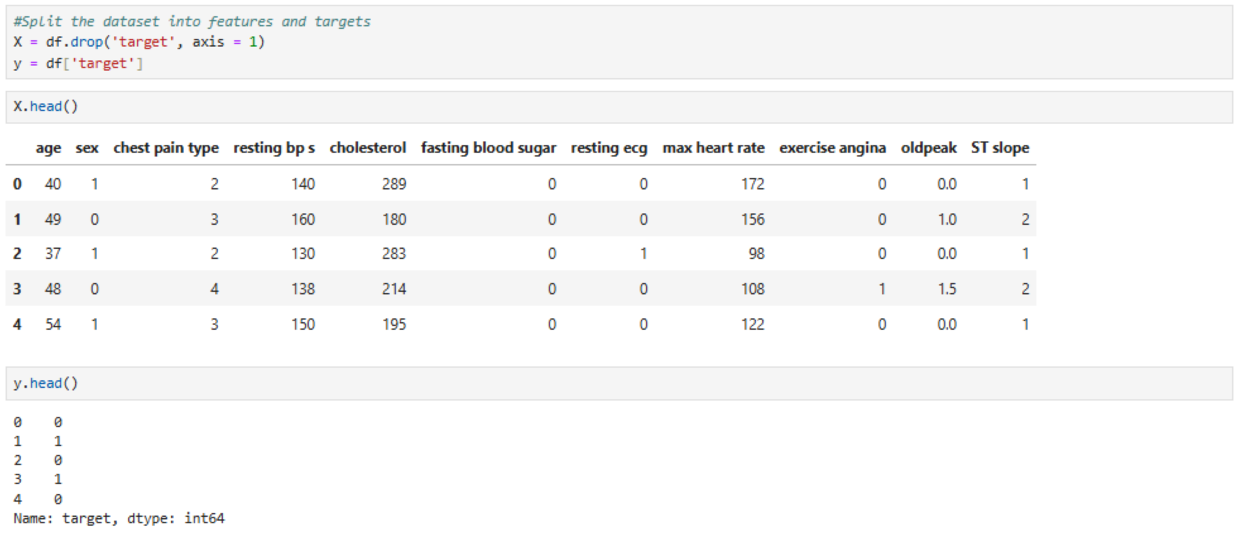
	age	sex	chest pain type	resting bp s	cholesterol	fasting blood sugar	resting ecg	max heart rate	exercise angina	oldpeak	ST slope	target
0	40	1	2	140	289	0	0	172	0	0.0	1	0
1	49	0	3	160	180	0	0	156	0	1.0	2	1
2	37	1	2	130	283	0	1	98	0	0.0	1	0
3	48	0	4	138	214	0	0	108	1	1.5	2	1
4	54	1	3	150	195	0	0	122	0	0.0	1	0

```
df.tail()
```

	age	sex	chest pain type	resting bp s	cholesterol	fasting blood sugar	resting ecg	max heart rate	exercise angina	oldpeak	ST slope	target
1185	45	1	1	110	264	0	0	132	0	1.2	2	1
1186	68	1	4	144	193	1	0	141	0	3.4	2	1
1187	57	1	4	130	131	0	0	115	1	1.2	2	1
1188	57	0	2	130	236	0	2	174	0	0.0	2	1
1189	38	1	3	138	175	0	0	173	0	0.0	1	0

Code Block 2.1: Import Libraries for Plotting and Data Filtering

Next, we split the Feature and Output data with the Code Block below.



```python
#Split the dataset into features and targets
X = df.drop('target', axis = 1)
y = df['target']
```

```python
X.head()
```

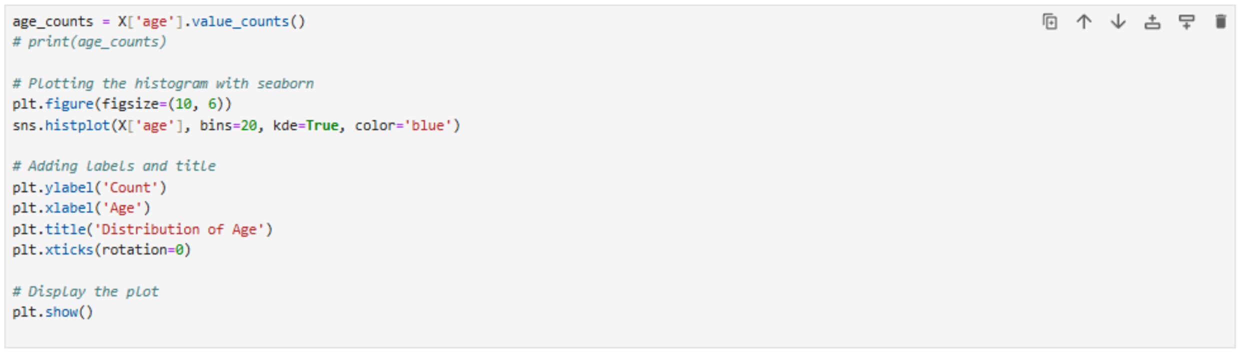
	age	sex	chest pain type	resting bp s	cholesterol	fasting blood sugar	resting ecg	max heart rate	exercise angina	oldpeak	ST slope
0	40	1	2	140	289	0	0	172	0	0.0	1
1	49	0	3	160	180	0	0	156	0	1.0	2
2	37	1	2	130	283	0	1	98	0	0.0	1
3	48	0	4	138	214	0	0	108	1	1.5	2
4	54	1	3	150	195	0	0	122	0	0.0	1

```python
y.head()
```

```
0    0
1    1
2    0
3    1
4    0
Name: target, dtype: int64
```

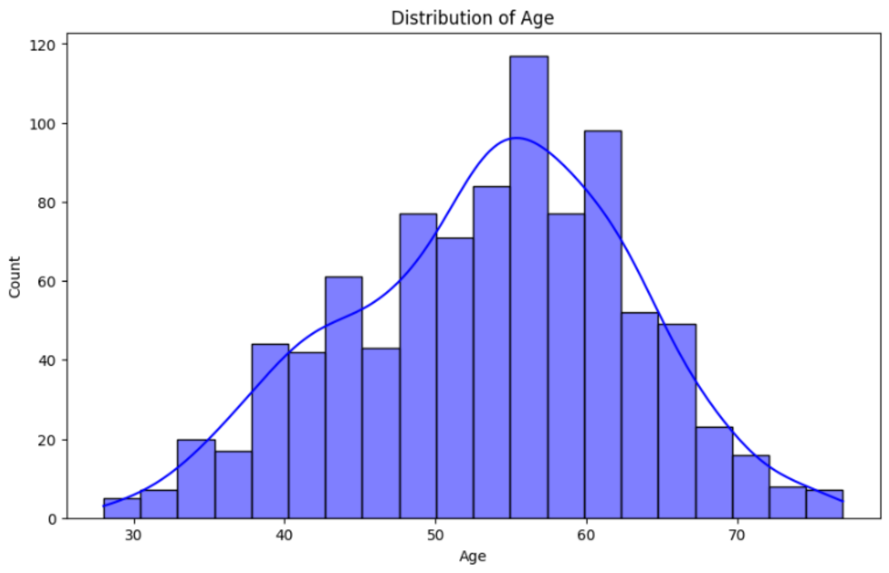
Code Block 2.2: Split Feature and Output Data using Pandas drop Function

Histograms are invaluable tools for analyzing the distribution of data. Code Block 2.3 below was used to generate all the histograms (with different sets of data extracted for each feature) presented in this section, providing a clear visualization of data distributions for various parameters.



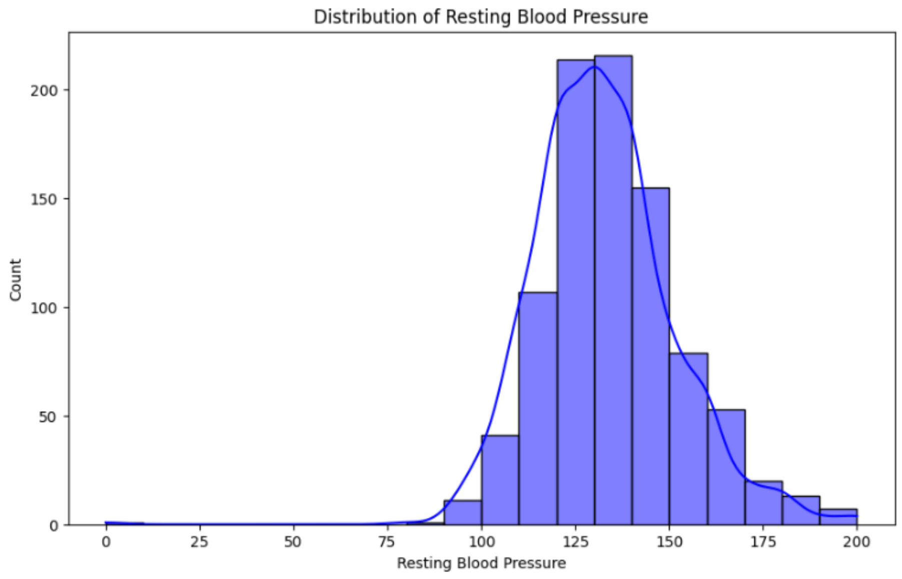
```python
age_counts = X['age'].value_counts()
# print(age_counts)

# Plotting the histogram with seaborn
plt.figure(figsize=(10, 6))
sns.histplot(X['age'], bins=20, kde=True, color='blue')

# Adding labels and title
plt.ylabel('Count')
plt.xlabel('Age')
plt.title('Distribution of Age')
plt.xticks(rotation=0)

# Display the plot
plt.show()
```

Code Block 2.3: Plotting Histogram



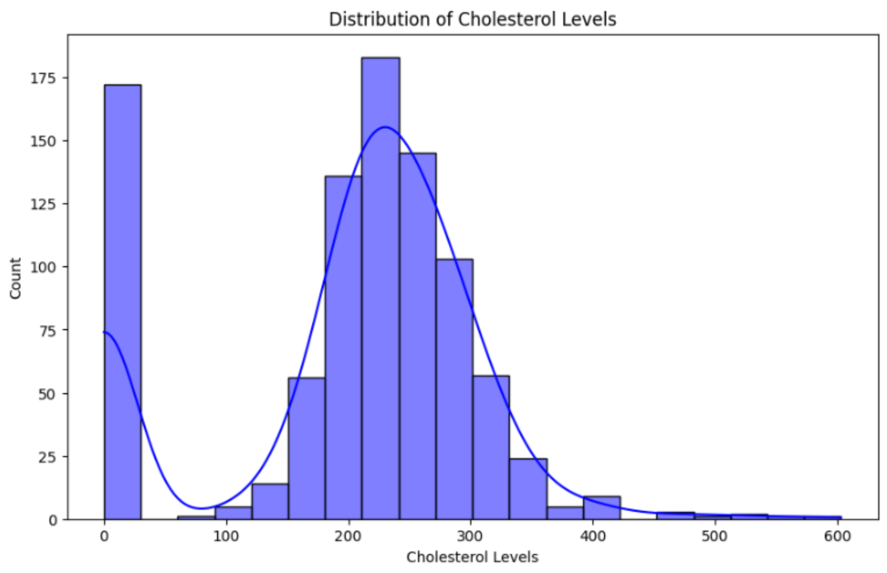
Plot 2.1: Distribution of Age Histogram

The histogram above illustrates the distribution of age within the dataset. By visualizing the age distribution, we can observe that most of the population falls within the age range of 40 to 60 years. The histogram also reveals a roughly normal distribution, with a peak around the age of 55.



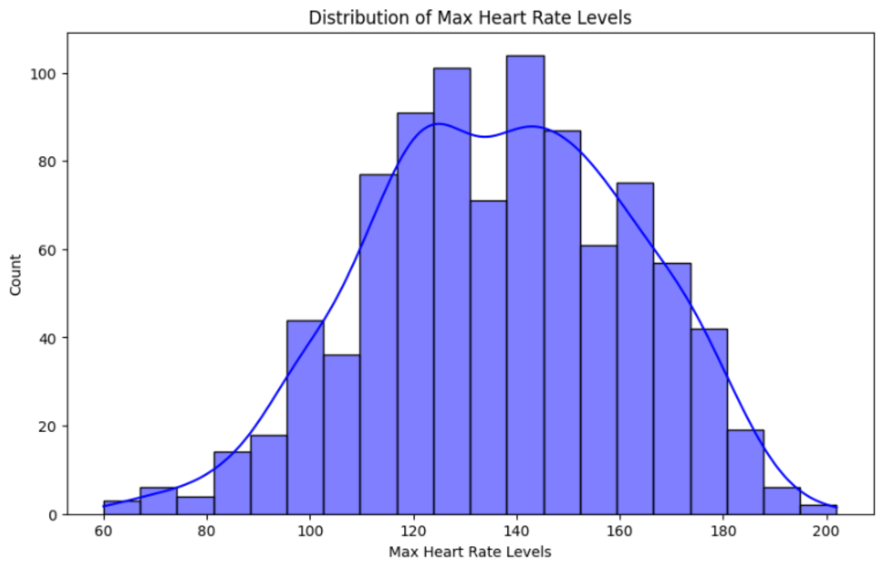
Plot 2.2: Resting Blood Pressure

The histogram above depicts the distribution of resting blood pressure values. The data is centered around a resting blood pressure of approximately 125 mmHg, indicating that this is the most common value among the population. The distribution exhibits a slight right skew, with a few individuals having higher resting blood pressure values up to 200 mmHg.



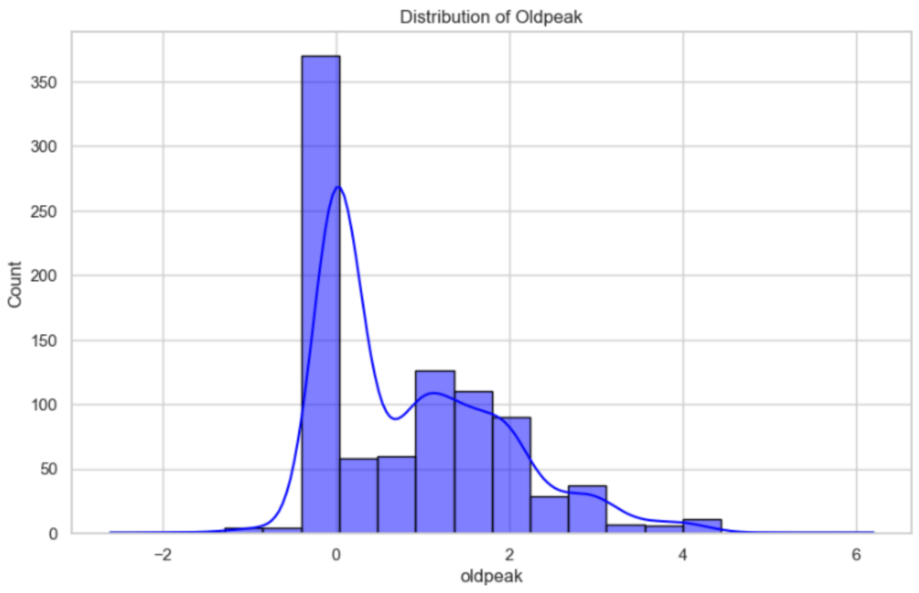
Plot 2.3: Cholesterol Levels

The histogram above shows the distribution of cholesterol levels within the dataset. Most individuals have cholesterol levels centered around 200 mg/dL, indicating this is a common range within the population. The distribution is right-skewed, with a long tail extending towards higher cholesterol values, reaching up to 600 mg/dL. Notably, there is a significant count of individuals with a cholesterol level of zero, which might indicate missing or abnormal data points that require further investigation.



Plot 2.4: Max Heart Rate Level

The histogram above illustrates the distribution of maximum heart rate levels. The data is centered around a maximum heart rate of approximately 140 beats per minute (bpm), indicating that this is the most common value within the population. The distribution appears to be roughly normal, with most values clustering around the mean and tapering off symmetrically on both sides.

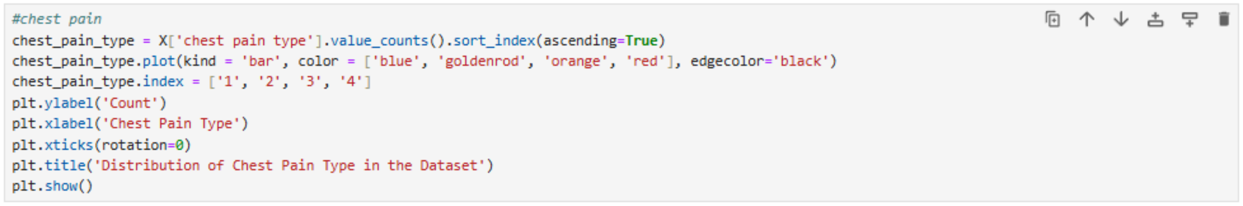


Plot 2.5: Distribution of Oldpeak

The histogram above shows the distribution of oldpeak values, which represent ST depression induced by exercise relative to rest. The x-axis indicates the oldpeak values, while the y-axis represents the count of individuals corresponding to each oldpeak value.

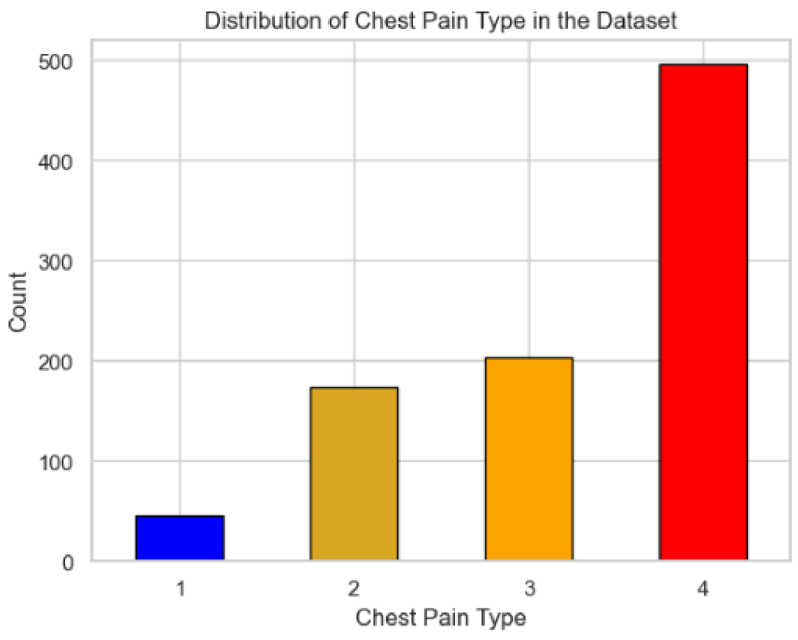
From the plot, it is evident that over 350 individuals have an oldpeak value close to 0, indicating minimal ST depression. The distribution is right-skewed, with a long tail extending towards higher oldpeak values. A smaller number of individuals exhibit higher oldpeak values, indicating greater ST depression induced by exercise. This distribution highlights that most individuals in the dataset experience little to no ST depression during exercise, while a few have significant ST depression.

Code Block 2.4 was used to create a bar plot to compare the number of Chest Pain Types throughout the data set. Plot 2.6 below is the output plot.



```
#chest pain
chest_pain_type = X['chest pain type'].value_counts().sort_index(ascending=True)
chest_pain_type.plot(kind = 'bar', color = ['blue', 'goldenrod', 'orange', 'red'], edgecolor='black')
chest_pain_type.index = ['1', '2', '3', '4']
plt.ylabel('Count')
plt.xlabel('Chest Pain Type')
plt.xticks(rotation=0)
plt.title('Distribution of Chest Pain Type in the Dataset')
plt.show()
```

Code Block 2.4: Plotting Chest Pain Type

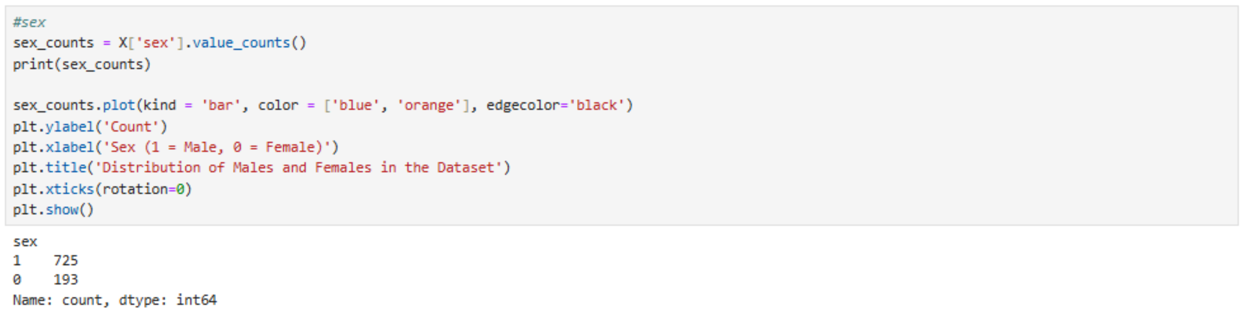


Plot 2.6: Distribution of Various Chest Pain Types

The bar plot above displays the distribution of chest pain types. Each chest pain type is represented by a number on the x-axis, ranging from 1 to 4. The count of individuals experiencing each type is shown on the y-axis.

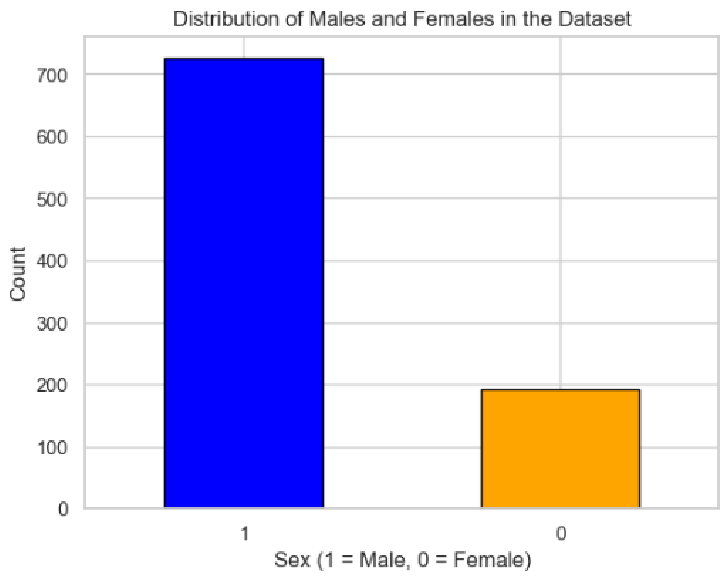
From the plot, it is evident that most individuals (almost 500) experience chest pain type 4, which is significantly higher than the other types. Chest pain types 2 and 3 are also relatively common, with around 200 individuals each, while chest pain type 1 is the least common, with fewer than 100 individuals. This distribution highlights that chest pain type 4 is the most prevalent among the population in the dataset, suggesting a focus for further medical investigation and analysis.

Code Block 2.5 below was used to make the rest of the bar plots in this section. Different sets of data were sliced for each feature in the dataset.


```
#sex
sex_counts = X['sex'].value_counts()
print(sex_counts)

sex_counts.plot(kind = 'bar', color = ['blue', 'orange'], edgecolor='black')
plt.ylabel('Count')
plt.xlabel('Sex (1 = Male, 0 = Female)')
plt.title('Distribution of Males and Females in the Dataset')
plt.xticks(rotation=0)
plt.show()
```

```
sex
1    725
0    193
Name: count, dtype: int64
```

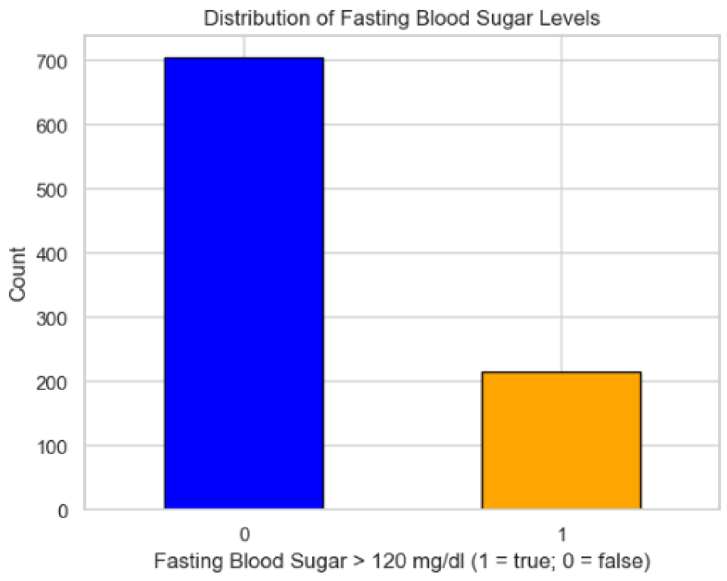
Code Block 2.5: Plotting Bar Plots



Plot 2.7: Distribution of Males and Females

The bar plot above shows the distribution of males and females within the dataset. The x-axis represents the sex, where 1 corresponds to males and 0 corresponds to females. The y-axis represents the count of individuals in each category.

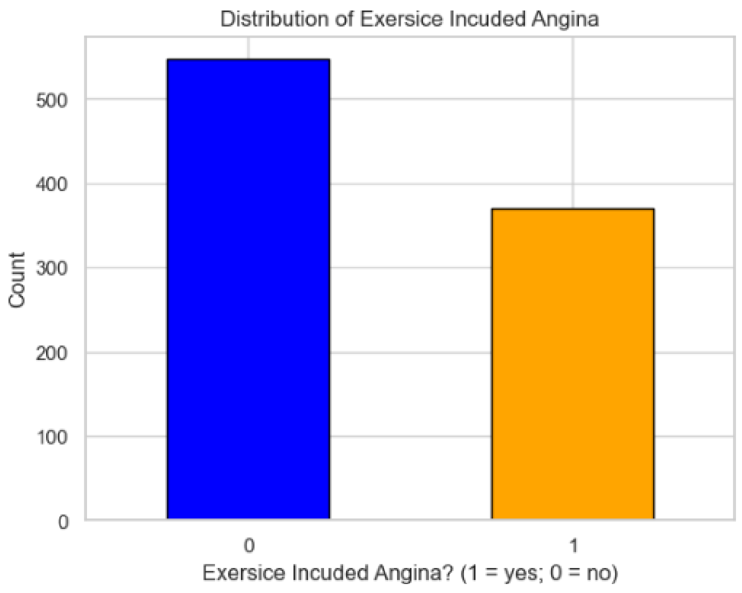
The plot clearly indicates a significant gender imbalance, with males (represented by the blue bar) comprising most of the dataset at over 700 individuals. In contrast, females (represented by the orange bar) make up a much smaller portion of the dataset, with fewer than 200 individuals. This uneven distribution suggests that males are more prominently represented in this dataset, which could influence the analysis and findings.



Plot 2.8: Distribution of Fasting Blood Sugar Levels

The bar plot above illustrates the distribution of fasting blood sugar levels. The x-axis represents the fasting blood sugar categories, with 1 indicating levels greater than 120 mg/dl and 0 indicating levels of 120 mg/dl or less. The y-axis displays the count of individuals in each category.

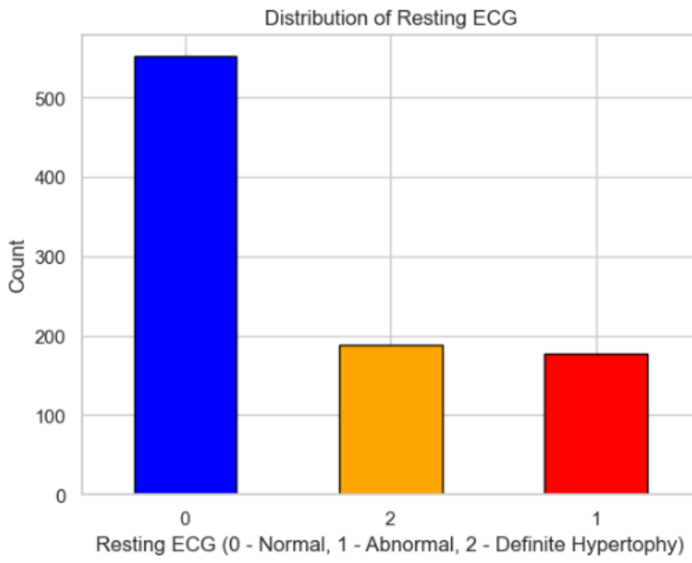
From the plot, it is evident that most individuals in the dataset (represented by the blue bar) have a fasting blood sugar level of 120 mg/dl or less, with a count of over 700. In contrast, a smaller proportion of individuals (represented by the orange bar) have fasting blood sugar levels greater than 120 mg/dl, with fewer than 200 individuals.



Plot 2.9: Distribution of Exercise Included Angina

Plot 2.9 above depicts the distribution of exercise-induced angina within the dataset. The x-axis indicates whether the individual experienced exercise-induced angina, where 1 represents "yes" and 0 represents "no". The y-axis shows the count of individuals in each category.

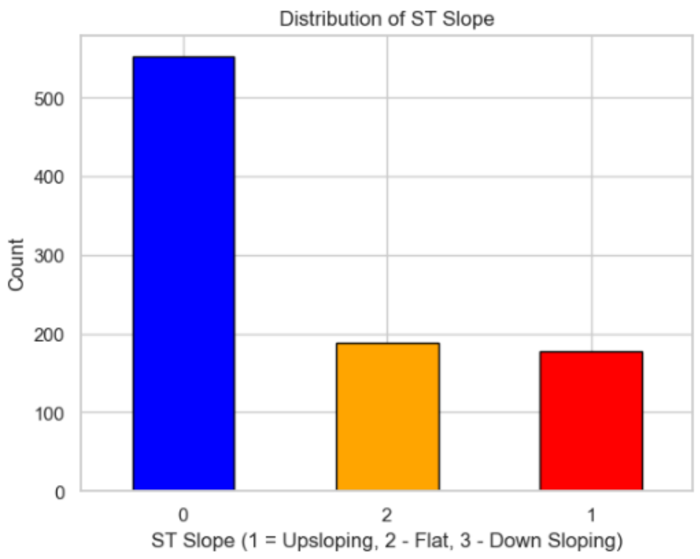
From the plot, it is evident that a larger number of individuals in the dataset (represented by the blue bar) did not experience exercise-induced angina, with a count of over 500. In comparison, a smaller number of individuals (represented by the orange bar) did experience exercise-induced angina, with fewer than 400 individuals.



Plot 2.10: Resting ECG

Plot 2.10 above illustrates the distribution of resting ECG results. The x-axis represents the three categories of resting ECG results: 0 for normal, 1 for abnormal, and 2 for definite hypertrophy. The y-axis shows the count of individuals in each category.

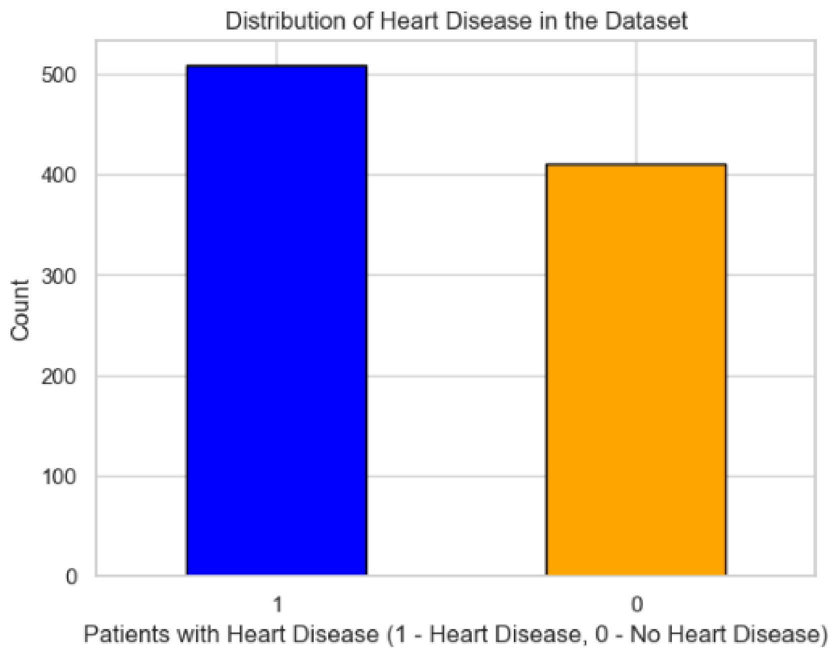
From the plot, most individuals have a normal resting ECG (represented by the blue bar), with a count of over 500. The next most common category is definite hypertrophy (represented by the orange bar), followed closely by abnormal results (represented by the red bar), each with fewer than 200 individuals. This distribution indicates that normal resting ECG results are prevalent within this population, while abnormal and hypertrophic results are less common but still significant.



Plot 2.11: ST Slope Distribution

The bar plot above illustrates the distribution of ST slope categories. The x-axis represents the ST slope types, where 1 corresponds to upsloping, 2 corresponds to flat, and 3 corresponds to downsloping. The y-axis shows the count of individuals in each category.

From the plot, it is evident that most individuals in the dataset have an upsloping ST slope (represented by the blue bar), with a count of over 500. The flat ST slope category (represented by the orange bar) and the downsloping ST slope category (represented by the red bar) each have fewer individuals, with counts of around 200. This distribution indicates that upsloping ST slopes are the most common in this population, while flat and downsloping ST slopes are less frequent.



Plot 2.12: Number of Patients with Heart Disease

The bar plot above illustrates the distribution of heart disease in the dataset. The x-axis indicates whether patients have heart disease or not, where 1 represents patients with heart disease and 0 represents patients without heart disease. The y-axis shows the count of individuals in each category.

From the plot, it is evident that there are more patients with heart disease (represented by the blue bar) than without, with a count of over 500. In contrast, there are fewer patients without heart disease (represented by the orange bar), with a count of around 400. This distribution suggests that heart disease is prevalent in this population. Ideally, for a Binary Classification Model, we would have an even number of patients with and without heart disease. We will see how this affects the model outcomes moving forward.

Data Preprocessing

Data preprocessing is a critical step in the data analysis workflow that prepares raw data for further training, analysis and modeling. This section details the processes undertaken to clean, transform, and organize the dataset, ensuring it is in the optimal format for analysis. Key preprocessing steps include splitting the data into training and testing sets, scaling the features to ensure uniformity, and handling any missing or inconsistent values.

To complete the planned preprocessing steps, we must have all the necessary libraries imported. These include NumPy, Pandas, and Scikit-Learn.

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

Code Block 3.1: Import necessary Libraries

The Pandas library was used for data import and filtering, NumPy was used for array manipulation and calculation. Lastly, scikit-learn was used to scale and split the data for training.

To ensure the quality and integrity of the data before training our model, the first step involves removing any duplicate entries from the dataset. Duplicate entries can skew the results and reduce the accuracy of the model.

```
df.drop_duplicates(inplace = True)
df.reset_index(inplace = True, drop = True)
df.info()
```

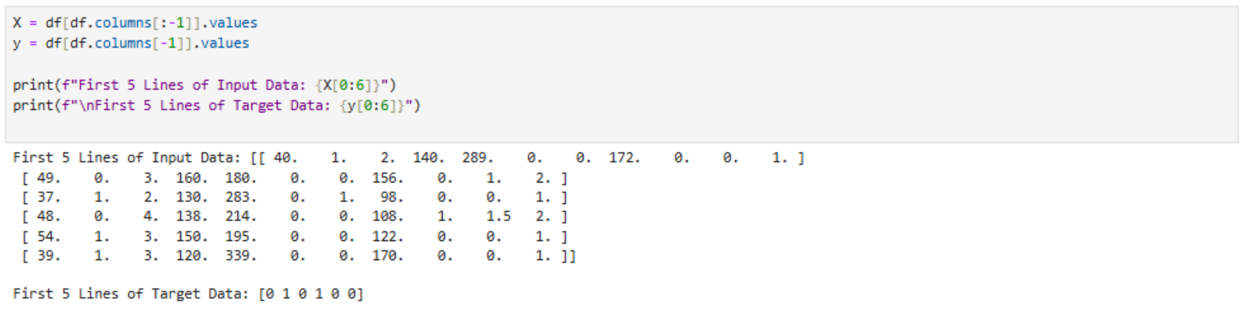
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 918 entries, 0 to 917
Data columns (total 12 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   age                  918 non-null    int64
 1   sex                  918 non-null    int64
 2   chest pain type      918 non-null    int64
 3   resting bp s         918 non-null    int64
 4   cholesterol          918 non-null    int64
 5   fasting blood sugar  918 non-null    int64
 6   resting ecg          918 non-null    int64
 7   max heart rate       918 non-null    int64
 8   exercise angina      918 non-null    int64
 9   oldpeak              918 non-null    float64
 10  ST slope             918 non-null    int64
 11  target               918 non-null    int64
dtypes: float64(1), int64(11)
memory usage: 86.2 KB
```

Code Block 3.2: Dropping Duplicates

We achieved this by utilizing the built-in `drop_duplicates` method in pandas. After loading the dataset into a dataframe, the duplicates were dropped, and the index was reset to maintain a clean, sequential order of entries. As illustrated in Code Block 3.2, our dataset now contains 918 unique entries and 12 columns, each with no missing values.

The next step in preprocessing our data is splitting it into training, validation and testing datasets. This step is vital for evaluating the performance of our machine learning model and ensuring its generalizability to new, unseen data.

To start, we need to distinguish our input features from our target variable. This is shown in Code Block 3.3 below.

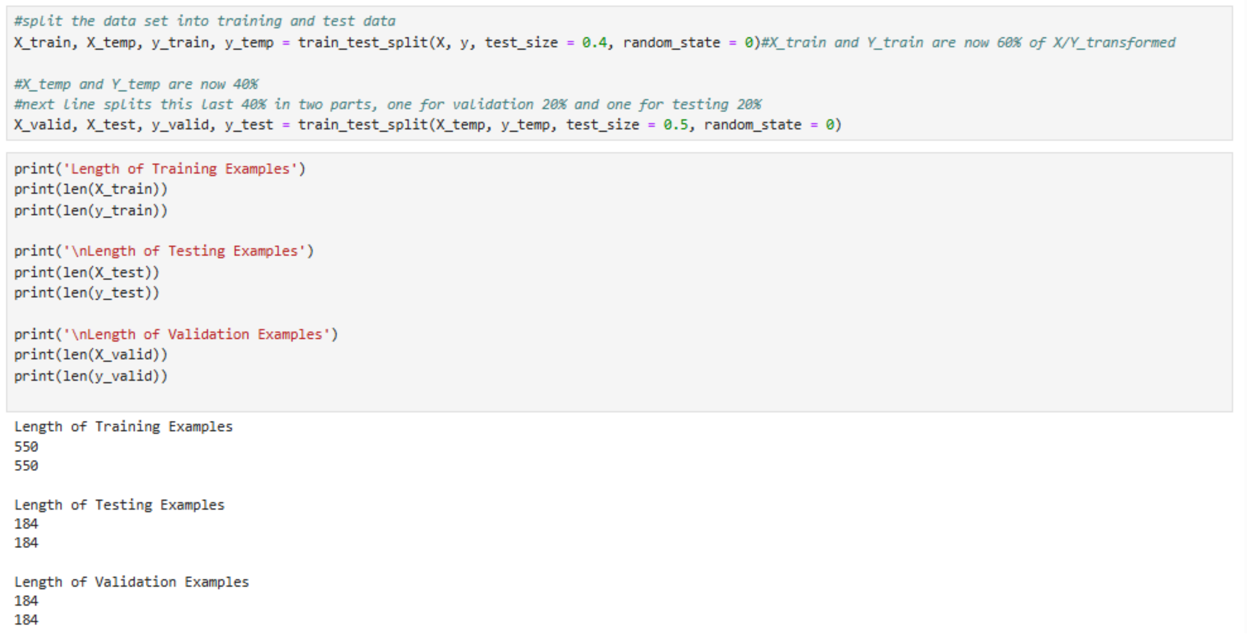


```
X = df[df.columns[:-1]].values
y = df[df.columns[-1]].values

print(f"First 5 Lines of Input Data: {X[0:6]}")
print(f"\nFirst 5 Lines of Target Data: {y[0:6]}")
```

```
First 5 Lines of Input Data: [[ 40.    1.    2.  140.  289.    0.    0.  172.    0.    0.    1. ]
 [ 49.    0.    3.  160.  180.    0.    0.  156.    0.    1.    2. ]
 [ 37.    1.    2.  130.  283.    0.    1.   98.    0.    0.    1. ]
 [ 48.    0.    4.  138.  214.    0.    0.  108.    1.    1.5   2. ]
 [ 54.    1.    3.  150.  195.    0.    0.  122.    0.    0.    1. ]
 [ 39.    1.    3.  120.  339.    0.    0.  170.    0.    0.    1. ]]

First 5 Lines of Target Data: [0 1 0 1 0 0]
```

Code Block 3.3: Separate Input and Target Data

We will divide the dataset into three segments: training data, validation data, and test data. The training dataset will comprise 60% of the total data, the validation dataset will make up 20%, and the remaining 20% will be used as the test dataset. To accomplish this, we use the `train_test_split` function from the Scikit-Learn library, which simplifies the data splitting process.



```
#split the data set into training and test data
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size = 0.4, random_state = 0)#X_train and Y_train are now 60% of X/Y_transformed

#X_temp and Y_temp are now 40%
#next line splits this last 40% in two parts, one for validation 20% and one for testing 20%
X_valid, X_test, y_valid, y_test = train_test_split(X_temp, y_temp, test_size = 0.5, random_state = 0)
```

```
print('Length of Training Examples')
print(len(X_train))
print(len(y_train))

print('\nLength of Testing Examples')
print(len(X_test))
print(len(y_test))

print('\nLength of Validation Examples')
print(len(X_valid))
print(len(y_valid))
```

```
Length of Training Examples
550
550

Length of Testing Examples
184
184

Length of Validation Examples
184
184
```

Code Block 3.4: Split the data for training, validation and testing

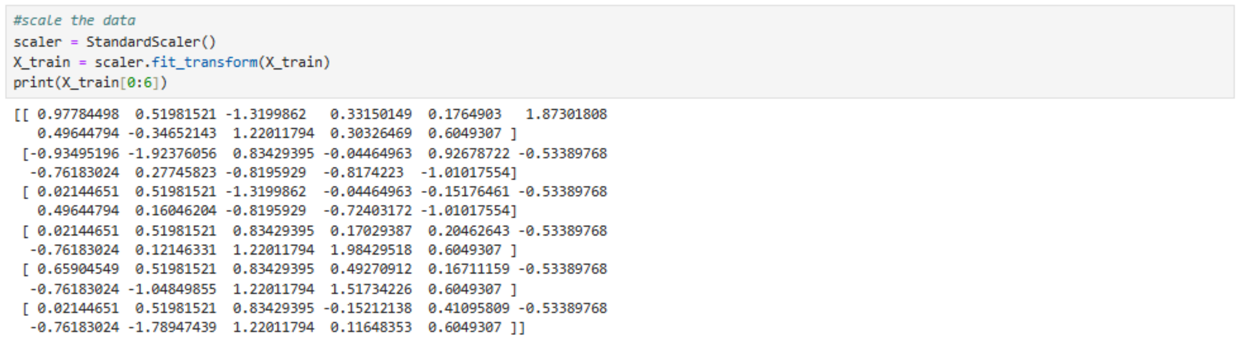
The first line of code splits the data into 60% and 40%, with 60% being the training data and the remaining 40% (`X_temp` & `y_temp`) being split again into validation and test data. We later verified the length of each dataset to ensure consistency. This approach ensures that we have a robust and representative sample for training, validation, and testing our model.

- **Training Set:** 60% of the total data
- **Validation Set:** 20% of the total data
- **Test Set:** 20% of the total data

By splitting the data in this manner, we can effectively train our model, tune its hyperparameters, and evaluate its performance on unseen data, ultimately ensuring its reliability and robustness.

The next essential step in preprocessing our data is scaling the training data. Scaling is a crucial step because it standardizes the range of the independent features in the dataset, ensuring that each feature contributes equally to the analysis. When features are on different scales, the algorithm might give undue importance to features with larger ranges, leading to biased results. For example, in our dataset, features like 'age' and 'cholesterol' might be on entirely different scales. Without scaling, the model might interpret 'cholesterol' as being more significant than 'age' simply due to its larger numerical values.

To achieve this, we use the `StandardScaler` from Scikit-Learn, which transforms the data to have a mean of zero and a standard deviation of one. This method ensures that each feature contributes equally to the model, improving the model's performance and convergence speed. Code Block 3.5 below demonstrates this process:



```
#scale the data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
print(X_train[0:6])
```

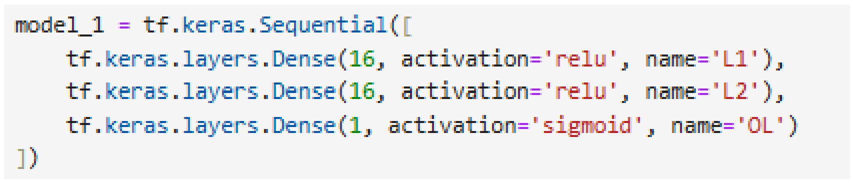
```
[[ 0.97784498  0.51981521 -1.3199862   0.33150149  0.1764903   1.87301808
   0.49644794 -0.34652143  1.22011794  0.30326469  0.6049307 ]
 [-0.93495196 -1.92376056  0.83429395 -0.04464963  0.92678722 -0.53389768
  -0.76183024  0.27745823 -0.8195929  -0.8174223  -1.01017554]
 [ 0.02144651  0.51981521 -1.3199862  -0.04464963 -0.15176461 -0.53389768
   0.49644794  0.16046204 -0.8195929  -0.72403172 -1.01017554]
 [ 0.02144651  0.51981521  0.83429395  0.17029387  0.20462643 -0.53389768
  -0.76183024  0.12146331  1.22011794  1.98429518  0.6049307 ]
 [ 0.65904549  0.51981521  0.83429395  0.49270912  0.16711159 -0.53389768
  -0.76183024 -1.04849855  1.22011794  1.51734226  0.6049307 ]
 [ 0.02144651  0.51981521  0.83429395 -0.15212138  0.41095809 -0.53389768
  -0.76183024 -1.78947439  1.22011794  0.11648353  0.6049307 ]]
```

Now that our data is scaled and preprocessed, we are ready to move on to the next crucial phase: model selection. This involves evaluating different machine learning algorithms to identify the one that best fits our dataset and yields the highest performance. In the upcoming section, we will explore various models, tune their hyperparameters, and select the most suitable model for our predictive task.

Neural Network Structure Selection

In the following section, we will create multiple Neural Network structures, test them, and then choose which structures performed best and take them to the next phase of development. The 4 model structures chosen and the reasoning for choosing them can be found below.

Model 1:



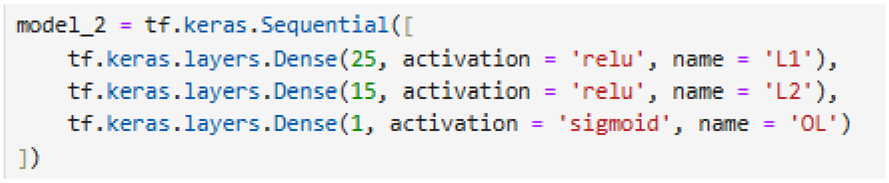
```python
model_1 = tf.keras.Sequential([
    tf.keras.layers.Dense(16, activation='relu', name='L1'),
    tf.keras.layers.Dense(16, activation='relu', name='L2'),
    tf.keras.layers.Dense(1, activation='sigmoid', name='OL')
])
```

Code Block 4.1: Model 1 Tensorflow Implementation

Model 1 consists of three layers, the first two being Dense layers containing 16 neurons each with ReLU activation functions. The thought behind this structure was that since the first two layers are identical, the second layer would be able to build on the patterns detected by the first layer, enhancing the model's ability to learn intricate data representations. This approach leverages the simplicity and effectiveness of feedforward neural networks while maintaining a balance between model complexity and computational efficiency.

The final layer is the output layer, where there is only one neuron with a sigmoid activation function. This is ideal for a binary classification task, as it outputs a probability value between 0 and 1, indicating the likelihood of belonging to one of the two classes.

Model 2:



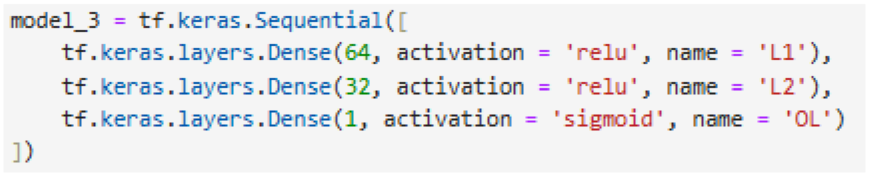
```python
model_2 = tf.keras.Sequential([
    tf.keras.layers.Dense(25, activation = 'relu', name = 'L1'),
    tf.keras.layers.Dense(15, activation = 'relu', name = 'L2'),
    tf.keras.layers.Dense(1, activation = 'sigmoid', name = 'OL')
])
```

Code Block 4.2: Model 2 Tensorflow Implementation

Model 2 has the same number of layers as Model 1 but has a different number of neurons in the first two layers. The first layer in Model 2 has 25 neurons; this aims to capture even more detailed and complex patterns in the input data, enhancing the model's ability to learn from intricate data representations. Layer 2 in this model has 15 neurons, ten fewer than the first layer. Both the first two layers have ReLU activation functions, and the output layer has one neuron with a sigmoid activation function.

In model 2, we increased the number of neurons in the first layer to better capture and handle non-linear relationships in the data. By having a slightly smaller second layer compared to the first, the model balances complexity and computational efficiency, ensuring it can generalize well without being overly complex or prone to overfitting.

Model 3:

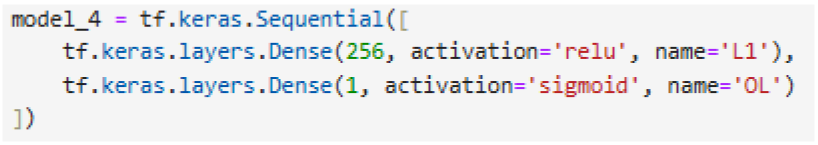

```
model_3 = tf.keras.Sequential([
    tf.keras.layers.Dense(64, activation = 'relu', name = 'L1'),
    tf.keras.layers.Dense(32, activation = 'relu', name = 'L2'),
    tf.keras.layers.Dense(1, activation = 'sigmoid', name = 'OL')
])
```

Code Block 4.5: Model 3 Tensorflow Implementation

Model 3 is different from the previous three models; the structure is meant to be simple yet effective. The first two layers have 64 and 32 neurons with ReLU activation functions, respectively and the final output layer has one neuron with a sigmoid activation function.

This model architecture is designed to efficiently extract complex and detailed features from the input data, potentially improving classification accuracy. The inclusion of hidden layers with a significant number of neurons allows the model to learn deep representations. Model 3 aims to balance complexity and depth, providing a robust framework for handling the diverse features within the heart disease dataset.

Model 4:


```
model_4 = tf.keras.Sequential([
    tf.keras.layers.Dense(256, activation='relu', name='L1'),
    tf.keras.layers.Dense(1, activation='sigmoid', name='OL')
])
```

Code Block 4.7: Model 4 Tensorflow Implementation

Model 4 consists of one hidden layer and an output layer. The first and only hidden layer has 256 neurons with a ReLU activation function. The final output layer has one neuron with a sigmoid activation function.

This network structure is wider but shallower, which can be beneficial for datasets with limited depth but requiring high-capacity feature learning. A single large hidden layer can effectively capture the relationships between features, making it simpler to train and interpret. This approach captures a wide range of patterns, resulting in reliable performance in binary classification.

Parameter Optimization

The structure of a neural network plays a crucial role in the performance of a machine learning algorithm. Different architectures are designed to capture varying levels of detail and generalization. The four models we have designed each have unique advantages and disadvantages, which we will evaluate through testing.

To determine their performance, each model will be trained and evaluated using the same training, validation, and test datasets. They will be compiled with identical parameters, except for the one parameter each parametric study will focus on. Initially, we will identify the ideal regularization parameters for the hidden layers while keeping the Adam optimizer's learning rate at its default value of 0.001.

Regularization

For this machine learning project, L2 regularization was chosen over L1 and L1L2 regularization due to its specific advantages in handling the dataset and the nature of the problem. L2 regularization, also known as Ridge regularization, is effective in situations where we want to ensure that all features contribute to the model prediction without driving any coefficients to zero. This is particularly important for predicting heart disease, where multiple medical parameters are likely to provide valuable information.

L2 regularization works by adding a penalty equivalent to the square of the magnitude of coefficients to the loss function, which helps in distributing weights more evenly and preventing any single feature from dominating the prediction process. This is beneficial in our context, as it helps manage collinear features and ensures the model does not overly rely on any one parameter, thereby improving generalization.

In contrast, L1 regularization (Lasso) can drive some coefficients to zero, effectively performing feature selection. While this is useful in high-dimensional datasets with many irrelevant features, it might not be ideal for our heart disease dataset, where each feature could contribute meaningfully to the prediction.

We will conduct a parametric study on the regularization parameter and refine it based on the results. Code Block 5.1 demonstrates how multiple regularization parameters are tested on Model 1. This approach will be similarly applied to Models 2, 3, and 4, with appropriate adjustments to variable names.

```
for i in regularization_values:
    print(f"REGULARIZATION PARAMETER: {i}")

    model_1_reg = tf.keras.Sequential([
        tf.keras.layers.Dense(16, activation='relu', name='L1', kernel_regularizer = l2(i)),
        tf.keras.layers.Dense(16, activation='relu', name='L2', kernel_regularizer = l2(i)),
        tf.keras.layers.Dense(1, activation='sigmoid', name='OL')
    ])

    model_1_reg.compile(optimizer = tf.keras.optimizers.Adam(),
            loss = tf.keras.losses.BinaryCrossentropy(),
            metrics = ['accuracy'])

    history = model_1_reg.fit(X_train, y_train, batch_size = 16, epochs = 30, validation_data = (X_valid, y_valid))

    plot_accuracy(history)
    plot_loss(history)

    print("\nModel Prediction on Test set")
    results= model_1_reg.evaluate(X_test, y_test)

    y_predicted_m1_reg = model_1_reg.predict(X_test)
    y_predicted_m1_reg = y_predicted_m1_reg.flatten()
    y_predicted_m1_reg = np.where(y_predicted_m1_reg > 0.5, 1, 0)

    print(f"\nConfusion Matrix")
    cm = confusion_matrix(y_test, y_predicted_m1_reg)
    print(cm)

    print(classification_report(y_test, y_predicted_m1_reg))
```

Code Block 5.1: Testing Initial Regularization values

The initial regularization values tested were 0.0001, 0.001, 0.01, and 0.1. These values were further refined in a subsequent phase of testing. Regularization is important because it helps prevent overfitting by adding a penalty for larger weights in the model. This encourages the model to keep weights small, ensuring it generalizes better to unseen data. By controlling the complexity of the model, regularization helps achieve a balance between fitting the training data well and maintaining good performance on new, unseen data.

In Code Block 5.1, we start by creating the model with a regularization parameter defined by the current value of the for-loop iteration variable `‘i’`. The model is then compiled and fit with the training data. After training, we capture various plots and metrics for record-keeping. Finally, the trained model is evaluated on unseen test data, with the primary focus on the F1-Score from the classification report. This report provides overall accuracy as well as accuracies for predicting each class, in this case, patients with and without heart disease.

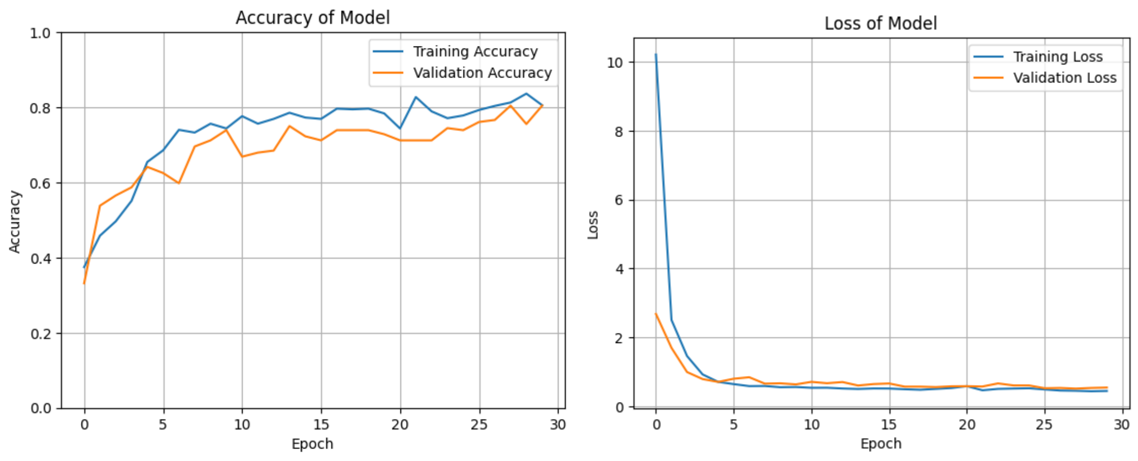
The regularization parameter will be further refined around values that yield an overall accuracy of 80% or above. The final regularization parameter for each model will be judged based on higher criteria to ensure optimal performance.

Table 5.1 below highlights Model 1’s accuracy over the above regularization parameters.

Model 1 + Regularization Parameter			
Regularization Parameter	F1-Score (0)	F1-Score (1)	Accuracy
0.0001	80	80	80
0.001	79	81	80
0.01	77	84	82
0.1	73	78	76

Table 5.1: Model 1 – Initial Regularization Parameter Performance Metrics (Evaluated on Test Data)

For Model 1, the regularization parameter will be refined from 0.001 to 0.01. That's where the highest F1-score accuracies were found, especially for predicted cases that have heart disease, reaching a stellar 84%.



Plot 5.1: Model 1, Regularization Parameter 0.001

The first graph in Plot 5.1 illustrates the accuracy of the model over 30 epochs for both the training and validation datasets. The training accuracy steadily improves, reaching around 80%. The validation accuracy also follows a similar trend, indicating that the model is learning effectively and generalizing well to unseen data. However, there are slight fluctuations in validation accuracy, which could be attributed to the model fine-tuning its parameters.

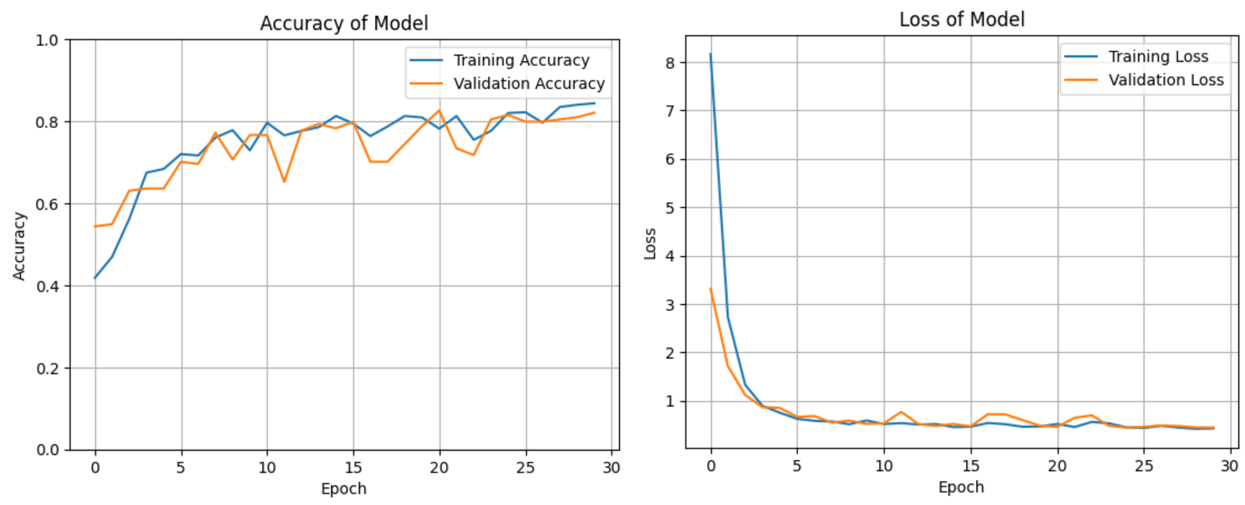
The second graph in Plot 5.1 shows the loss of the model over 30 epochs for both the training and validation datasets. The training loss decreases rapidly within the first few epochs and stabilizes, suggesting the model is effectively minimizing error on the training set. The validation loss mirrors this trend, with a close alignment to the training loss, indicating that the model is not overfitting and is performing well on the validation set. This overall consistency between training and validation loss reinforces the model's robustness and reliability.

Model 2 + Regularization Parameter			
Regularization Parameter	F1-Score (0)	F1-Score (1)	Accuracy
0.0001	77	83	80
0.001	80	84	82
0.01	79	80	79
0.1	57	79	72

Table 5.2: Model 2 – Initial Regularization Parameter Performance Metrics (Evaluated on Test Data)

For Model 2, the regularization parameter will be refined from 0.0001 to 0.001, as that's where the highest F1-scores and overall accuracies were found.

Model 2 had a wider range of successful regularization parameters; the following plots show the accuracy and loss of Model 2 with a regularization parameter of 0.001.



Plot 5.2: Model 2, Regularization Parameter 0.001

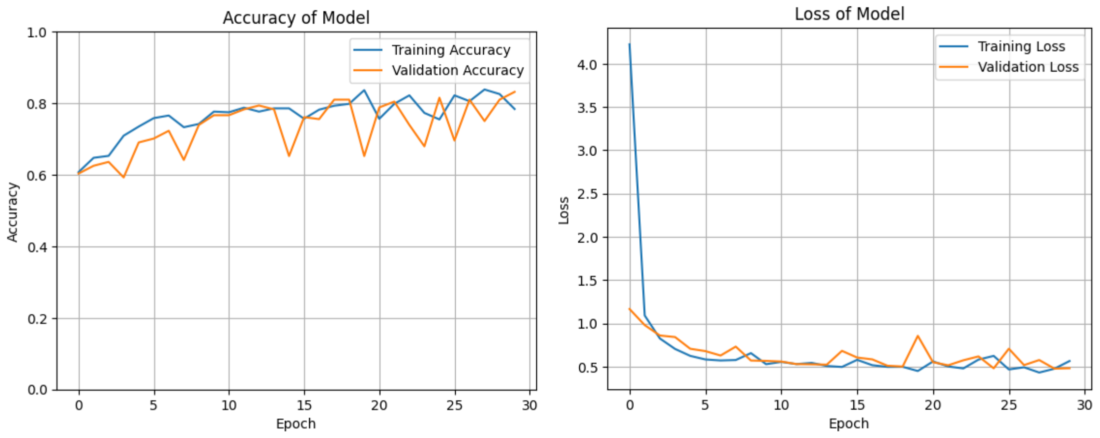
The graph on the left from Plot 5.2 displays the training and validation accuracy over 30 epochs. The training accuracy shows a steady increase, reaching approximately 82%. Likewise, the validation accuracy also improves, closely mirroring the training accuracy trend. This close alignment suggests that the model is effectively generalizing to unseen data with minimal overfitting. The minor fluctuations in validation accuracy indicate stable performance across epochs.

The graph on the right of Plot 5.2 shows the training and validation loss over 30 epochs. The training loss drops sharply within the first few epochs and then stabilizes, indicating effective error minimization during training. The validation loss follows a similar trend to the training loss, further confirming that the model is not overfitting and performs well on the validation data. The close match between training and validation loss underscores the model's robustness and generalization capabilities.

Model 3 + Regularization Parameter			
Regularization Parameter	F1-Score (0)	F1-Score (1)	Accuracy
0.0001	79	78	79
0.001	80	83	82
0.01	76	68	72
0.1	78	84	82

Table 5.3: Model 3 – Initial Regularization Parameter Performance Metrics (Evaluated on Test Data)

For Model 3, the regularization parameter will be refined around 0.001, as that's where the highest F1-score and overall accuracies were found.



Plot 5.3: Model 3, Regularization Parameter 0.001

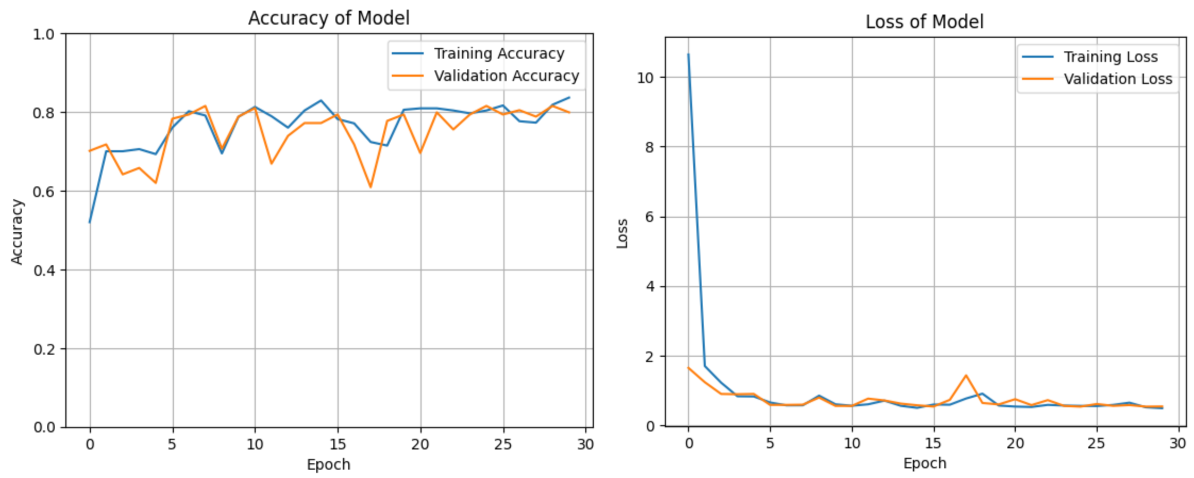
The graph on the left of Plot 5.3 illustrates the training and validation accuracy over 30 epochs. Training accuracy demonstrates consistent improvement, ultimately reaching around 82%. Similarly, validation accuracy follows an upward trend, closely aligning with the training accuracy. This close alignment between training and validation accuracies indicates good generalization to unseen data, with minimal overfitting. The slight variations in validation accuracy and loss suggest a different learning rate can help the model perform better, due to the noise in the validation curves.

In Model 3, Regularization Parameter 0.001, the training loss drops sharply within the initial epochs and then stabilizes, indicating effective error minimization during training. The validation loss closely mirrors the training loss trend, further supporting that the model is not overfitting and performs well on validation data. The close alignment between training and validation losses underscores the model's robustness and its capability to generalize effectively.

Model 4 + Regularization Parameter			
Regularization Parameter	F1-Score (0)	F1-Score (1)	Accuracy
0.0001	43	77	67
0.001	66	82	76
0.01	83	86	85
0.1	14	73	59

Table 5.4: Model 4 – Initial Regularization Parameter Performance Metrics (Evaluated on Test Data)

For Model 4, the regularization parameter will be refined around 0.01, as that's where the highest F1-score and accuracy were found and so far, our highest overall accuracy and highest heart disease prediction accuracy. The following plots show the accuracy and loss of the training and validation over 30 epochs.



Plot 5.4: Model 4, Regularization Parameter 0.01

The accuracy plot on the left of Plot 5.4 displays the training and validation accuracy over 30 epochs. The training accuracy shows improvement, ultimately reaching around 80%. The validation accuracy follows a similar trend, indicating good generalization to unseen data. However, there are noticeable fluctuations in the validation accuracy, indicating some noise.

The loss plot on the right of Plot 5.4 shows the training and validation loss over 30 epochs. The training loss decreases significantly during the initial epochs and then stabilizes, reflecting effective error minimization. The validation loss follows a similar pattern, indicating that the model is generalizing well without overfitting.

Regularization Refinement

In the previous section, each model structure was tested along with a generalized set of regularization parameters. Each model now has a refined range we can test over once again. They go as follows:

Model 1: Regularization Parameter Refinement 0.001 to 0.01

Model 2: Regularization Parameter Refinement 0.0001 to 0.001

Model 3: Regularization Parameter Refinement centered around 0.001

Model 4: Regularization Parameter Refinement centered around 0.01

```
#regularization values refined
m1_reg_refined = [0.001,0.0019,0.0028,0.0037,0.0046,0.0055,0.0064,0.0073,0.0082,0.0091]
m2_reg_refined = [0.00018, 0.00026, 0.00034, 0.00042, 0.0005, 0.00059, 0.00067, 0.00075, 0.00083, 0.00091]
m3_reg_refined = [0.0005, 0.00061, 0.00072, 0.00083, 0.00094, 0.001, 0.0011, 0.0012, 0.0013, 0.0014, 0.0015]
m4_reg_refined = [0.0054, 0.0063, 0.0072, 0.0081, 0.009, 0.01, 0.011, 0.012, 0.013, 0.014, 0.015]
```

Code Block 5.2: Refined Regularization Parameters

Above, Code Block 5.2 displays how the refined regularization values are stored in their own lists in python. We will be compiling, training and testing the model for each of those refined values. The following Code Block was used to test Model 1 with its parameters, the same structure was used for the other models with different variable names.

```
for i in m1_reg_refined:
    print(f"REGULARIZATION PARAMETER: {i}")

    model_1_reg = tf.keras.Sequential([
        tf.keras.layers.Dense(16, activation='relu', name='L1', kernel_regularizer = l2(i)),
        tf.keras.layers.Dense(16, activation='relu', name='L2', kernel_regularizer = l2(i)),
        tf.keras.layers.Dense(1, activation='sigmoid', name='OL')
    ])

    model_1_reg.compile(optimizer = tf.keras.optimizers.Adam(),
            loss = tf.keras.losses.BinaryCrossentropy(),
            metrics = ['accuracy'])

    history = model_1_reg.fit(X_train, y_train, batch_size = 16, epochs = 30, validation_data = (X_valid, y_valid))

    plot_accuracy(history)
    plot_loss(history)

    print("\nModel Prediction on Test set")
    results= model_1_reg.evaluate(X_test, y_test)

    y_predicted_m1_reg = model_1_reg.predict(X_test)
    y_predicted_m1_reg = y_predicted_m1_reg.flatten()
    y_predicted_m1_reg = np.where(y_predicted_m1_reg > 0.5, 1, 0)

    print(f"\nConfusion Matrix")
    cm = confusion_matrix(y_test, y_predicted_m1_reg)
    print(cm)

    print(classification_report(y_test, y_predicted_m1_reg))
```

Code Block 5.3: Model 1 – Test Refined Regularization Values

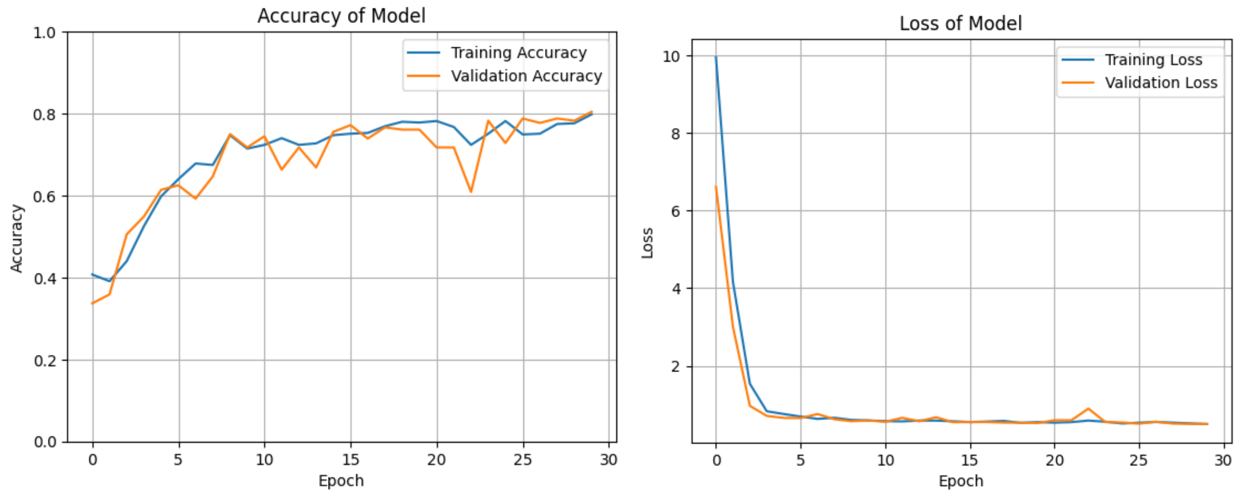
After testing each model, only the models with an accuracy of 80% or higher in all three categories will move on to the learning rate study; they also must show an improvement from the previous model parameters tested. The following is a summary of the testing on the refined regularization values that passed the given criteria.

Regularization Parameter Refinement – Model 1

The following are the F1-Scores and overall accuracies from Model 1 and its refined regularization parameters.

Model 1 + Regularization Parameter Refined (0.001 - 0.01)			
Regularization Parameter	F1-Score (0)	F1-Score (1)	Accuracy
0.001	83	85	84
0.0019	75	83	79
0.0028	76	82	79
0.0037	79	76	78
0.0046	77	87	80
0.0055	79	86	83
0.0064	81	82	82
0.0073	78	82	80
0.0082	70	82	78
0.0091	72	83	79

Table 5.5: Model 1 – Refined Regularization Parameter Performance Metrics (Evaluated on Test Data)



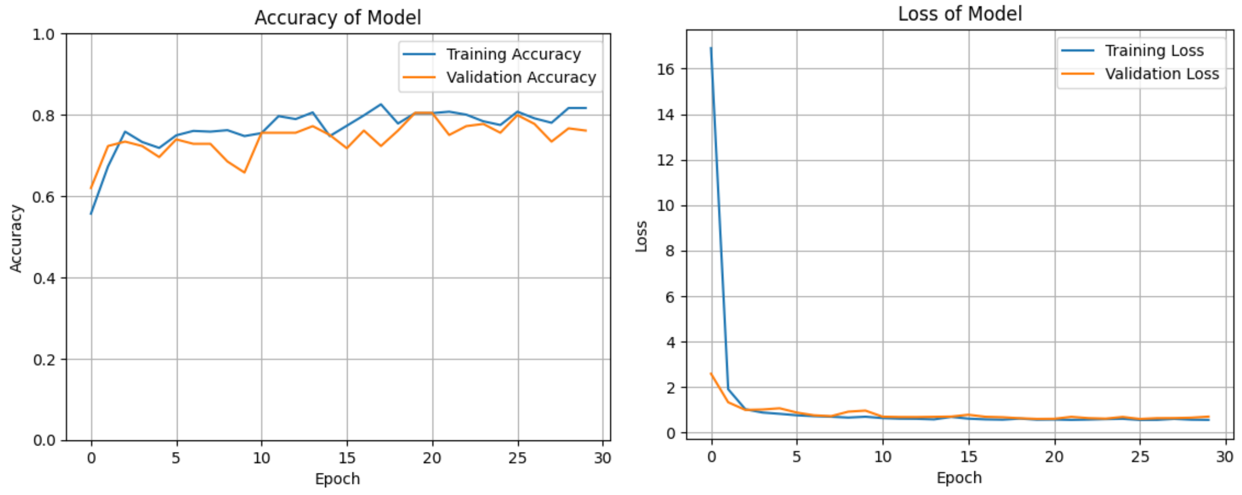
Plot 5.5: Model 1, Regularization Parameter 0.001

Model 1, with a regularization parameter of 0.001, demonstrated solid performance over 30 epochs. The training loss decreased from 9.94 to around 0.50, while the validation loss stabilized around 0.50. The training accuracy reached 79.82%, and the validation accuracy was 80.43%. On the test set, Model 1 achieved an accuracy of 84.24% with a loss of 0.4534. The classification results showed balanced performance across classes, with a high accuracy of 84%.

The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.3 above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 801us/step - loss: 0.4534 - accuracy: 0.8424
6/6 [==============================] - 0s 998us/step
```

The following plots are the accuracy and loss of Model 1 with a Regularization parameter of 0.0064.



Plot 5.6: Model 1, Regularization Parameter 0.0064

The model, trained with a regularization parameter of 0.0064, shows a steady improvement in accuracy across 30 epochs, achieving a final training accuracy of approximately 81.6% and a validation accuracy of around 76.1%. The training and validation loss also decreased significantly, indicating effective learning and good generalization to new data. On the test set, the model achieves an accuracy of 82%.

The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.3 above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 1ms/step - loss: 0.5625 - accuracy: 0.8152
6/6 [==============================] - 0s 800us/step
```

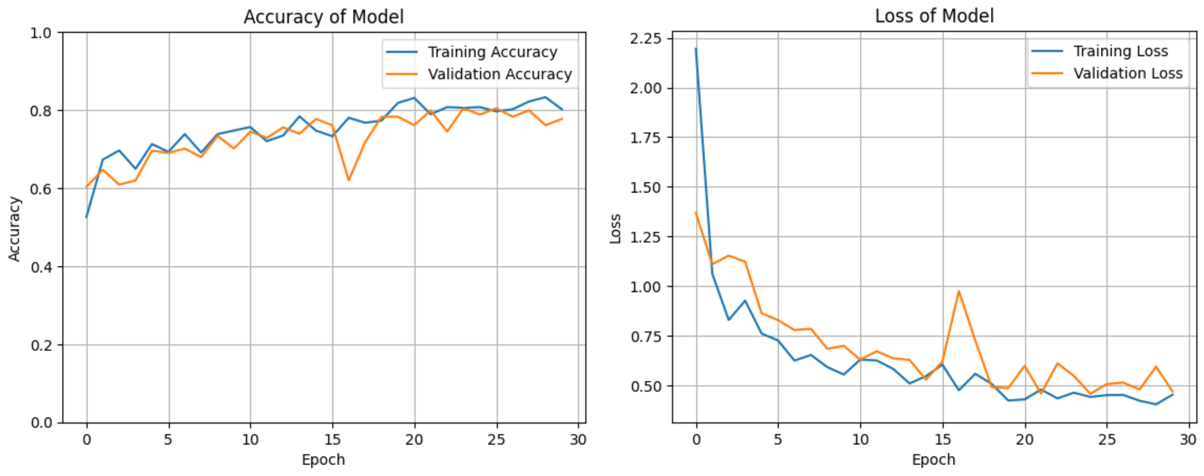
Next, we will analyze the final regularization parameters for Model 2.

Regularization Parameter Refinement – Model 2

The following are the F1-Score and accuracy from Model 2 and its refined regularization parameters.

Model 2 + Regularization Parameter Refined (0.0001 - 0.001)			
Regularization Parameter	F1-Score (0)	F1-Score (1)	Accuracy
0.00018	85	87	86
0.00026	81	85	83
0.00034	77	83	80
0.00042	79	83	82
0.0005	80	80	80
0.00059	79	84	82
0.00067	82	83	83
0.00075	78	76	77
0.00083	75	83	80
0.00091	77	82	80

Table 5.6: Model 2 – Refined Regularization Parameter Performance Metrics (Evaluated on Test Data)



Plot 5.7: Model 2, Regularization Parameter 0.00018

The first regularization value tested for Model 2 was 0.00018, and it proved to be the best-performing model thus far, achieving an accuracy of 86% and correctly classifying patients with heart disease 87% of the time.

In the final epoch, the model reached a training accuracy of 80% and a validation accuracy of 78%. The losses for the training and validation sets were 0.45 and 0.46, respectively. These metrics indicate that the model is on the right track and does not have a high variance issue.

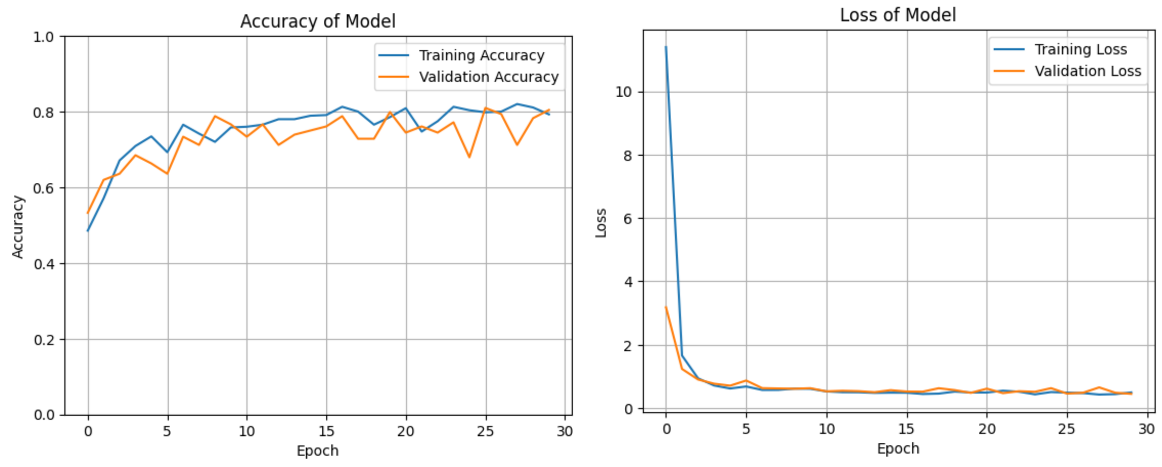
The noise observed in both graphs in Plot 5.7 can likely be attributed to the learning rate. Optimizing the learning rate should help smooth out the accuracy and loss curves, leading to more stable and consistent performance.

The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.3 (with edited variables to fit Model 2) above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 1ms/step - loss: 0.4003 - accuracy: 0.8641
```

The loss calculated on the test set is below both the training and validation sets, indicating that the model generalizes well to unseen data. This suggests that the model is not overfitting and is effectively capturing the underlying patterns in the data.

The following is an analysis of the Model 2's performance with a regularization parameter of 0.00026.



Plot 5.8: Model 2, Regularization Parameter 0.00026

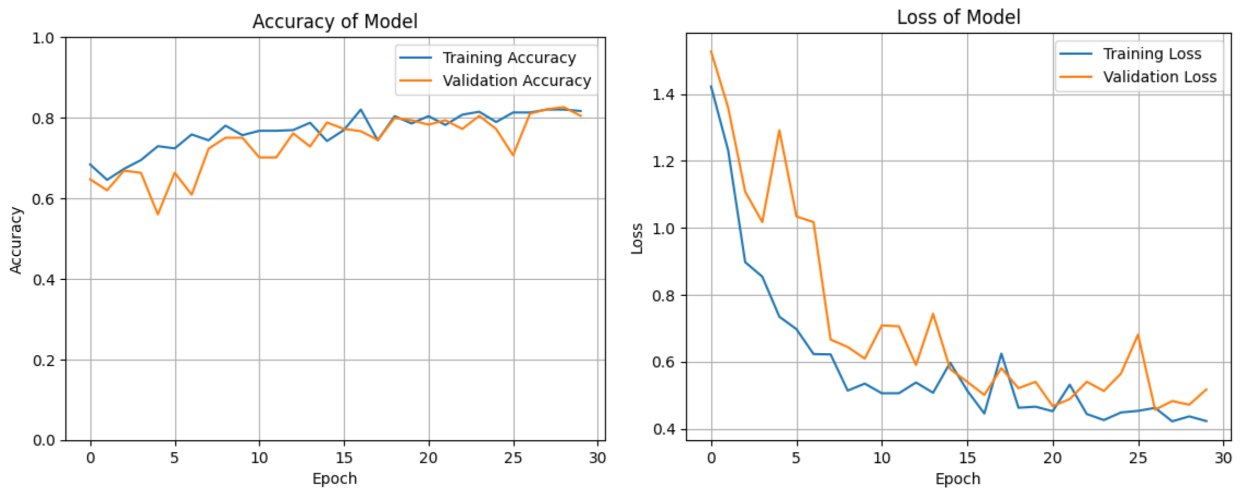
A regularization parameter of 0.00026 performed very well on this dataset. It was able to predict up to an overall accuracy of 83% and above 80% for both specific classes.

In the final epoch of training, the model performed with an accuracy of 79% and a loss of 0.5, and an accuracy of 80% and a loss of 0.45, on the training and validation sets respectively. These measurements indicate there is not a high variance issue within this model configuration.

The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.3 (with edited variables to fit Model 2) above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 881us/step - loss: 0.4195 - accuracy: 0.8315
```

Finally for Model 2, we will analyze the final regularization parameter, 0.0067.



Plot 5.9: Model 2, Regularization Parameter 0.00067

Model 2, with a regularization parameter of 0.00067, showed strong performance on both training and validation datasets over 30 epochs. The training loss decreased from approximately 1.42 to 0.42, while the validation loss reduced from 1.53 to 0.51, indicating effective learning and minimal overfitting. On the test set, the model achieved an accuracy of 82.61% with a loss of 0.4754, reflecting its robustness and generalization ability. Despite some fluctuations, the model maintained a high accuracy, demonstrating its reliability.

To further improve Model 2, optimizing the learning rate could enhance convergence speed and effectiveness. The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.3 (with edited variables to fit Model 2) above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 801us/step - loss: 0.4754 - accuracy: 0.8261
```

Next, we will analyze Model 5's performance with a refined regularization parameter.

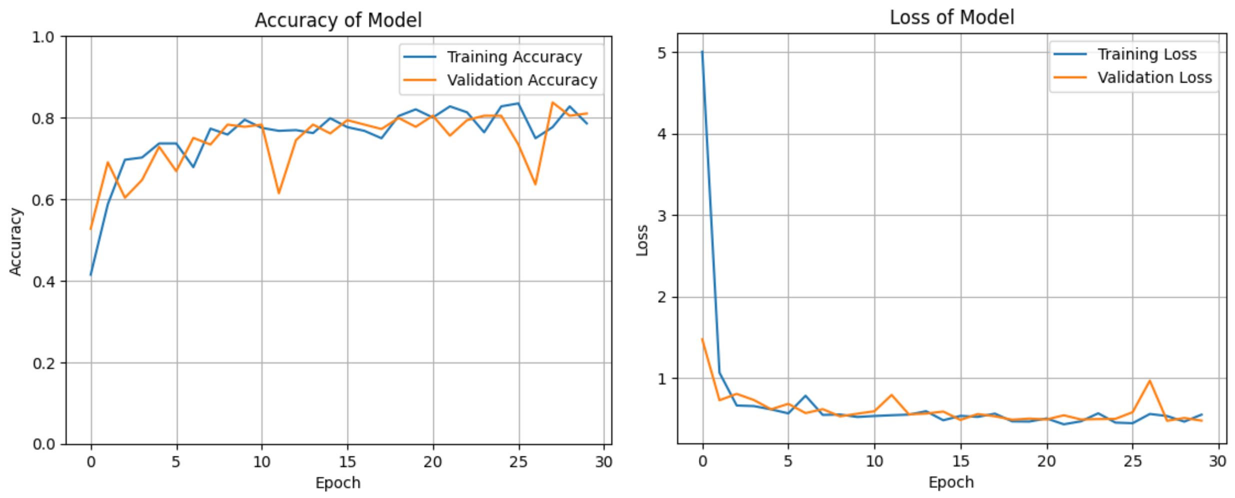
Regularization Parameter Refinement – Model 3

The following are the F1-Score and accuracy from Model 3 and its refined regularization parameters.

Model 3 + Regularization Parameter Refined (0.001 +-)			
Regularization Parameter	F1-Score (0)	F1-Score (1)	Accuracy
0.0005	78	85	82
0.00061	81	83	82
0.00072	81	86	84
0.00083	83	87	85
0.00094	75	85	81
0.001	82	84	83
0.0011	79	82	80
0.0012	81	82	82
0.0013	80	79	79
0.0014	80	85	83
0.0015	83	84	83

Table 5.7: Model 3 – Refined Regularization Parameter Performance Metrics (Evaluated on Test Data)

The first Model 3 regularization parameter scored an accuracy above 80% in all three categories and improved Model 5's performance was 0.00072. Below we can find information on the models' training as well as test data performance.



Plot 5.10: Model 3, Regularization Parameter 0.00072

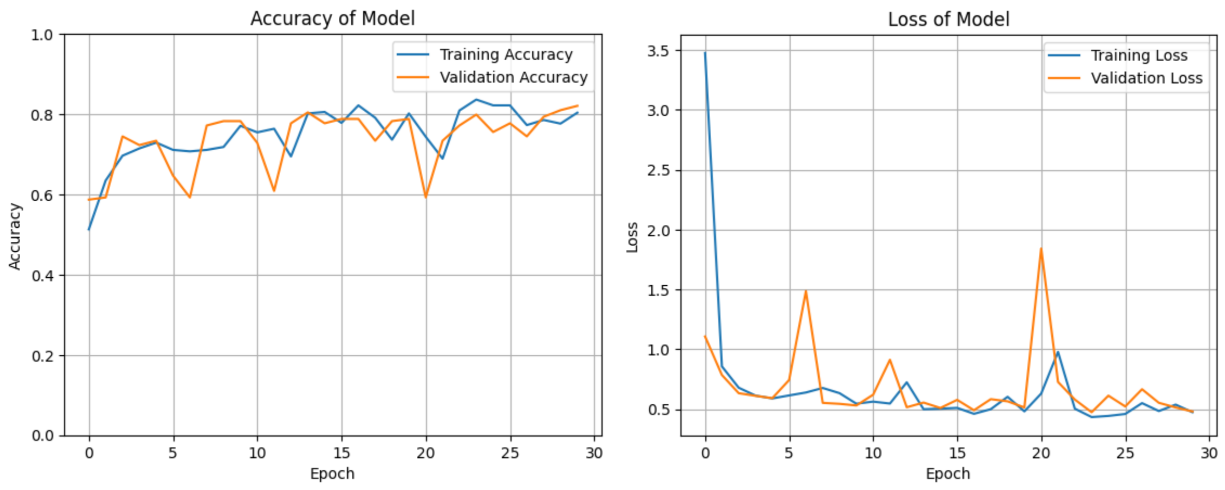
Model 3, with a regularization parameter of 0.00072, exhibited robust performance across both training and validation datasets over 30 epochs. The training loss dramatically decreased from 5.00 to approximately 0.54, while the validation loss also saw significant reductions, stabilizing around 0.48. The accuracy steadily improved, with training accuracy reaching 78.55% and validation accuracy at 80.98%.

On the test set, Model 3 achieved an accuracy of 84.24% with a loss of 0.4431, indicating strong generalization capabilities. The model's high performance is evidenced by its ability to maintain a balance between minimizing loss and maximizing accuracy throughout the training process.

The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.3 (with edited variables to fit Model 3) above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 801us/step - loss: 0.4431 - accuracy: 0.8424
```

Next, we will look at Model 3 with a regularization parameter of 0.00083.



Plot 5.11: Model 3, Regularization Parameter 0.00083

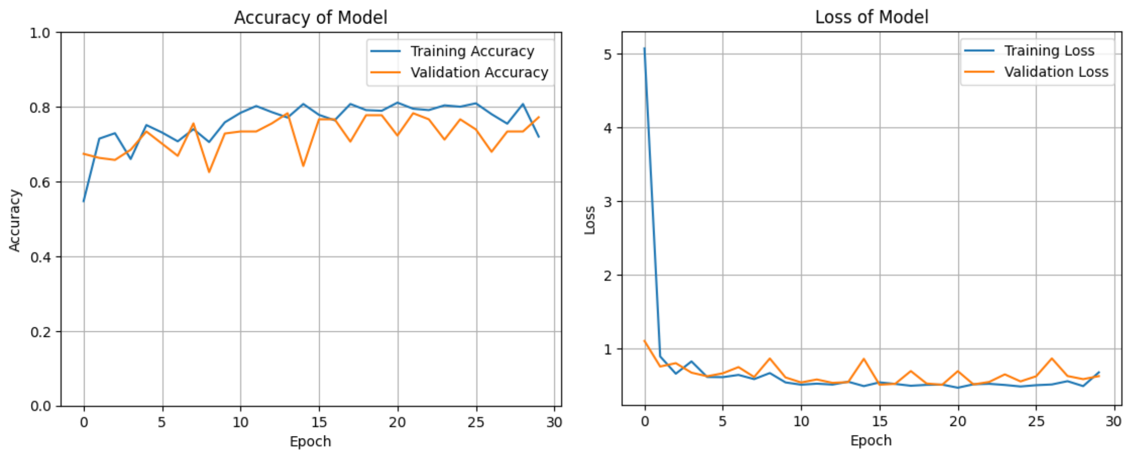
Model 3 demonstrated effective learning with a regularization parameter of 0.00072 over 30 epochs. The training loss decreased significantly from 3.47 to around 0.47, while the validation loss stabilized at approximately 0.48, indicating good learning and generalization. The model achieved a training accuracy of 80.36% and a validation accuracy of 82.07%.

On the test set, Model 3 achieved an impressive accuracy of 85.33% with a loss of 0.4275, indicating strong generalization capability. Despite some fluctuations, the model maintained high accuracy throughout the training process. This has been one of our best models yet and for further improvement, optimizing the learning rate could enhance convergence and overall performance.

The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.3 (with edited variables to fit Model 3) above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 853us/step - loss: 0.4275 - accuracy: 0.8533
```

Next, we will look at Model 3 with a regularization parameter of 0.001. This model configuration was tested previously in the initial regularization parameter study. Running the same model configuration multiple times can ensure its consistency and reliability. Below are the outputs and explanation of testing.



Plot 5.12: Model 3, Regularization Parameter 0.001

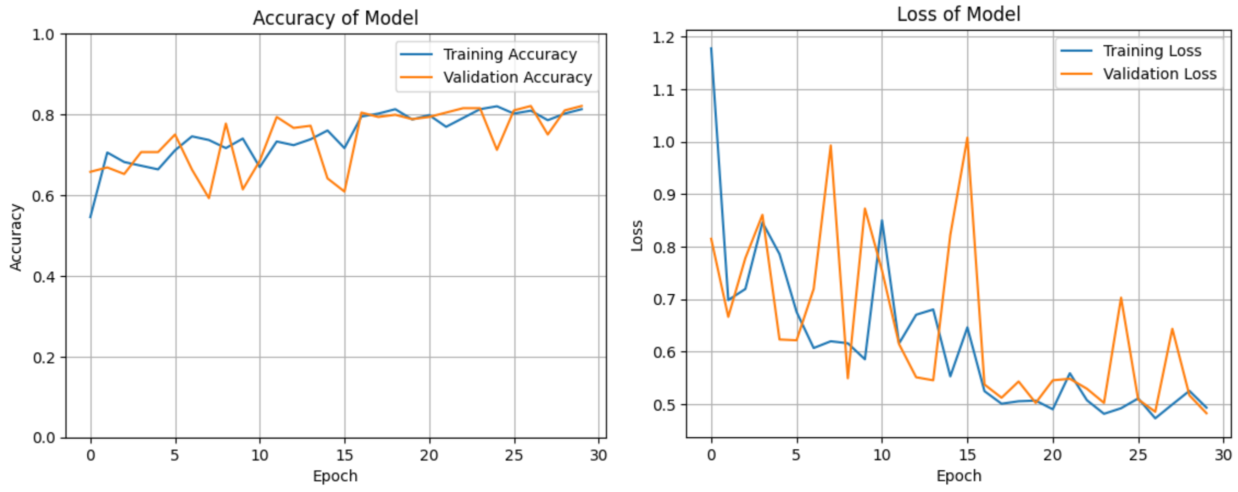
Model 3, with a regularization parameter of 0.001, showed consistent performance over 30 epochs. The training loss decreased from 5.07 to around 0.67, while the validation loss stabilized around 0.62. Training accuracy reached 72%, and validation accuracy was 77.17%. On the test set, Model 3 achieved an accuracy of 83.15% with a loss of 0.5598, indicating strong generalization.

Running models more than once is essential due to the inherent randomness in training processes. Multiple runs help ensure the model's performance is consistent and not due to random initialization or data splits.

The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.3 (with edited variables to fit Model 3) above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 1ms/step - loss: 0.5598 - accuracy: 0.8315
```

Next, we will look at Model 3's performance with a regularization parameter of 0.0014.



Plot 5.12: Model 3, Regularization Parameter 0.0014

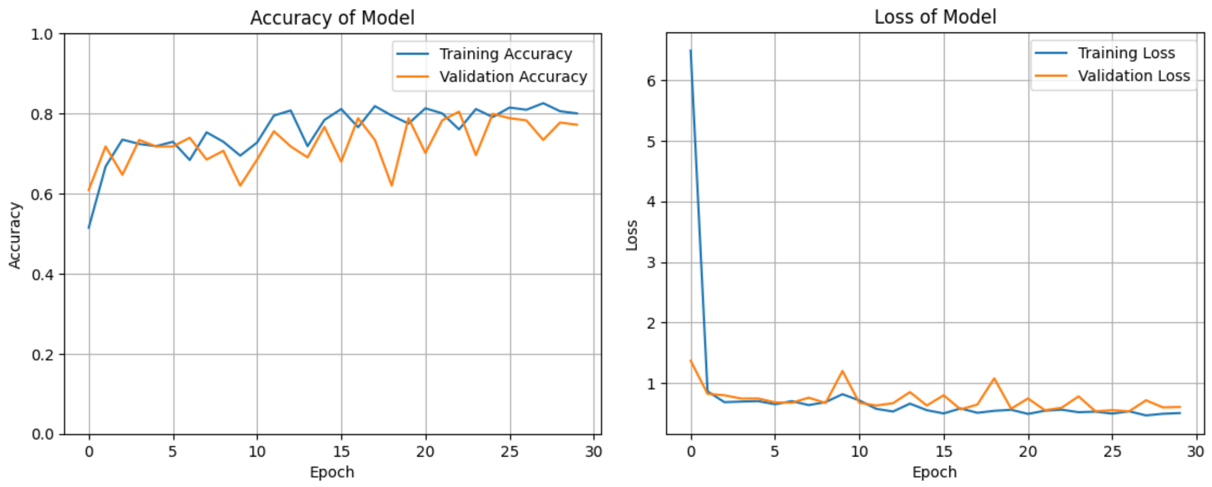
Model 3, with a regularization parameter of 0.0014, showed consistent performance over 30 epochs. The training loss decreased from 1.18 to around 0.49, while the validation loss stabilized around 0.48. The training accuracy reached 81.27%, and the validation accuracy was 82.07%. On the test set, Model 3 achieved an accuracy of 82.61% with a loss of 0.4454. The classification report results showed balanced performance across classes with a high overall accuracy of 83%.

A well-optimized learning rate can further enhance this model's performance by ensuring faster convergence and preventing overfitting or underfitting. Running models more than once is essential to ensure that performance metrics are consistent and not due to random variations in initialization or data splits.

The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.3 (with edited variables to fit Model 3) above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 801us/step - loss: 0.4454 - accuracy: 0.8261
```

Lastly for Model 3, we will look at its performance with a regularization parameter of 0.0015.



Plot 5.13: Model 3, Regularization Parameter 0.0015

Model 3, with a regularization parameter of 0.0015, showed promising performance over 30 epochs. The training loss decreased from 6.49 to around 0.50, while the validation loss stabilized around 0.60. The training accuracy reached 80.00%, and the validation accuracy was 77.17%. On the test set, Model 3 achieved an accuracy of 83.15% with a loss of 0.5031.

The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.3 (with edited variables to fit Model 3) above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 801us/step - loss: 0.5031 - accuracy: 0.8315
```

To conclude the regularization parameter refinement section, we will evaluate Model 4's performance with further refined regularization parameters.

Regularization Parameter Refinement – Model 4

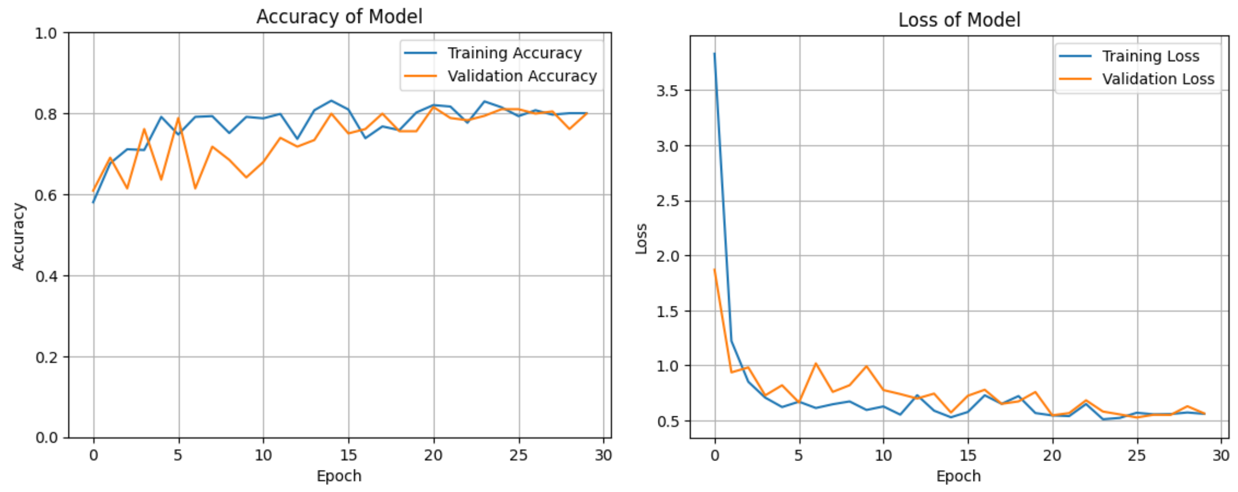
The table below shows a summary of all F1-scores and accuracies from each refined regularizati on parameter.

Model 4 + Regularization Parameter Refined (0.01 +-)			
Regularization Parameter	F1-Score (0)	F1-Score (1)	Accuracy
0.0054	75	67	71
0.0063	60	81	74
0.0072	71	83	79
0.0081	72	60	67
0.009	79	77	78
0.01	69	83	78
0.011	71	54	64
0.012	82	85	84
0.013	82	87	85
0.014	79	77	78
0.015	73	60	68

Table 5.8: Model 4 – Refined Regularization Parameter Accuracy (Evaluated on Test Data)

As mentioned at the start of this section, a model configuration is set to move forward if both F1-scores and accuracy are above 80% and improvement in any of the categories was made with the addition of a refined regularization parameter.

First, we will analyze Model 4 with a regularization parameter of 0.012.



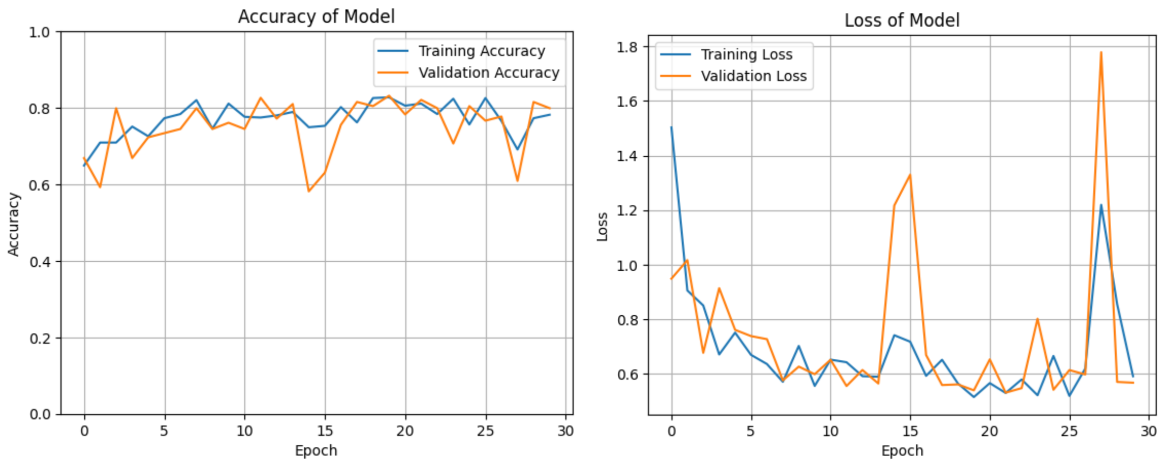
Plot 5.14: Model 4, Regularization Parameter 0.012

Model 4, with a regularization parameter of 0.012, demonstrated robust performance over 30 epochs. The training loss decreased from 3.83 to around 0.56, while the validation loss stabilized around 0.56. The training accuracy reached 80.00%, and the validation accuracy was 79.89%. On the test set, Model 4 achieved an accuracy of 83.70% with a loss of 0.4819. The classification report results showed balanced performance across classes with a high overall accuracy of 84%.

The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.3 (with edited variables to fit Model 4) above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 1ms/step - loss: 0.4819 - accuracy: 0.8370
```

Lastly, we will analyze the outputs of Model 4 with a regularization parameter of 0.013.



Plot 5.15: Model 4, Regularization Parameter 0.013

Model 4, with a regularization parameter of 0.013, showed strong performance over 30 epochs. The training loss decreased from 1.50 to around 0.59, while the validation loss stabilized around 0.57. The training accuracy reached 78.18%, and the validation accuracy was 79.89%. On the test set, Model 4 achieved an accuracy of 84.78% with a loss of 0.5640. The classification report results showed balanced performance across classes with a high accuracy of 85%.

The model outputs draw some concern with the noise in Plot 5.15, but nonetheless the performance on unseen data is promising enough for this configuration to move forward, especially since the accuracy is already higher than our goal of 84.61%. A well-optimized learning rate can further enhance this model's performance by ensuring faster convergence and preventing overfitting or underfitting.

The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.3 (with edited variables to fit Model 7) above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 920us/step - loss: 0.5640 - accuracy: 0.8478
```

Regularization Refinement Summary

The regularization parametric studies significantly enhanced model performance overall. The primary aim of this study was to mitigate overfitting, ensuring that our models perform as well on unseen data as they do on training data. Although there were some concerns regarding noise in the training and validation accuracy and loss plots, we anticipate improvements in these areas during the upcoming learning rate optimization phase.

Once again, the criteria for a model configuration to move forward to the learning rate parametric studies were an improvement on the overall F1-Scores, as well as having both classes being predicted at 80% or higher on unseen data.

When we initially tested Model 1 with a generalized regularization parameter, our maximum accuracy on unseen (test) data was 81.52%. After refinement, we have two regularization parameters (0.001 & 0.0064) to pair with Model 1 that deliver overall accuracies of 84.24% and 81.52%, respectively. The refined regularization parameters also increased the F1-score for both classes above 80%.

Model 2 performed even better than Model 1 with refined regularization parameters (0.00018, 0.00026, and 0.00067). Initially, when we tested a general range of regularization values, our overall accuracy on test data was 82.07%. When the regularization parameter 0.00018 was tested, the overall accuracy on test data increased to a staggering 86.41%, while predicting heart disease patients correctly at an accuracy of 87%, our best model configuration to date. The other two configurations chosen to move forward both showed steady improvements in all categories.

Model 3 had the highest number of model configurations to pass the earlier defined criteria set. Regularization parameters 0.00072, 0.00083, 0.0014, and 0.0015 were all selected to proceed, and all configurations scored above 80% in all criteria. The highest overall accuracy came from Model 7 with regularization parameter 0.00083 at 85.33%, which is a higher accuracy than our set goal of 84.61%.

Model 4 showed improvements as well; the regularization parameter was further refined to 0.012 and 0.013. The close range of the two values indicated an ideal value was found. Both configurations improved upon the initial regularization study, and Model 4 with a 0.013 regulation parameter was able to achieve an overall accuracy of 83.7%.

Learning Rate

In machine learning algorithms, the learning rate is a crucial hyperparameter that determines the step size at each iteration while moving towards a minimum of the loss function. Essentially, it controls how much to change the model in response to the estimated error each time the model weights are updated. A well-chosen learning rate ensures that the model converges efficiently to an optimal solution, avoiding the pitfalls of overshooting or excessively slow convergence. In the context of predicting heart disease, selecting an appropriate learning rate is vital for achieving accurate and reliable predictions, as it influences the stability and performance of the model throughout the training process.

As observed in the earlier section, all model configurations selected for the learning rate study achieved relatively high accuracy. However, some of the training data exhibited significant noise. Optimizing the learning rate is expected to mitigate this issue, leading to smoother training curves and potentially improved model performance.

These are the current model configurations:

- Model 1, with regularization parameters of 0.001 and 0.0064
- Model 2, with regularization parameters of 0.00018, 0.00026, and 0.00067
- Model 3, with regularization parameters of 0.00072, 0.00083, 0.001, 0.0014, and 0.0015
- Model 4, with regularization parameters of 0.012 and 0.013

Each model configuration will be tested on an initial set of learning rates: 0.1, 0.01, 0.001, and 0.0001. From there, the learning rates will get refined like they did for the regularization values.

The addition of learning rate tuning aims to increase the overall accuracy of the models. The new criteria set for the initial learning rate study is an overall accuracy of 84% and above and an F1-Score of predicting positive cases at 85% or above. Achieving high accuracy in predicting positive medical cases is crucial, especially in the context of heart disease, as early and accurate detection can significantly improve patient outcomes. High predictive accuracy ensures that patients at risk are identified promptly, allowing for timely intervention and treatment, which can reduce the likelihood of severe complications and improve the overall quality of life.

The refined regularization parameters and initial learning rates have been defined in Python Jupyter Notebook as follows in Code Block 5.3 below. Each model has its own set of refined regularization values and a generalized set of learning rates that it will use during training and evaluation in Code Block 5.4.

```
#Refined Regularization Values with Learning Rate
m1_reg_lr = [0.001]
m2_reg_lr = [0.00018, 0.00026, 0.00067]
m5_reg_lr = [0.00072, 0.00083, 0.0014, 0.0015]
m7_reg_lr = [0.012, 0.013]

#Learning rate values
learning_rates = [0.1, 0.01, 0.001, 0.0001]
```

Code Block 5.3: Regularization Learning rate values in Python

Code Block 5.4 below is the code for pairs Model 1's regularization and learning rates values, it is also the structure for how the other model configurations were trained and evaluated.

```
for reg in m1_reg_lr:
    for lr in learning_rates:
        print(f"REGULARIZATION PARAMETER: {reg}")
        print(f"LEARNING RATE = {lr}")

        model_1_reg_lr = tf.keras.Sequential([
            tf.keras.layers.Dense(16, activation='relu', name='L1', kernel_regularizer = l2(reg)),
            tf.keras.layers.Dense(16, activation='relu', name='L2', kernel_regularizer = l2(reg)),
            tf.keras.layers.Dense(1, activation='sigmoid', name='OL')
        ])

        model_1_reg_lr.compile(optimizer = tf.keras.optimizers.Adam(learning_rate = lr),
                loss = tf.keras.losses.BinaryCrossentropy(),
                metrics = ['accuracy'])

        history = model_1_reg_lr.fit(X_train, y_train, batch_size = 16, epochs = 30, validation_data = (X_valid, y_valid))

        plot_accuracy(history)
        plot_loss(history)

        print("\nModel Prediction on Test set")
        results= model_1_reg_lr.evaluate(X_test, y_test)

        y_predicted_m1 = model_1_reg_lr.predict(X_test)
        y_predicted_m1 = y_predicted_m1.flatten()
        y_predicted_m1 = np.where(y_predicted_m1 > 0.5, 1, 0)

        print(f"\nConfusion Matrix")
        cm = confusion_matrix(y_test, y_predicted_m1)
        print(cm)

        print(classification_report(y_test, y_predicted_m1))
```

Code Block 5.4: Test Refined Regularization values with initial Learning Rates

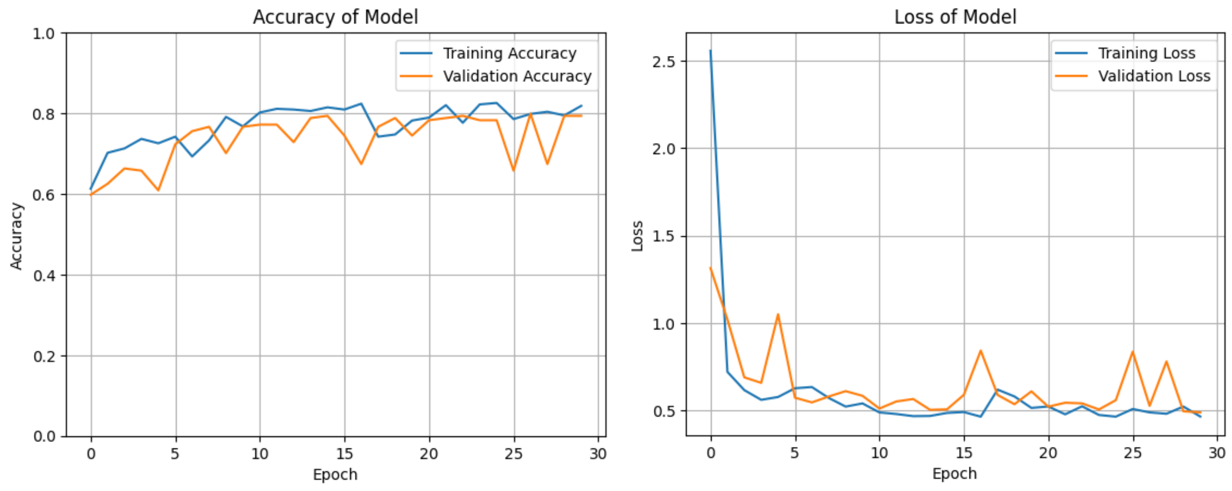
For each combination of these hyperparameters, the model is initialized and compiled with the Adam optimizer and binary cross-entropy loss, using accuracy as the performance metric. Model 1 is then trained on the training data for 30 epochs with a batch size of 16, and its performance is validated on the validation data. After training, the accuracy and loss over the epochs are plotted to visualize the model's performance. The model is evaluated on the test data, and predictions are made. These predictions are then refined to produce binary outcomes. The performance of the model on the test set is assessed by generating and printing a confusion matrix and a classification report, which provide insights into precision, recall, and F1-score. This process is repeated for each combination of regularization parameter and learning rate, enabling a thorough analysis of how these hyperparameters impact the model's performance and helping in the selection of optimal values

Initial Learning Rate – Model 1

Model 1 + Regularization Refined + Learning Rate				
Regularization Parameter	Learning Rate	F1-Score (0)	F1-Score (1)	Accuracy
0.001	0.1	0	72	56
	0.01	82	87	85
	0.001	75	83	80
	0.0001	67	68	67
0.0064	0.1	0	72	56
	0.01	75	71	73
	0.001	79	85	83
	0.0001	51	58	55

Table 5.9: Model 1 – Refined Regularization Parameter + Initial Learning Rate Accuracy (Evaluated on Test Data)

Model 1 with a regularization parameter of 0.001 and a learning rate of 0.01 demonstrates robust performance, which is evident from its training, validation, and test metrics. Throughout the 30 epochs of training, the model's accuracy improved steadily, reaching over 81% by the final epoch. The validation accuracy mirrored this trend, peaking at 79.35%, which indicates that the model generalizes well to unseen data. This is further supported by the significant reduction in both training and validation losses, with the final validation loss recorded at 0.4889. Such a reduction signifies effective learning and a decrease in prediction errors over time.



Plot 5.16: Model 1, Regularization Parameter 0.001 and Learning rate of 0.01

The output code below shows the accuracy calculated with the evaluate command in TensorFlow from Code Block 5.4 (with edited variables to fit Model 7) above:

```
Model Prediction on Test set
6/6 [==============================] - 0s 801us/step - loss: 0.4426 - accuracy: 0.8478
6/6 [==============================] - 0s 809us/step
```

Upon evaluating the model on the test set, it achieved an impressive accuracy of 84.78%, which is already higher than the goal we set out for. This high-test accuracy demonstrates that the model performs well on new, unseen data, reinforcing its generalization capabilities. A closer look at the confusion matrix reveals a balanced performance across both classes. The model shows precision and recall values around 0.85 for each class, indicating that it is not biased towards any specific class. This balance is crucial in applications where both false positives and false negatives carry significant consequences.

	Precision	Recall	F1-Score	Support
0	0.84	0.8	0.82	81
1	0.85	0.88	0.87	103
accuracy			0.85	184
macro avg	0.85	0.84	0.84	184
weighted avg	0.85	0.85	0.85	184

Table 5.10: Performance Metrics for Model 1 (Regularization: 0.001, Learning Rate: 0.01) on Test Data

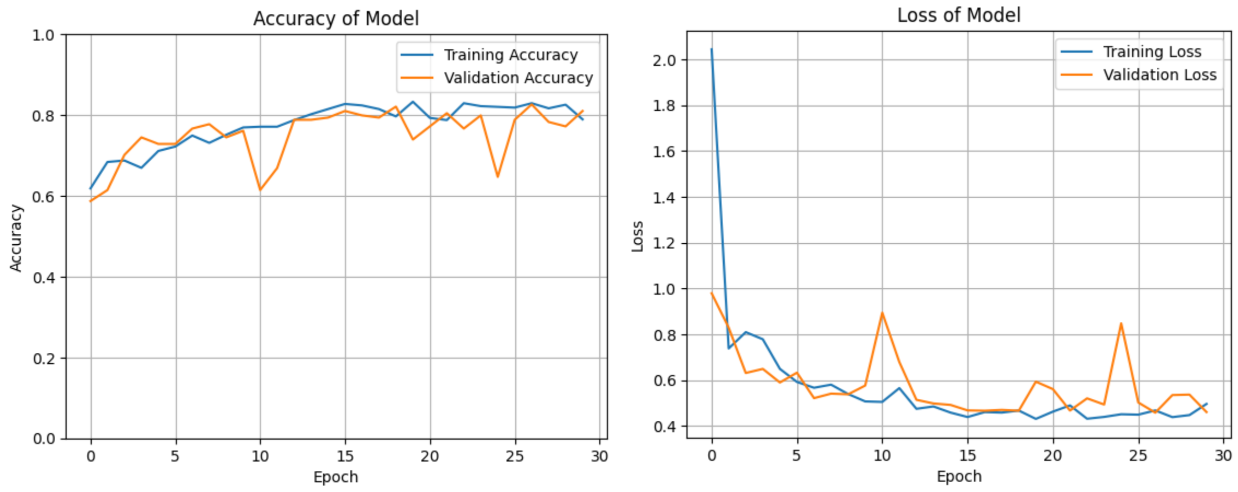
The F1-scores, which are 0.82 for class 0 and 0.87 for class 1, further underscore the model's effectiveness. The F1-score is a harmonic mean of precision and recall, and these high values reflect that the model maintains a good balance between identifying true positives while minimizing false positives and false negatives. This balance makes the model reliable for real-world applications where both precision and recall are critical.

Initial Learning Rate – Model 2

Model 2 + Regularization Refined + Learning Rate				
Regularization Parameter	Learning Rate	F1-Score (0)	F1-Score (1)	Accuracy
0.00018	0.1	0	72	56
	0.01	78	75	77
	0.001	80	81	81
	0.0001	64	66	65
0.00026	0.1	0	72	56
	0.01	81	87	84
	0.001	79	79	79
	0.0001	67	74	71
0.00067	0.1	0	72	56
	0.01	80	86	84
	0.001	67	47	59
	0.0001	71	71	71

Table 5.11: Model 2 – Refined Regularization Parameter + Initial Learning Rate Accuracy (Evaluated on Test Data)

Above in Table 5.11, we see the F1-Score and Accuracies for each model 2 configuration tested. Model 2 with a regularization of 0.00018 did not seem to initially improve performance. The two following highlighted configurations were able to excel both with a learning rate of 0.01. The following is an evaluation of their performance. First, we will look at Model 2 with a regularization parameter 0.00026 and a learning rate of 0.01.



Plot 5.17: Model 2, Regularization Parameter 0.00026 and Learning rate of 0.01

The model was trained over 30 epochs with a learning rate of 0.01 and a regularization parameter of 0.00026. The training loss started at 2.04 and significantly decreased to around 0.5, while validation loss exhibited fluctuations but generally showed a decreasing trend, finishing at approximately 0.46. This indicates improved fit to the data, although there were instances of overfitting and noise, evident in occasional spikes.

Training accuracy began at 62% and improved to about 79%, while validation accuracy started at 59% and increased to around 81%. The final validation accuracy of 80.98% and training accuracy of 78.91% demonstrate good generalization on unseen data. On the test set, the model achieved a loss of 0.4348 and an accuracy of 84.24%, indicating strong performance and generalization capabilities.

```
Model Prediction on Test set
6/6 [==============================] - 0s 801us/step - loss: 0.4348 - accuracy: 0.8424
```

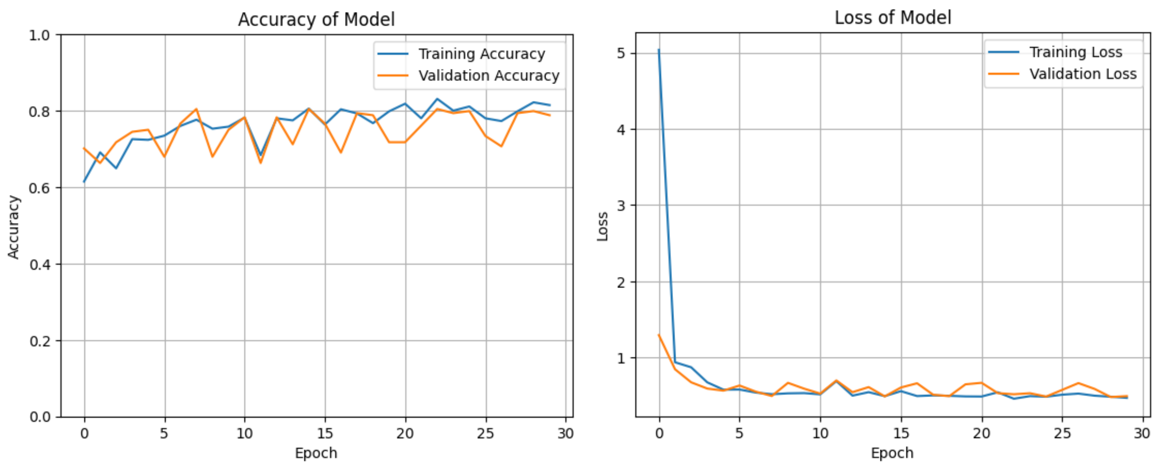
The confusion matrix shows the model correctly identified 62 instances of class 0 and 93 instances of class 1, with 19 false positives and 10 false negatives.

	Precision	Recall	F1-Score	Support
0	0.86	0.77	0.81	81
1	0.83	0.9	0.87	103
accuracy			0.84	184
macro avg	0.85	0.83	0.84	184
weighted avg	0.84	0.84	0.84	184

Table 5.12: Performance Metrics for Model 2 (Regularization: 0.00026, Learning Rate: 0.01) on Test Data

In conclusion, the model demonstrates solid performance with a good balance between precision and recall, and consistent training and validation accuracy suggests good generalization. Periodic fluctuations in validation metrics highlight the importance of regularization and potential learning rate adjustments for enhanced stability.

The following is an analysis of Model 2's performance with a regularization value of 0.00067 and a learning rate of 0.01.



Plot 5.18: Model 2, Regularization Parameter 0.00067 and Learning rate of 0.01

The model underwent training over 30 epochs, utilizing a learning rate of 0.01 and a regularization parameter of 0.00067. Throughout this process, the training loss started at 5.04 and dramatically decreased to around 0.5, while the validation loss also showed a decline, stabilizing near 0.5. This trend suggests that the model effectively improved its fit to the data, although some fluctuation indicates periods of overfitting and noise.

In terms of accuracy, the training accuracy began at approximately 61% and rose to around 81% by the end of the training period. Validation accuracy started at 70% and increased to 79%. The final validation accuracy of 78.80% and training accuracy of 81.45% indicate that the model generalized well on the unseen data. On the test set, the model achieved a loss of 0.4633 and an accuracy of 0.8370, showcasing its strong performance and generalization capabilities.

```
Model Prediction on Test set
6/6 [==============================] - 0s 1ms/step - loss: 0.4633 - accuracy: 0.8370
```

The confusion matrix revealed that the model correctly identified 61 instances of class 0 and 93 instances of class 1, with 20 false positives and 10 false negatives. The precision was 0.86 for class 0 and 0.82 for class 1, while the recall was 0.75 for class 0 and 0.90 for class 1.

	Precision	Recall	F1-Score	Support
0	0.86	0.75	0.8	81
1	0.82	0.9	0.86	103
accuracy			0.84	184
macro avg	0.84	0.83	0.83	184
weighted avg	0.84	0.84	0.84	184

Table 5.13: Performance Metrics for Model 2 (Regularization: 0.00067, Learning Rate: 0.01) on Test Data

In summary, the model exhibits solid performance with a commendable balance between precision and recall. The consistent training and validation accuracy, alongside a robust test accuracy, suggest effective generalization. However, the periodic fluctuations in validation metrics underscore the importance of regularization and possibly fine-tuning the learning rate to enhance model stability.

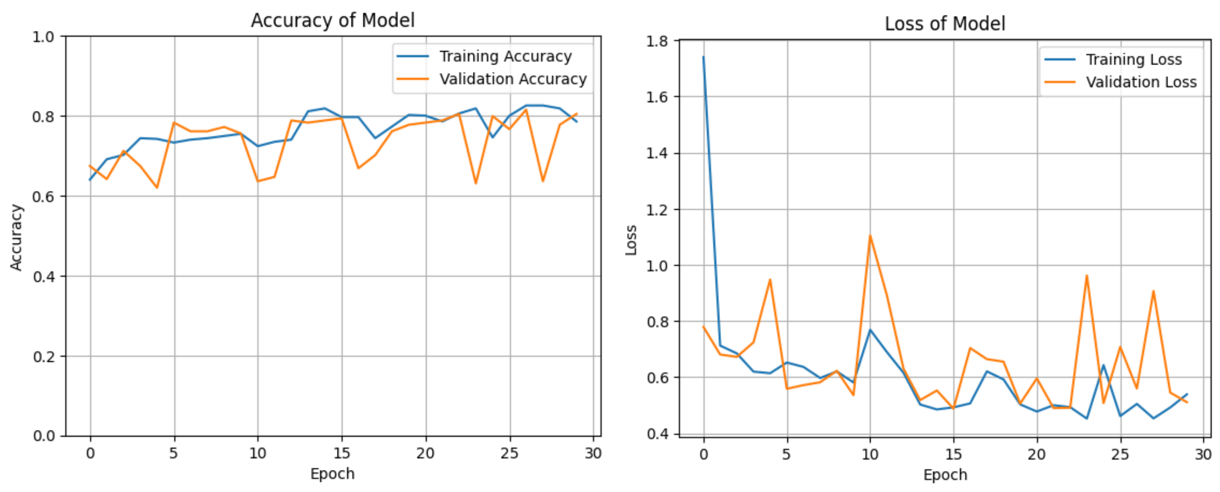
Initial Learning Rate – Model 3

Model 3 + Regularization Refined + Learning Rate				
Regularization Parameter	Learning Rate	F1-Score (0)	F1-Score (1)	Accuracy
0.00072	0.1	0	72	56
	0.01	59	80	73
	0.001	81	86	84
	0.0001	78	80	79
0.00083	0.1	0	72	56
	0.01	81	86	84
	0.001	73	84	80
	0.0001	73	82	79
0.001	0.1	0	72	56
	0.01	78	86	83
	0.001	74	85	81
	0.0001	76	81	79
0.0014	0.1	0	72	56
	0.01	81	85	83
	0.001	78	84	82
	0.0001	73	79	77
0.0015	0.1	0	72	56
	0.01	81	82	82
	0.001	53	79	71
	0.0001	79	82	81

Table 5.14: Model 3 – Refined Regularization Parameter + Initial Learning Rate Accuracy (Evaluated on Test Data)

In Table 5.14, we observe the F1-Scores and accuracies for various configurations of Model 3, each tested with different regularization parameters and learning rates. Notably, Model 3 exhibited fewer successful configurations meeting the set criteria compared to Model 2. This outcome is understandable, as delving deeper into hyperparameter optimization reveals that each model architecture has unique requirements to achieve optimal performance. Consequently, more configurations tend to perform sub optimally due to the specific needs of the model's structure. As the highlighted dark green rows indicate, only a subset of configurations successfully met the performance criteria, underscoring the complexity and sensitivity of hyperparameter tuning in neural network models.

The following is an analysis of Model 3's performance with a regularization value of 0.00072 and a learning rate of 0.001.



Plot 5.20: Model 3, Regularization Parameter 0.00072 and Learning rate of 0.001

The model was trained over 30 epochs with a learning rate of 0.001 and a regularization parameter of 0.00072. During the training, the loss initially started at 1.74 and decreased to around 0.54 by the end of the training period. Validation loss followed a similar pattern, initially high but stabilizing around 0.51, though with notable fluctuations indicating periods of overfitting and noise.

Training accuracy began at approximately 64% and improved to 79%, while validation accuracy started at 67% and increased to 80%. These results demonstrate that the model was able to learn effectively from the training data and generalize reasonably well to the validation data. The final validation accuracy of 80.43% and training accuracy of 78.55% indicate that the model generalized well on unseen data. On the test set, the model achieved a loss of 0.4798 and an accuracy of 83.70%, showcasing robust performance.

```
Model Prediction on Test set
6/6 [==============================] - 0s 801us/step - loss: 0.4798 - accuracy: 0.8370
```

The confusion matrix shows that the model correctly identified 64 instances of class 0 and 90 instances of class 1, with 17 false positives and 13 false negatives. The precision for class 0 was 0.83, and for class 1, it was 0.84. Recall was 0.79 for class 0 and 0.87 for class 1.

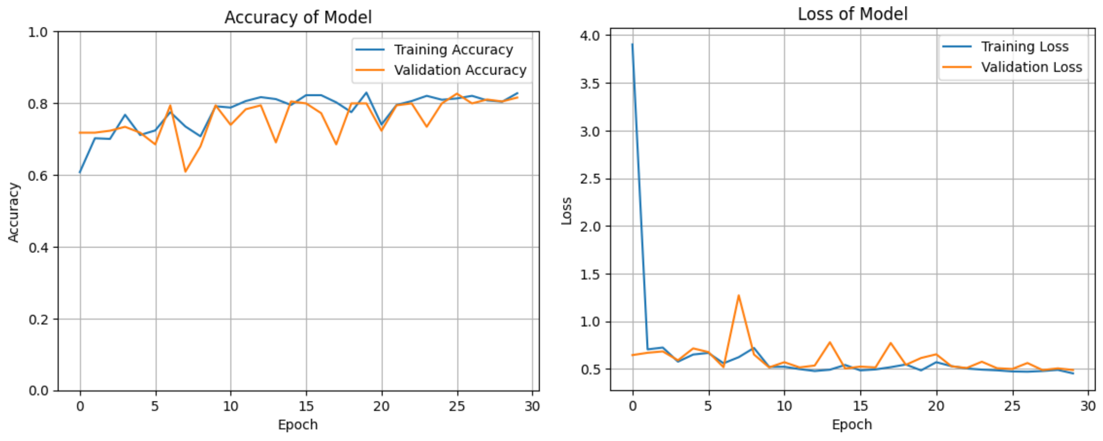
	Precision	Recall	F1-Score	Support
0	0.83	0.79	0.81	81
1	0.84	0.87	0.86	103
accuracy			0.84	184

macro avg	0.84	0.83	0.83	184
weighted avg	0.84	0.84	0.84	184

Table 5.15: Performance Metrics for Model 3 (Regularization: 0.00072, Learning Rate: 0.001) on Test Data

Overall accuracy stood at 0.84, with both the macro and weighted average F1-scores being 0.84. In summary, the model performed well, with a good balance between precision and recall. The consistent training and validation accuracy, alongside robust test accuracy, indicates effective generalization. However, the fluctuations in validation metrics suggest the need for fine-tuning the learning rate and regularization to enhance stability and performance.

Next is an analysis of Model 3's performance, with a regularization value of 0.00083 and a learning rate of 0.01.



Plot 5.21: Model 3, Regularization Parameter 0.00083 and Learning rate of 0.01

The model was trained over 30 epochs using a learning rate of 0.01 and a regularization parameter of 0.00083. The initial training loss was 3.90, which decreased significantly to around 0.45 by the end of the training period. Validation loss showed a similar decreasing trend, ending at approximately 0.49, though with occasional spikes indicating some instability and overfitting during the training process.

Training accuracy began at approximately 61% and improved to around 83%, while validation accuracy started at 71% and increased to 82%. These results illustrate that the model was able to effectively learn from the training data and generalize well to the validation data. The final validation accuracy of 81.52% and training accuracy of 82.73% suggest good generalization capabilities.

On the test set, the model achieved a loss of 0.4304 and an accuracy of 83.70%, indicating strong performance and generalization.

```
Model Prediction on Test set
6/6 [==============================] - 0s 801us/step - loss: 0.4304 - accuracy: 0.8370
```

The confusion matrix shows that the model correctly identified 65 instances of class 0 and 89 instances of class 1, with 16 false positives and 14 false negatives. Precision for class 0 was 0.82, and for class 1, it was 0.85. Recall was 0.80 for class 0 and 0.86 for class 1. Overall accuracy was 0.84, with both the macro and weighted average F1-scores being 0.84.

	Precision	Recall	F1-Score	Support
0	0.82	0.8	0.81	81
1	0.85	0.86	0.86	103
accuracy			0.84	184
macro avg	0.84	0.83	0.83	184
weighted avg	0.84	0.84	0.84	184

Table 5.16: Performance Metrics for Model 3 (Regularization: 0.00083, Learning Rate: 0.01) on Test Data

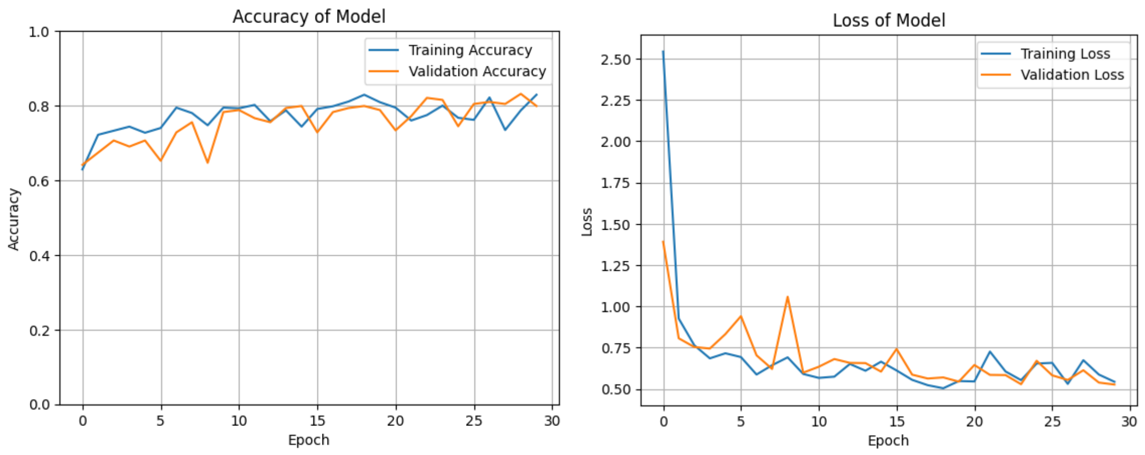
In conclusion, the model demonstrates a balanced performance between precision and recall. Consistent training and validation accuracy, along with robust test accuracy, indicate effective generalization.

Initial Learning Rate – Model 4

Model 4 + Regularization Refined + Learning Rate				
Regularization Parameter	Learning Rate	F1-Score (0)	F1-Score (1)	Accuracy
0.012	0.1	0	72	56
	0.01	81	85	83
	0.001	82	85	84
	0.0001	79	84	82
0.013	0.1	0	72	56
	0.01	75	74	74
	0.001	82	84	83
	0.0001	82	85	84

Table 5.17: Model 4 – Refined Regularization Parameter + Initial Learning Rate Accuracy (Evaluated on Test Data)

In Table 5.17, we observe the F1-Scores and accuracies for various configurations of Model 4, each tested with different regularization parameters and learning rates. Notably, Model 4 exhibited successful configurations in both refined regularization values, meeting the set criteria. We will now analyze the two successful configurations.



Plot 5.22: Model 4, Regularization Parameter 0.012 and Learning rate of 0.001

The model was trained for 30 epochs with a learning rate of 0.001 and a regularization parameter of 0.012. The initial training loss was 2.54, which dropped significantly to approximately 0.54 by the end of the training period. Validation loss followed a similar decreasing trend, ending at around 0.53, although there were occasional spikes indicative of overfitting and noise.

Training accuracy started at about 63% and improved to around 83%, while validation accuracy began at 64% and increased to 83%. These metrics indicate that the model effectively learned from the training data and generalized well to the validation data. The final validation accuracy of 79.89% and training accuracy of 82.91% suggest that the model has good generalization capabilities. On the test set, the model achieved a loss of 0.4761 and an accuracy of 83.70%, demonstrating strong performance.

```
Model Prediction on Test set
6/6 [==============================] - 0s 1ms/step - loss: 0.4761 - accuracy: 0.8370
```

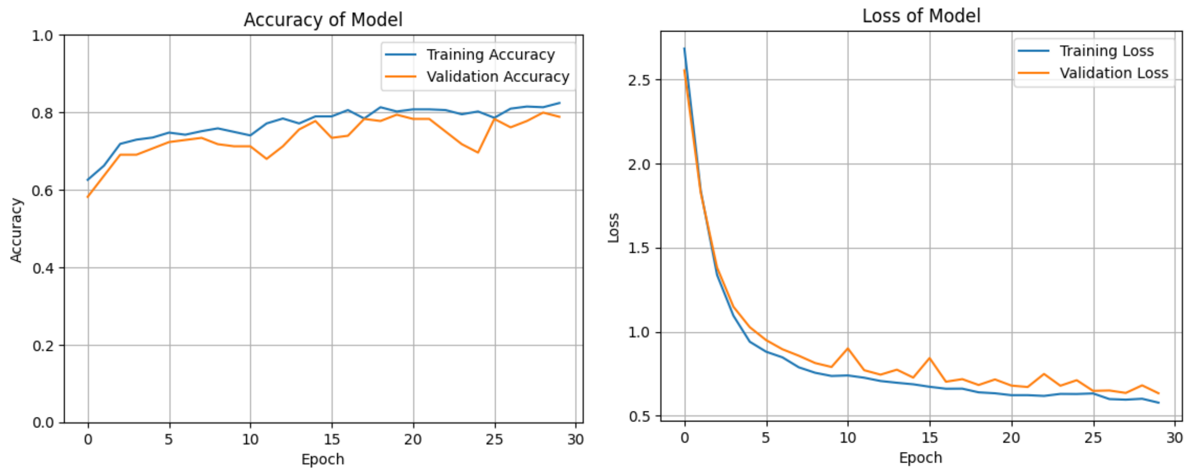
The confusion matrix shows the model correctly identified 67 instances of class 0 and 87 instances of class 1, with 14 false positives and 16 false negatives. The precision for class 0 was 0.81, and for class 1, it was 0.86. Recall was 0.83 for class 0 and 0.84 for class 1. Overall accuracy was 0.84, with both macro and weighted average F1-scores being 0.84.

	Precision	Recall	F1-Score	Support
0	0.81	0.83	0.82	81
1	0.86	0.84	0.85	103
accuracy			0.84	184
macro avg	0.83	0.84	0.84	184
weighted avg	0.84	0.84	0.84	184

Table 5.18: Performance Metrics for Model 4 (Regularization: 0.012, Learning Rate: 0.001) on Test Data

In conclusion, the model exhibited a balanced performance with good precision and recall. The consistent training and validation accuracy, along with robust test accuracy, indicate effective generalization.

Next, is an analysis of Model 4's performance with a regularization value of 0.013 and a learning rate of 0.0001.



Plot 5.23: Model 4, Regularization Parameter 0.013 and Learning rate of 0.0001

The model was trained for 30 epochs with a learning rate of 0.0001 and a regularization parameter of 0.013. The training loss began at 2.68 and decreased substantially to around 0.58 by the end of the training period. The validation loss showed a similar downward trend, ending at approximately 0.63, though there were occasional fluctuations indicating potential overfitting and instability.

Training accuracy started at around 63% and improved to approximately 82%, while validation accuracy began at 58% and increased to 79%. These results suggest that the model effectively learned from the training data and generalized well to the validation data. The final validation accuracy of 78.80% and training accuracy of 82.36% indicate good generalization capabilities. On the test set, the model achieved a loss of 0.5710 and an accuracy of 84.24%, exceeding our specified criteria.

```
Model Prediction on Test set
6/6 [==============================] - 0s 801us/step - loss: 0.5710 - accuracy: 0.8424
```

The confusion matrix reveals that the model correctly identified 66 instances of class 0 and 89 instances of class 1, with 15 false positives and 14 false negatives. Precision for class 0 was 0.82, and for class 1, it was 0.86. The recall was 0.81 for class 0 and 0.86 for class 1. Overall accuracy stood at 0.84, with both macro and weighted average F1-scores being 0.84.

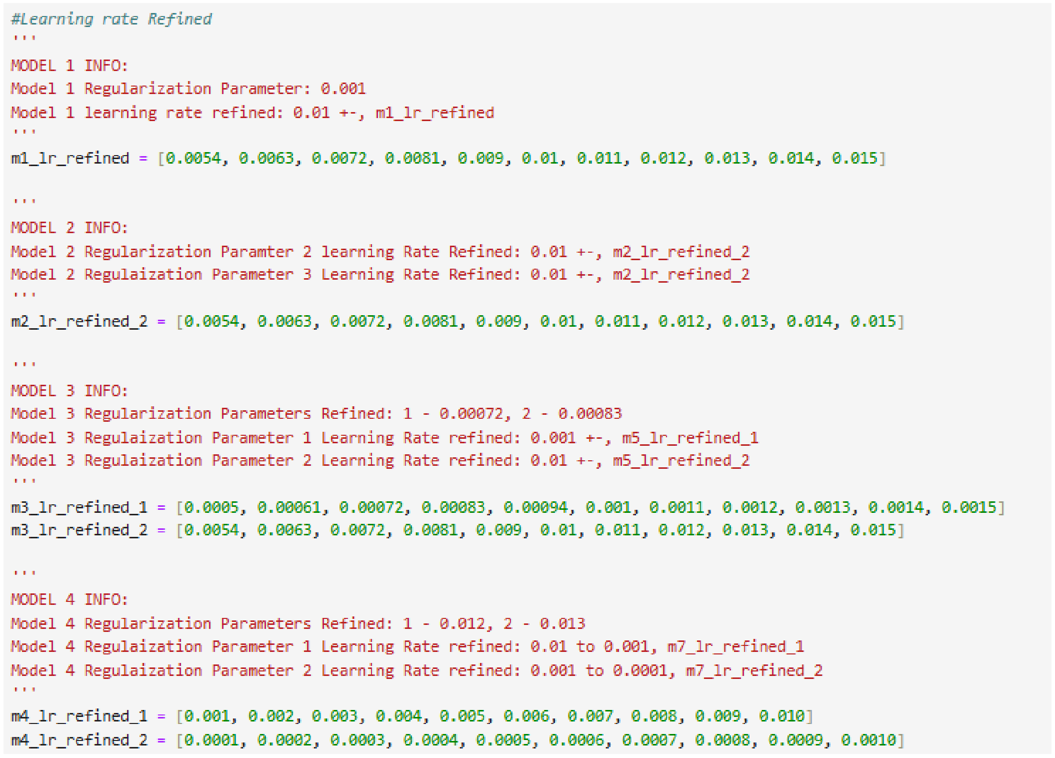
	precision	Recall	F1-Score	Support
0	0.82	0.81	0.82	81
1	0.86	0.86	0.86	103
accuracy			0.84	184
macro avg	0.84	0.84	0.84	184
weighted avg	0.84	0.84	0.84	184

Table 5.19: Performance Metrics for Model 7 (Regularization: 0.012, Learning Rate: 0.0001) on Test Data

In conclusion, the model displayed a balanced performance with strong precision and recall. The consistent training and validation accuracy, along with robust test accuracy, indicate effective generalization. However, the observed fluctuations in validation metrics highlight the need for further hyperparameter tuning to enhance model stability and overall performance.

Learning Rate Refinement

The initial learning rate study tested each model configuration over a broad set of learning rates in hopes to find a range where we can refine our values and further optimize our model. Below are the new learning rates for each model, as they were written in Python. The regularization parameters need to be updated as well, as some model configurations did not meet the specified criteria.



```python
#Learning rate Refined
'''
MODEL 1 INFO:
Model 1 Regularization Parameter: 0.001
Model 1 learning rate refined: 0.01 +-, m1_lr_refined
'''
m1_lr_refined = [0.0054, 0.0063, 0.0072, 0.0081, 0.009, 0.01, 0.011, 0.012, 0.013, 0.014, 0.015]

'''
MODEL 2 INFO:
Model 2 Regularization Paramter 2 learning Rate Refined: 0.01 +-, m2_lr_refined_2
Model 2 Regulaization Parameter 3 Learning Rate Refined: 0.01 +-, m2_lr_refined_2
'''
m2_lr_refined_2 = [0.0054, 0.0063, 0.0072, 0.0081, 0.009, 0.01, 0.011, 0.012, 0.013, 0.014, 0.015]

'''
MODEL 3 INFO:
Model 3 Regularization Parameters Refined: 1 - 0.00072, 2 - 0.00083
Model 3 Regulaization Parameter 1 Learning Rate refined: 0.001 +-, m5_lr_refined_1
Model 3 Regulaization Parameter 2 Learning Rate refined: 0.01 +-, m5_lr_refined_2
'''
m3_lr_refined_1 = [0.0005, 0.00061, 0.00072, 0.00083, 0.00094, 0.001, 0.0011, 0.0012, 0.0013, 0.0014, 0.0015]
m3_lr_refined_2 = [0.0054, 0.0063, 0.0072, 0.0081, 0.009, 0.01, 0.011, 0.012, 0.013, 0.014, 0.015]

'''
MODEL 4 INFO:
Model 4 Regularization Parameters Refined: 1 - 0.012, 2 - 0.013
Model 4 Regulaization Parameter 1 Learning Rate refined: 0.01 to 0.001, m7_lr_refined_1
Model 4 Regulaization Parameter 2 Learning Rate refined: 0.001 to 0.0001, m7_lr_refined_2
'''
m4_lr_refined_1 = [0.001, 0.002, 0.003, 0.004, 0.005, 0.006, 0.007, 0.008, 0.009, 0.010]
m4_lr_refined_2 = [0.0001, 0.0002, 0.0003, 0.0004, 0.0005, 0.0006, 0.0007, 0.0008, 0.0009, 0.0010]
```

Code Block 5.5: Refined Learning Rates in Python

```
#Refined Regularization Values with Learning Rate
m1_reg_lr = [0.001]
m2_reg_lr = [0.00018, 0.00026, 0.00067]
m3_reg_lr = [0.00072, 0.00083, 0.0014, 0.0015]
m4_reg_lr = [0.012, 0.013]
```

Code Block 5.6: Final Regularization Values

To train, compile and evaluate all the different model configurations, Code Block 5.7 is used with the refined learning rates as well as the final regularization values. Code Bock 5.7 below is slightly modified to fit the specified hyperparameters of each model configuration.

```
for reg in m1_reg_lr:
    for lr in m1_lr_refined:
        print(f"REGULARIZATION PARAMETER: {reg}")
        print(f"LEARNING RATE = {lr}")

        model_1_reg_lr = tf.keras.Sequential([
            tf.keras.layers.Dense(16, activation='relu', name='L1', kernel_regularizer = l2(reg)),
            tf.keras.layers.Dense(16, activation='relu', name='L2', kernel_regularizer = l2(reg)),
            tf.keras.layers.Dense(1, activation='sigmoid', name='OL')
        ])

        model_1_reg_lr.compile(optimizer = tf.keras.optimizers.Adam(learning_rate = lr),
                loss = tf.keras.losses.BinaryCrossentropy(),
                metrics = ['accuracy'])

        history = model_1_reg_lr.fit(X_train, y_train, batch_size = 16, epochs = 30, validation_data = (X_valid, y_valid))

        plot_accuracy(history)
        plot_loss(history)

        print("\nModel Prediction on Test set")
        results= model_1_reg_lr.evaluate(X_test, y_test)

        y_predicted_m1 = model_1_reg_lr.predict(X_test)
        y_predicted_m1 = y_predicted_m1.flatten()
        y_predicted_m1 = np.where(y_predicted_m1 > 0.5, 1, 0)

        print(f"\nConfusion Matrix")
        cm = confusion_matrix(y_test, y_predicted_m1)
        print(cm)

        print(classification_report(y_test, y_predicted_m1))
```

Code Block 5.7: Model 1 – Test Refined Learning Rates

Model Configurations that made it to the Final Selection section need an overall accuracy of 85% or higher, an F1-Score (1) of 85% of higher, as well as smooth accuracy and loss training curves with no signs of overfitting.

```
for reg in m3_reg_lr:

    learning_rate_for_reg_param = []

    if reg == m3_reg_lr[0]:
        learning_rate_for_reg_param = m3_lr_refined_1
    else:
        learning_rate_for_reg_param = m3_lr_refined_2

    for lr in learning_rate_for_reg_param:
        print(f"REGULARIZATION PARAMETER {reg}")
        print(f"LEARNING RATE = {lr}")

        model_3_reg_lr = tf.keras.Sequential([
            tf.keras.layers.Dense(64, activation = 'relu', name = 'L1', kernel_regularizer = l2(reg)),
            tf.keras.layers.Dense(32, activation = 'relu', name = 'L2', kernel_regularizer = l2(reg)),
            tf.keras.layers.Dense(1, activation = 'sigmoid', name = 'OL')
        ])

        model_3_reg_lr.compile(optimizer = tf.keras.optimizers.Adam(learning_rate = lr),
                loss = tf.keras.losses.BinaryCrossentropy(),
                metrics = ['accuracy'])

        history = model_3_reg_lr.fit(X_train, y_train, batch_size = 16, epochs = 30, validation_data = (X_valid, y_valid))

        print("\nModel Prediction on Test set")
        results= model_3_reg_lr.evaluate(X_test, y_test)

        plot_accuracy(history)
        plot_loss(history)

        y_predicted_m3 = model_3_reg_lr.predict(X_test)
        y_predicted_m3 = y_predicted_m3.flatten()
        y_predicted_m3 = np.where(y_predicted_m3 > 0.5, 1, 0)

        print(f"\nConfusion Matrix")
        cm = confusion_matrix(y_test, y_predicted_m3)
        print(cm)

        print(classification_report(y_test, y_predicted_m3))
```

Code Block 5.8: Refined Learning Rate for Model 3

Code Block 5.8 above, shows how all model configurations were tested for Model 3's refined learning rate study. Since Model 3 had multiple regularization values, a slight edit to the code had to be done to ensure the correct combination of regularization parameters and learning rates.

Learning Rate Refinement – Model 1

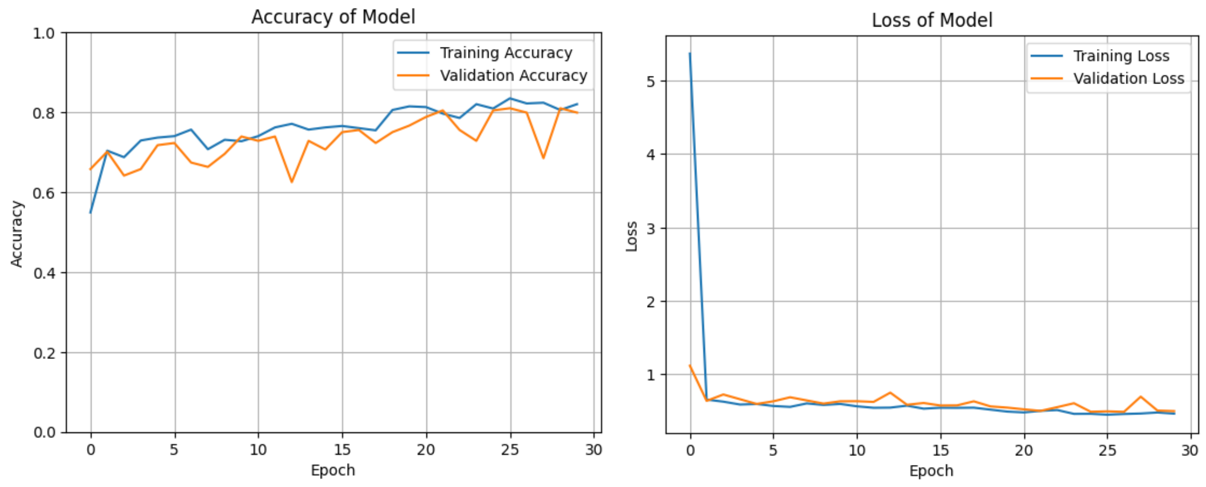
Model 1 + Regularization Refined + Learning Rate Refined				
Regularization Parameter	Learning Rate Refined	F1-Score (0)	F1-Score (1)	Accuracy
0.001	0.0054	81	86	84
	0.0063	81	85	83
	0.0072	77	85	82
	0.0081	79	85	83
	0.009	82	82	82
	0.01	81	81	81
	0.011	82	87	85
	0.012	80	83	82
	0.013	72	83	79
	0.014	65	82	76
	0.015	31	76	64

Table 5.20: Model 1 – Refined Regularization Parameter + Refined Learning Rate Accuracy (Evaluated on Test Data)

From Model 1's final optimization cycle, only one model configuration was chosen to move forward. Model 1, with an L2 regularization parameter of 0.001 and a learning rate of 0.011, clearly stood out among the other tested configurations, demonstrating superior performance. This configuration exhibited optimal generalization capabilities and minimized overfitting, indicating that we have achieved an ideal balance between bias and variance. The following is the model configurations performance on the test set.

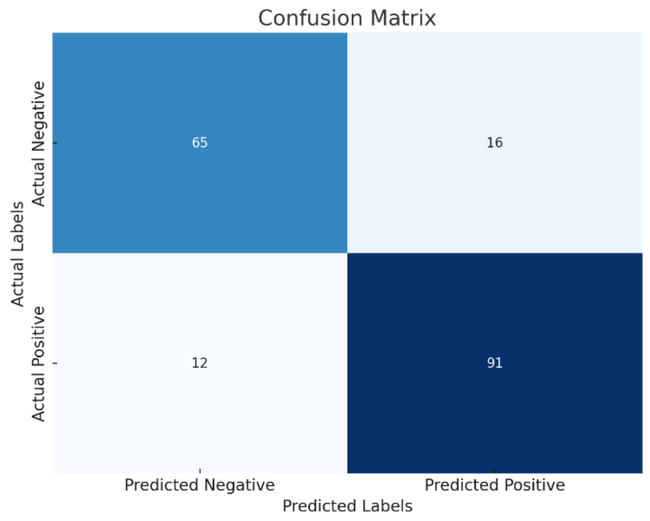
```
Model Prediction on Test set
6/6 [==============================] - 0s 807us/step - loss: 0.4386 - accuracy: 0.8478
6/6 [==============================] - 0s 2ms/step
```

The following are this model configuration accuracy and loss plots during training over the training and validation dataset



Plot 5.24: Model 1, Regularization Parameter 0.001 and Learning rate of 0.011

The model's performance, as illustrated by the loss and accuracy plots, indicates effective learning and good generalization. The training and validation loss curves converge quickly and stabilize around similar values, which suggests that the model is learning effectively without significant overfitting. Both training and validation accuracies show consistent improvement over the epochs, with final validation accuracy reaching approximately 0.8, demonstrating robust performance on unseen data.



Plot 5.25: Confusion Matrix - Model 1, L2 Regularization 0.001 and Learning Rate 0.011

The confusion matrix provides a detailed view of the model's classification capabilities. The model correctly classified 65 out of 81 samples for class 0 and 91 out of 103 samples for class 1, resulting in an overall accuracy of 84.78% on the test set.

	Precision	Recall	F1-Score	Support
0	0.84	0.8	0.82	81
1	0.85	0.88	0.87	103

accuracy			0.85	184
macro avg	0.85	0.84	0.84	184
weighted avg	0.85	0.85	0.85	184

Table 5.21: Performance Metrics for Model 1 (Regularization: 0.001, Learning Rate: 0.011) on Test Data

The precision, recall, and F1-score for class 0 are 0.84, 0.80, and 0.82, respectively, while for class 1, they are 0.85, 0.88, and 0.87. These metrics indicate balanced performance across both classes, with a slightly better performance on class 1.

The chosen regularization parameter of 0.001 and a learning rate of 0.011 reflect a careful approach to prevent overfitting while ensuring smooth learning dynamics. Despite some fluctuations in validation accuracy during training, which may suggest minor instability due to the complexity of the dataset or model, the overall trend remains positive, leading to strong final performance.

Learning Rate Refinement – Model 2

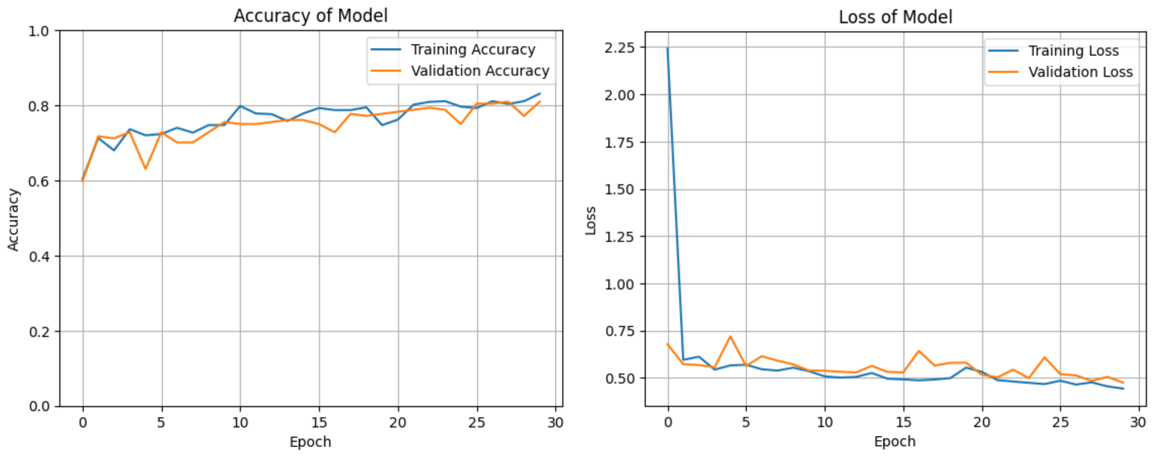
Model 2 + Regularization Refined + Learning Rate Refined				
Regularization Parameter	Learning Rate	F1-Score (0)	F1-Score (1)	Accuracy
0.00026	0.0054	79	86	83
	0.0063	79	86	83
	0.0072	76	85	82
	0.0081	62	81	75
	0.009	79	86	83
	0.01	82	82	82
	0.011	82	79	80
	0.012	83	87	85
	0.013	81	87	84
	0.014	81	85	83
	0.015	78	85	82
0.00067	0.0054	81	85	83
	0.0063	83	86	85
	0.0072	80	85	83
	0.0081	80	78	79
	0.009	75	84	80
	0.01	81	85	83
	0.011	82	86	84
	0.012	78	89	83

	0.013	73	61	68
	0.014	81	84	83
	0.015	81	85	83

Table 5.22: Model 2 – Refined Regularization Parameter + Refined Learning Rate Accuracy (Evaluated on Test Data)

From Model 2's final optimization cycle, two of the configurations were chosen to move forward. Model 2, with an L2 regularization parameter of 0.00026 and a learning rate of 0.012, and L2 regularization parameter of 0.00067 and a learning rate of 0.0063. These two configurations stood out among the rest in terms of their F1-Scores and overall accuracies, indicating optimal generalization capabilities and minimized overfitting.

The first Model 2 configuration we will look at is L2 regularization parameter of 0.00026 and a learning rate of 0.012.

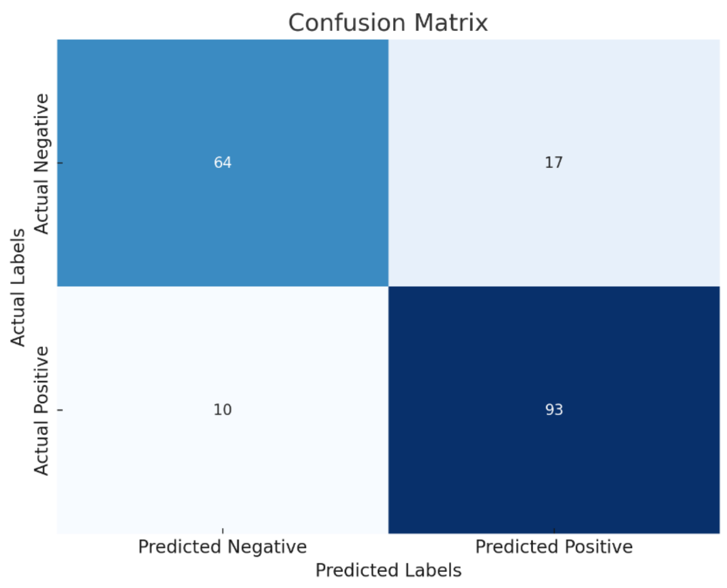


Plot 5.26: Model 2, Regularization Parameter 0.00026 and Learning rate of 0.012

The model's performance, as reflected in the provided metrics and visualizations, indicates strong learning and generalization capabilities. The training and validation loss curves show a clear convergence and stabilization, which suggests effective learning with minimal overfitting. Both losses remain low, and the validation loss closely follows the training loss, indicating good generalization to the validation set.

```
Model Prediction on Test set
6/6 [==============================] - 0s 776us/step - loss: 0.4246 - accuracy: 0.8533
```

The training and validation accuracy curves show consistent improvement over the epochs, with the final validation accuracy reaching approximately 81%. This demonstrates the model's robust performance on unseen data.



Plot 5.25: Confusion Matrix - Model 2, L2 Regularization 0.00026 and Learning Rate 0.012

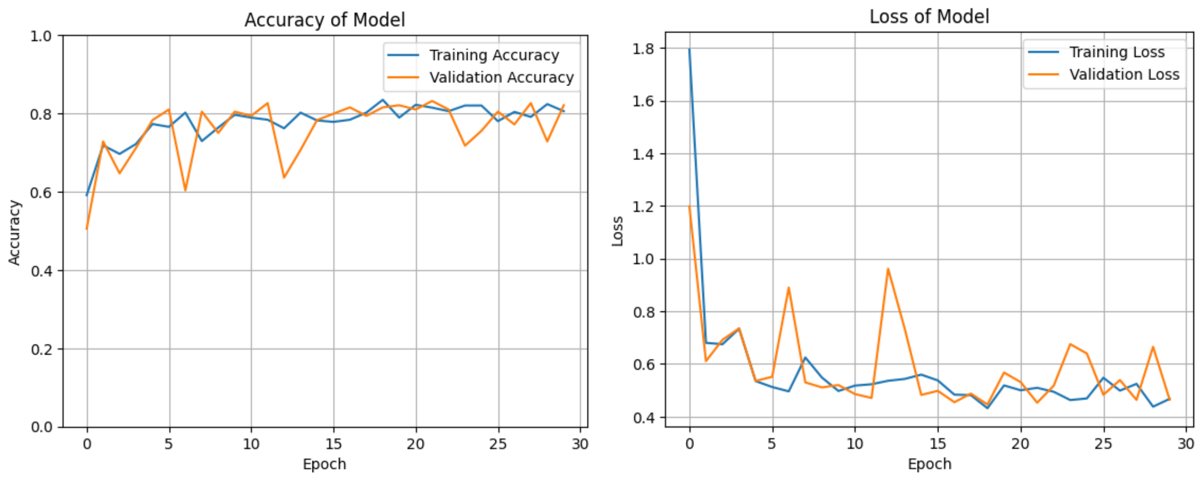
The confusion matrix provides a detailed view of the model's classification performance. The model correctly classified 64 out of 81 samples for class 0 and 93 out of 103 samples for class 1, resulting in an overall test set accuracy of 85.33%. The precision, recall, and F1-score for class 0 are 0.86, 0.79, and 0.83, respectively, while for class 1, they are 0.85, 0.90, and 0.87. These metrics indicate a balanced performance across both classes, with slightly better performance on class 1.

	Precision	Recall	F1-Score	Support
0	0.86	0.79	0.83	81
1	0.85	0.9	0.87	103
accuracy			0.85	184
macro avg	0.86	0.85	0.85	184
weighted avg	0.85	0.85	0.85	184

Table 5.23: Performance Metrics for Model 2 (Regularization: 0.00026, Learning Rate: 0.012) on Test Data

In summary, the model demonstrates good generalization with balanced performance across classes, effective regularization, and stable learning dynamics. The model achieves a final test accuracy of 85.33%, which is higher than our set goal of 84.61%, with balanced precision and recall metrics, indicating its reliability and robustness in classifying the provided dataset.

Next, we will analyze Model 2’s second configuration.

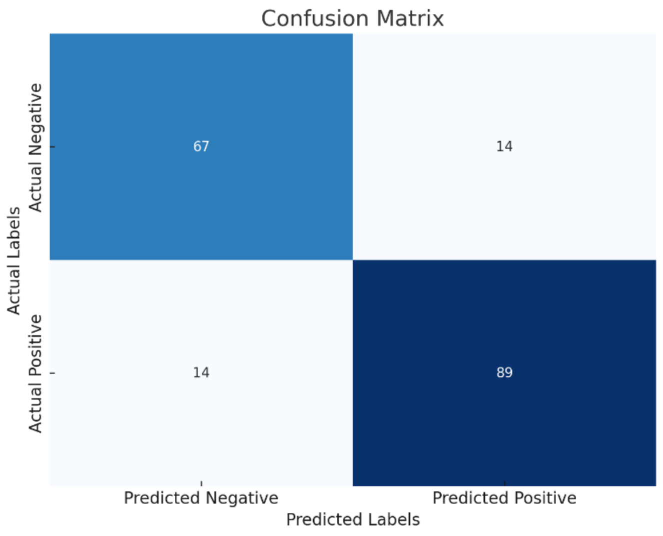


Plot 5.27: Model 2, Regularization Parameter 0.00067 and Learning rate of 0.0063

The model's performance, as depicted in the loss and accuracy plots, demonstrates effective learning and generalization. However, there is noticeable noise in the training signal, particularly in the validation loss curve. The training and validation loss curves show a rapid decrease initially, followed by fluctuations throughout the training epochs. The validation loss exhibits significant spikes, indicating variability in the model's performance on the validation set.

```
Model Prediction on Test set
6/6 [==============================] - 0s 825us/step - loss: 0.4349 - accuracy: 0.8478
```

The training and validation accuracy curves are more stable, showing consistent improvement and convergence, with final validation accuracy reaching approximately 0.82. This indicates that despite the noise in the loss signal, the model maintains robust performance on unseen data.



Plot 5.28: Confusion Matrix - Model 2, L2 Regularization 0.00067 and Learning Rate 0.0063

The confusion matrix provides further insight into the model's classification performance. The model correctly classified 67 out of 81 samples for class 0 and 89 out of 103 samples for class 1, resulting in an overall test set accuracy of 84.78%. The precision, recall, and F1-score for class 0 are 0.83 across the board, while for class 1, they are 0.86. These metrics indicate balanced performance across both classes.

	Precision	Recall	F1-Score	Support
0	0.83	0.83	0.83	81
1	0.86	0.86	0.86	103
accuracy			0.85	184
macro avg	0.85	0.85	0.85	184
weighted avg	0.85	0.85	0.85	184

Table 5.24: Performance Metrics for Model 2 (Regularization: 0.00067, Learning Rate: 0.0063) on Test Data

The chosen regularization parameter of 0.00067 and a learning rate of 0.0063 reflect an approach to mitigate overfitting and ensure smooth learning. However, the fluctuations in validation loss suggest that the model's training process could benefit from further fine-tuning of these hyperparameters. The noise in the training signal could be due to a variety of factors, including batch size, data variability, or model complexity.

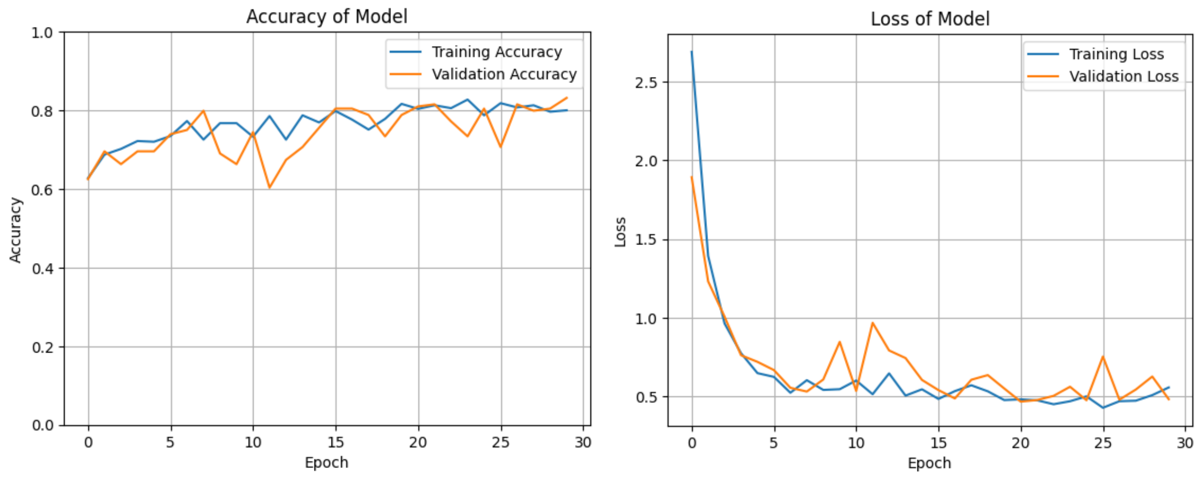
In summary, while the model demonstrates good generalization with balanced performance across classes, the noise in the training signal, particularly in the validation loss, indicates a need for further fine-tuning.

Learning Rate Refinement – Model 3

Model 3 + Regularization Refined + Learning Rate Refined				
Regularization Parameter	Learning Rate Refined	F1-Score (0)	F1-Score (1)	Accuracy
0.00072	0.0005	81	83	82
	0.00061	79	83	81
	0.00072	77	84	82
	0.00083	81	85	84
	0.00094	76	70	73
	0.001	82	83	83
	0.0011	78	86	83
	0.0012	83	84	84
	0.0013	83	87	85
	0.0014	73	84	80
	0.0015	79	74	77
0.00083	0.0054	80	80	80
	0.0063	80	82	81
	0.0072	65	82	76
	0.0081	83	82	82
	0.009	80	85	83
	0.01	81	87	84
	0.011	80	86	84
	0.012	80	84	83
	0.013	81	87	84
	0.014	73	84	80
	0.015	81	83	82

Table 5.25: Model 3 – Refined Regularization Parameter + Refined Learning Rate Accuracy (Evaluated on Test Data)

One Model 3 configuration was chosen from its final optimization cycle. Model 3, with an L2 regularization parameter of 0.00072 and a learning rate of 0.0013, demonstrated superior performance. The following plots illustrate the model's training and validation accuracy and loss over each epoch, highlighting the model's convergence behavior and generalization capabilities.



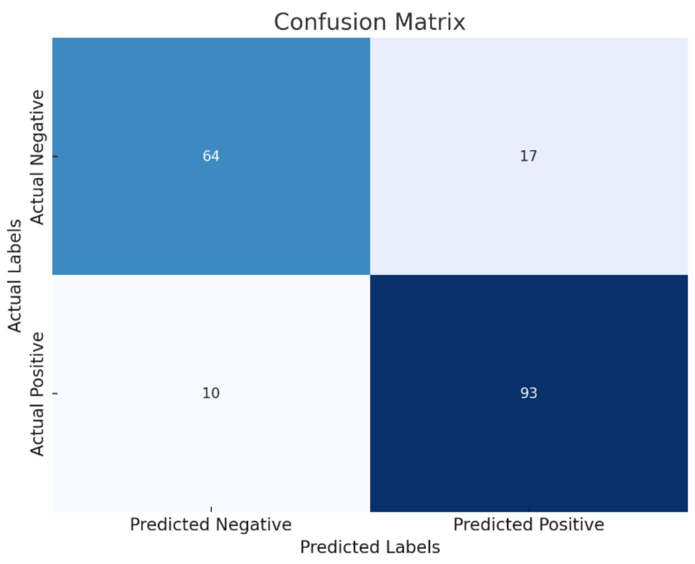
Plot 5.29: Model 3, Regularization Parameter 0.00072 and Learning rate of 0.0013

The performance of the model, as demonstrated by the provided plots and metrics, reflects its effective learning and generalization capabilities, albeit with some noise in the training signal. The training and validation loss curves indicate a rapid initial decrease, followed by fluctuations throughout the epochs. The validation loss shows notable spikes, indicating variability in the model's performance on the validation set.

Despite the fluctuations in loss, the training and validation accuracy curves are relatively stable, showing consistent improvement and convergence. The final validation accuracy reaches approximately 0.83, demonstrating the model's robust performance on unseen data.

```
Model Prediction on Test set
6/6 [==============================] - 0s 0s/step - loss: 0.4259 - accuracy: 0.8533
```

The confusion matrix offers detailed insight into the model's classification abilities. The model correctly classified 64 out of 81 samples for class 0 and 93 out of 103 samples for class 1, leading to an overall test set accuracy of 85.33%.



Plot 5.30: Confusion Matrix - Model 3, L2 Regularization 0.00072 and Learning Rate 0.0013

The precision, recall, and F1-score for class 0 are 0.86, 0.79, and 0.83, respectively. For class 1, these metrics are 0.85, 0.90, and 0.87, respectively, indicating balanced performance across both classes.

	Precision	Recall	F1-Score	Support
0	0.86	0.79	0.83	81
1	0.85	0.9	0.87	103
accuracy			0.85	184
macro avg	0.86	0.85	0.85	184
weighted avg	0.85	0.85	0.85	184

Table 5.26: Performance Metrics for Model 3 (Regularization: 0.00072, Learning Rate: 0.0013) on Test Data

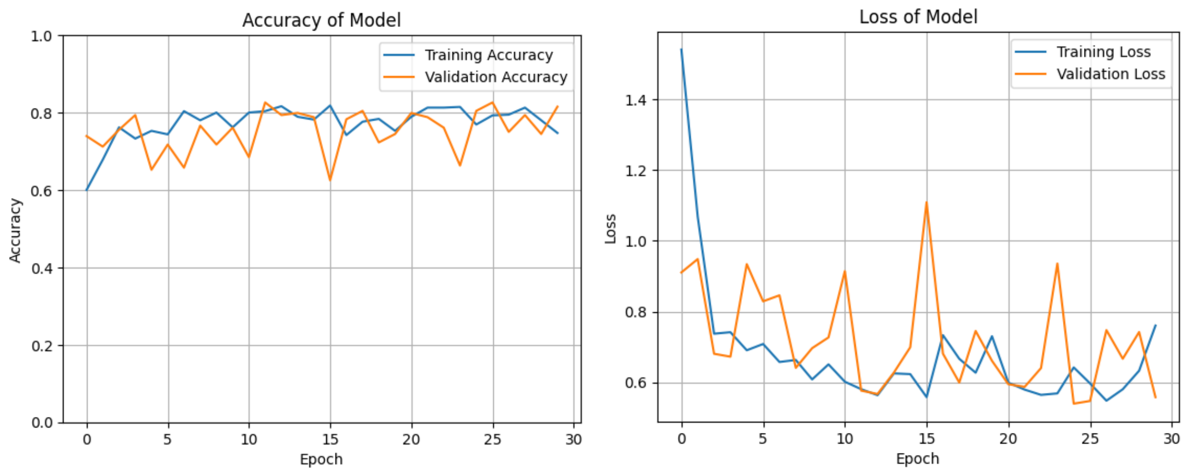
In summary, the model showcases good generalization with balanced performance across classes, effective regularization, and stable learning dynamics. The noise in the training signal, particularly in the validation loss, highlights the need for further fine-tuning to achieve more consistent training dynamics. Despite these fluctuations, the model achieves a final test accuracy of 85.33%.

Learning Rate Refinement – Model 4

Model 4 + Regularization + Learning Rate Refined				
Regularization Parameter	Learning Rate Refined	F1-Score (0)	F1-Score (1)	Accuracy
0.012	0.001	78	77	78
	0.002	76	72	74
	0.003	72	63	68
	0.004	82	86	84
	0.005	65	82	76
	0.006	77	75	76
	0.007	77	84	82
	0.008	79	83	81
	0.009	65	82	76
	0.01	75	80	78
0.013	0.0001	80	81	80
	0.0002	81	81	81
	0.0003	80	80	80
	0.0004	81	86	84
	0.0005	80	79	80
	0.0006	74	85	81
	0.0007	61	82	74
	0.0008	82	86	84
	0.0009	82	87	85
	0.001	83	86	85

Table 5.27: Model 4 – Refined Regularization Parameter + Refined Learning Rate Accuracy (Evaluated on Test Data)

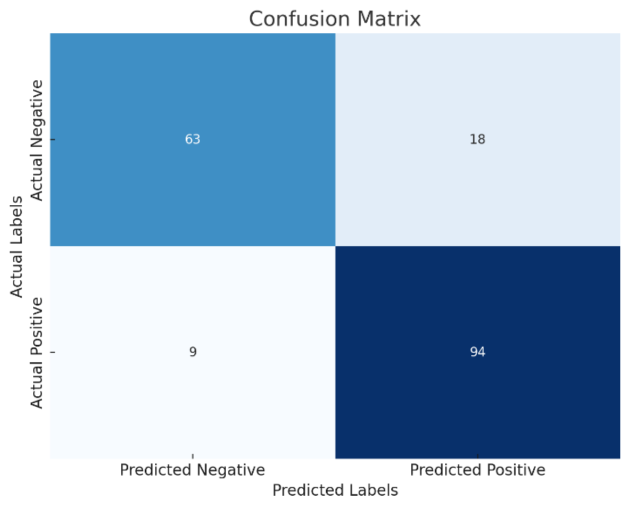
From Model 4's final optimization cycle, two configurations were selected to advance. The first configuration features an L2 regularization parameter of 0.013 and a learning rate of 0.0009, while the second configuration has an L2 regularization parameter of 0.013 and a learning rate of 0.001. These configurations distinguished themselves by achieving superior F1-Scores in both classes and high test data accuracies, reflecting their optimal generalization capabilities and reduced overfitting. The proximity of these optimal parameters indicates that the search effectively pinpointed a highly favorable range for model performance. Let's analyze both.



Plot 5.31: Model 4, Regularization Parameter 0.013 and Learning rate of 0.0009

The model's performance, as depicted by the loss and accuracy plots, indicates effective learning with some noise in the training signal. The training and validation loss curves show a sharp initial decrease, followed by fluctuations throughout the epochs. Notably, the validation loss exhibits variability, suggesting inconsistencies in the model's performance on the validation set.

Despite the fluctuations in loss, the training and validation accuracy curves show a more stable improvement, ultimately converging. The final validation accuracy reaches approximately 0.82, indicating robust performance on unseen data.



Plot 5.32: Confusion Matrix - Model 4, L2 Regularization 0.013 and Learning Rate 0.0009

The confusion matrix provides a detailed breakdown of the model's classification abilities. The model correctly classified 63 out of 81 samples for class 0 and 94 out of 103 samples for class 1, resulting in an overall test set accuracy of 85.33%.

	Precision	Recall	F1-Score	Support
0	0.88	0.78	0.82	81
1	0.84	0.91	0.87	103
accuracy			0.85	184
macro avg	0.86	0.85	0.85	184
weighted avg	0.86	0.85	0.85	184

Table 5.28: Performance Metrics for Model 4 (Regularization: 0.013, Learning Rate: 0.0009) on Test Data

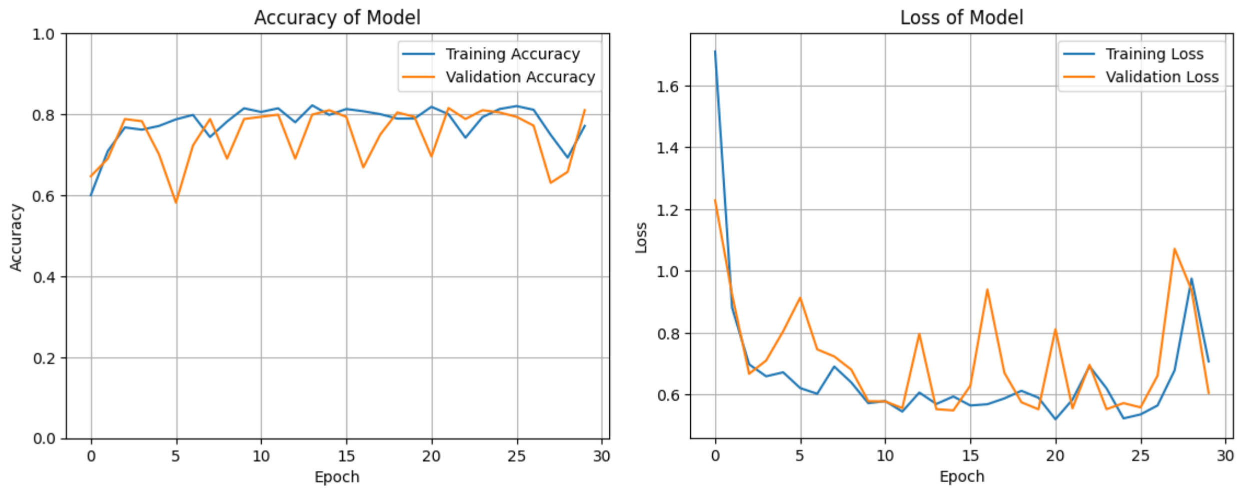
The precision, recall, and F1-score for class 0 are 0.88, 0.78, and 0.82, respectively. For class 1, these metrics are 0.84, 0.91, and 0.87, indicating a balanced performance across both classes.

The regularization parameter of 0.013 and a learning rate of 0.0009 suggest an approach focused on mitigating overfitting and ensuring stable learning. Despite these fluctuations, the model achieves a final test accuracy of 85.33%, demonstrating its reliability and robustness in classifying the provided dataset.

```
Model Prediction on Test set
6/6 [==============================] - 0s 772us/step - loss: 0.5279 - accuracy: 0.8533
```

In summary, the model exhibits good generalization with balanced performance across classes, effective regularization, and stable learning dynamics. The variability in the validation loss highlights the need for further fine-tuning to achieve more stable training. The noise in the training signal could be attributed to factors such as data variability, batch size, or model complexity.

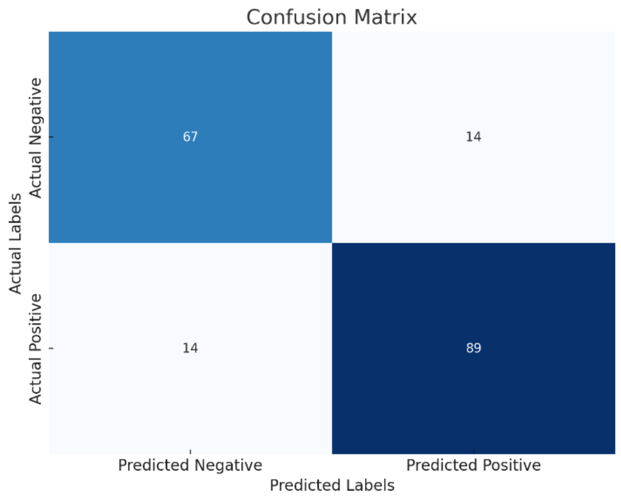
As mentioned earlier, the final Model 4 Configuration is very close in terms of learning rate to the first, indicating that the search effectively pinpointed a highly favorable range for model performance. The final Model 4 Configuration has an L2 regularization parameter of 0.013 and a learning rate of 0.001.



Plot 5.33: Model 4, Regularization Parameter 0.013 and Learning rate of 0.001

The model's performance, depicted through the loss and accuracy plots, demonstrates effective learning, although there is evident noise in the training signal. The training and validation loss curves show a steep initial decline followed by significant fluctuations. These fluctuations in the validation loss indicate inconsistencies in the model's performance on the validation set.

Despite the variations in loss, the training and validation accuracy curves exhibit a more stable improvement, ultimately converging. The final validation accuracy reaches approximately 0.81, reflecting strong performance on unseen data.



Plot 5.34: Confusion Matrix - Model 4, L2 Regularization 0.013 and Learning Rate 0.001

The confusion matrix offers a detailed view of the model's classification performance. The model accurately classified 67 out of 81 samples for class 0 and 89 out of 103 samples for class 1, leading to an overall test set accuracy of 85.33%.

```
Model Prediction on Test set
6/6 [==============================] - 0s 959us/step - loss: 0.5378 - accuracy: 0.8478
```

The precision, recall, and F1-score for class 0 are all 0.83, while for class 1, these metrics are 0.86, indicating a balanced performance across both classes.

	Precision	Recall	F1-Score	Support
0	0.83	0.83	0.83	81
1	0.86	0.86	0.86	103
accuracy			0.85	184
macro avg	0.85	0.85	0.85	184
weighted avg	0.85	0.85	0.85	184

Table 5.29: Performance Metrics for Model 4 (Regularization: 0.013, Learning Rate: 0.0001) on Test Data

The chosen regularization parameter of 0.013 and a learning rate of 0.001 suggest a strategy aimed at reducing overfitting and ensuring smooth learning. However, the fluctuations in the validation loss signal that further fine-tuning of these hyperparameters could enhance training stability. The noise in the training signal could be due to factors such as data variability, batch size, or model complexity.

In summary, the model shows good generalization with balanced performance across classes, effective regularization, and relatively stable learning dynamics. The variability in the validation loss underscores the need for further hyperparameter tuning to achieve more consistent training dynamics. Nonetheless, the model achieves a final test accuracy of 85.33%.

Learning Rate Refinement Summary

The learning rate is a crucial hyperparameter in machine learning algorithms that determines the step size at each iteration while moving towards a minimum of the loss function. Essentially, it controls how much to change the model in response to the estimated error each time the model weights are updated. A well-chosen learning rate ensures that the model converges efficiently to an optimal solution, avoiding the pitfalls of overshooting or excessively slow convergence. In the context of predicting heart disease, selecting an appropriate learning rate is vital for achieving accurate and reliable predictions, as it influences the stability and performance of the model throughout the training process.

As observed in the earlier section, all model configurations selected for the learning rate study achieved relatively high accuracy. However, some of the training data exhibited significant noise. Optimizing the learning rate is expected to mitigate this issue, leading to smoother training curves and potentially improved model performance.

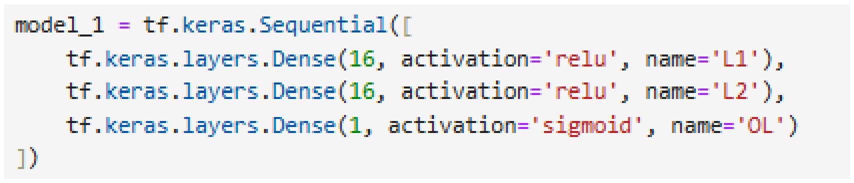
The initial learning rate study tested each model configuration over a broad set of learning rates (0.1, 0.01, 0.001, 0.0001) to identify a range for further refinement. From there, the learning rates were refined similarly to the regularization values previously. The criteria set for the initial learning rate study were an overall accuracy of 84% and an accuracy of predicting positive cases at 85% or above. Achieving high accuracy in predicting positive medical cases is crucial, especially in the context of heart disease, as early and accurate detection can significantly improve patient outcomes. High predictive accuracy ensures that patients at risk are identified promptly, allowing for timely intervention and treatment, which can reduce the likelihood of severe complications and improve the overall quality of life.

Final Model Selection and Analysis

The summarize the previous section, there were a total of six model configurations selected to move on to the final stage of analysis. One model will be selected in the end as the final model.

The following is a summary of the six final models

Model 1:



```
model_1 = tf.keras.Sequential([
    tf.keras.layers.Dense(16, activation='relu', name='L1'),
    tf.keras.layers.Dense(16, activation='relu', name='L2'),
    tf.keras.layers.Dense(1, activation='sigmoid', name='OL')
])
```

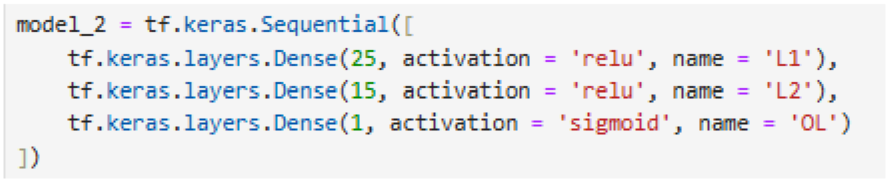
Model 1 consists of three layers: two hidden layers (L1 and L2) with 16 neurons each, both using the ReLU activation function. The output layer (OL) has a single neuron with a sigmoid activation function.

Model 1 Configuration 1:

L2 Regularization - 0.001

Learning Rate - 0.011

Model 2:



```
model_2 = tf.keras.Sequential([
    tf.keras.layers.Dense(25, activation = 'relu', name = 'L1'),
    tf.keras.layers.Dense(15, activation = 'relu', name = 'L2'),
    tf.keras.layers.Dense(1, activation = 'sigmoid', name = 'OL')
])
```

Model 2 is composed of three layers: an initial hidden layer (L1) with 25 neurons and a subsequent hidden layer (L2) with 15 neurons, both using the ReLU activation functions. The final output layer (OL) has a single neuron with a sigmoid activation function.

Model 2 Configuration 1:

L2 Regularization – 0.00026

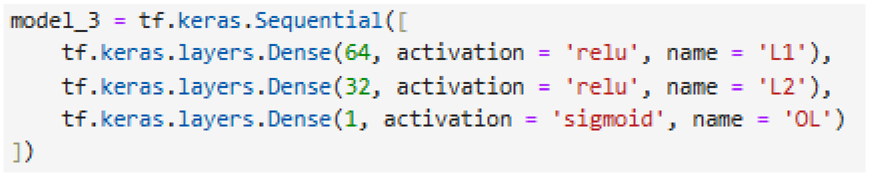
Learning Rate – 0.012

Model 2 Configuration 2:

L2 Regularization – 0.00067

Learning Rate – 0.0063

Model 3:



```
model_3 = tf.keras.Sequential([
    tf.keras.layers.Dense(64, activation = 'relu', name = 'L1'),
    tf.keras.layers.Dense(32, activation = 'relu', name = 'L2'),
    tf.keras.layers.Dense(1, activation = 'sigmoid', name = 'OL')
])
```

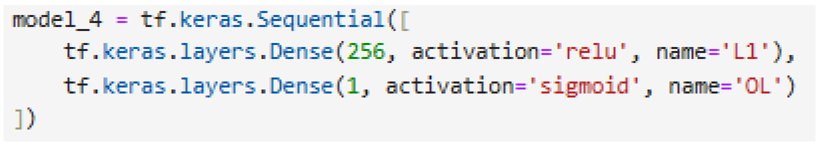
Model 3 features three layers: a first hidden layer (L1) with 64 neurons and a second hidden layer (L2) with 32 neurons, both utilizing the ReLU activation function. The output layer (OL) contains a single neuron with a sigmoid activation function.

<u>Model 3 Configuration 1</u>:

L2 Regularization – 0.00072

Learning Rate – 0.0013

Model 4:



```
model_4 = tf.keras.Sequential([
    tf.keras.layers.Dense(256, activation='relu', name='L1'),
    tf.keras.layers.Dense(1, activation='sigmoid', name='OL')
])
```

Model 4 consists of two layers: a hidden layer (L1) with 256 neurons using the ReLU activation function and L2 regularization with a parameter `i`. The output layer (OL) has a single neuron with a sigmoid activation function, indicating the model is likely used for binary classification.

<u>Model 4 Configuration 1</u>:

L2 Regularization – 0.013

Learning Rate – 0.0009

<u>Model 4 Configuration 2</u>:

L2 Regularization – 0.013

Learning Rate – 0.001

Choosing a Final Model

To identify the best model for heart disease prediction among the provided configurations, let's analyze the key metrics (accuracy, precision, recall, and F1-score) for each model. These metrics are crucial for evaluating the performance of classification models, especially in medical diagnosis, where both precision and recall are highly important.

1. **Accuracy** indicates the overall correctness of the model.
2. **Precision** measures the proportion of positive identifications that are actually correct.
3. **Recall** (or sensitivity) measures the proportion of actual positives that are correctly identified.
4. **F1-Score** is the harmonic mean of precision and recall, providing a single metric that balances both concerns.

Based on these metrics, we can analyze the performance of each model.

The first three models to be excluded are Model 3 Configuration 2, Model 4 Configuration 1, and Model 4 Configuration 2. Although these models meet our initial accuracy goal of over 84.61%, they do not show a significant advantage over Model 1 and Model 2 in terms of precision and recall. Additionally, these models exhibited the most noise in their training plots, indicating a lack of stability and efficiency. While the parameter optimization section aimed to address these issues, it is evident that further optimizations are still needed. Consequently, these three models are less favorable compared to the more stable and efficient configurations of Model 1 and Model 2.

The final three models are Model 1 Configuration 1, Model 2 Configuration 1, and Model 2 Configuration 2. The outputted data from these models can be reviewed in the index section, as seen in the Jupyter notebook.

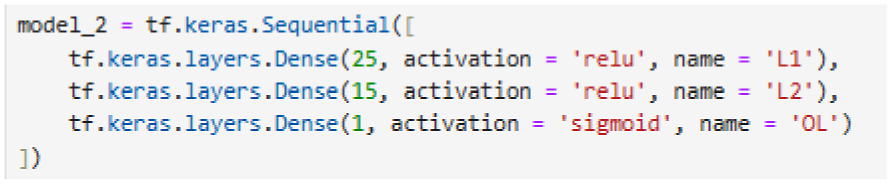
Between the three models, Model 1 Configuration 1 has been excluded primarily due to its lower validation accuracy of 0.8098 and slightly lower test accuracy of 0.8478 compared to the other models. These lower accuracies suggest less reliable performance on new, unseen data, indicating potential overfitting where the model may have learned the training data, including noise and outliers, too well, failing to generalize effectively. Additionally, the performance stability of Model 1 Configuration 1 is concerning. The fluctuations in validation loss and accuracy across epochs highlight instability in the learning process. For instance, in epoch 28, there is a notable drop in validation accuracy to 0.6848, pointing to potential inconsistencies.

In contrast, Model 2 Configuration 1 and Configuration 2 exhibit more stable and steady improvements in their validation metrics across epochs, indicating better convergence and consistency. Therefore, despite Model 1 Configuration 1's high precision and recall, its lower validation accuracy and performance instability make it less reliable for practical applications.

Between Model 2 Configuration 1 and Configuration 2, the decision is based on their performance metrics. Model 2 Configuration 1 exhibits a slightly higher test accuracy of 0.8533 compared to Configuration 2's 0.8478. More importantly, it demonstrates a higher recall rate of

0.90. In the context of heart disease prediction, recall is a crucial metric because it measures the model's ability to correctly identify positive cases. Missing a positive case (false negative) can be more critical than a false positive, as it could mean failing to identify a patient with heart disease, potentially leading to severe health consequences.

<u>Final Model</u>: Model 2 Configuration 1



```
model_2 = tf.keras.Sequential([
    tf.keras.layers.Dense(25, activation = 'relu', name = 'L1'),
    tf.keras.layers.Dense(15, activation = 'relu', name = 'L2'),
    tf.keras.layers.Dense(1, activation = 'sigmoid', name = 'OL')
])
```

<u>Model 2 Configuration 1</u>:

L2 Regularization – 0.00026

Learning Rate – 0.012

The higher recall in Model 2 Configuration 1 ensures that the model is more effective in identifying patients with heart disease, thus reducing the risk of undiagnosed cases. This, combined with its superior test accuracy, makes Model 2 Configuration 1 the most reliable model for heart disease prediction. It not only accurately predicts heart disease but also minimizes the chances of critical misses, thereby enhancing the overall reliability and safety of the predictive system.

This conclusion is drawn from a detailed analysis and comparison of the provided configurations, highlighting Model 2 Configuration 1’s superior test accuracy and recall, which are pivotal for effective heart disease prediction and patient safety.

Conclusion

In conclusion, the development of a machine learning model for heart disease prediction using TensorFlow has demonstrated significant promise. Through rigorous data preprocessing, feature engineering, and hyperparameter optimization, various model configurations were tested and refined to achieve a high level of accuracy and generalization. The primary objective of surpassing the accuracy benchmark of 84.61% was successfully met, with multiple models achieving and exceeding this target.

Among the tested models, Model 2 Configuration 1 emerged as the most reliable for heart disease prediction. This model exhibited a superior test accuracy of 85.33% and a high recall rate of 0.90, which is crucial for identifying positive cases of heart disease and minimizing the risk of undiagnosed cases. The balanced performance between precision and recall, along with consistent training and validation accuracy, underscores the model's robustness and effectiveness in a practical healthcare setting.

The final analysis also highlighted the importance of fine-tuning regularization parameters and learning rates to enhance model stability and performance. Despite some fluctuations in validation metrics, the selected models demonstrated strong generalization capabilities, minimizing overfitting and ensuring reliable predictions on unseen data. The detailed confusion matrix analysis further validated the models' efficacy in accurately classifying heart disease cases.

Overall, the project has successfully developed a robust predictive tool that can assist healthcare professionals in making informed decisions and improving patient care outcomes. The advancements in machine learning techniques and their application in medical diagnostics hold great potential for early detection and intervention in cardiovascular diseases, ultimately contributing to better health outcomes and reduced mortality rates. Future work may involve further refinement of hyperparameters, exploration of additional features, and integration of more diverse datasets to enhance the model's predictive power and applicability in broader clinical settings.

Enhancements and Future Work

One critical area for improving the performance of a neural network-based model is experimenting with various network structures. In this project, four different neural network structures were tested, each with varying layers and neurons. However, other architectures could further enhance the model's performance. Convolutional Neural Networks (CNNs), typically used for image data, can benefit structured data classification tasks by treating the input features as a 1D image, capturing local dependencies and patterns more effectively. Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs), useful for sequential data, can be applied to non-sequential data to capture temporal dependencies, aiding in understanding the progression of heart disease if temporal data is available.

Regularization is essential for preventing overfitting and improving the generalizability of the model. This study primarily used L2 regularization, but other techniques could be explored. Dropout regularization, which involves randomly dropping neurons during training, forces the network to learn more robust features. Testing various dropout rates (e.g., 0.2, 0.5) can help find the optimal balance. L1 regularization, which penalizes large weights and can lead to sparse models by driving some weights to zero, effectively performs feature selection. Elastic net regularization, combining L1 and L2 regularization, can provide a balance between feature selection and weight penalization, potentially leading to better performance.

The performance of neural networks heavily relies on hyperparameters such as learning rate, batch size, and the number of epochs. While grid search and manual adjustments were used in this study, more sophisticated techniques could enhance the optimization process. Random search, which involves randomly sampling hyperparameters, can sometimes be more efficient than grid search, especially when dealing with many hyperparameters. Bayesian optimization builds a probabilistic model of the function mapping hyperparameters to the objective and uses it to choose the most promising hyperparameters to evaluate.

Improving model evaluation metrics and interpretability is crucial for practical applications in healthcare. Beyond accuracy and F1-scores, the ROC-AUC score provides a more comprehensive evaluation of the model’s ability to discriminate between classes. Especially in imbalanced datasets, the precision-recall curve can give more insight into the performance of the model concerning the minority class (patients with heart disease). Ensuring that the predicted probabilities are well calibrated can enhance the model’s reliability in a real-world clinical setting.

Incorporating these improvements could significantly enhance the accuracy, generalization, and reliability of the heart disease prediction model. Experimenting with different neural network structures such as CNNs, RNNs, LSTMs, and attention mechanisms can provide more nuanced data representation and capture essential patterns. Applying advanced regularization techniques like dropout, L1 regularization, and elastic net regularization can help mitigate overfitting and improve model robustness. Leveraging sophisticated hyperparameter tuning methods such as random search, improving model evaluation metrics, and employing interpretability techniques can ensure the model's practical applicability in healthcare settings. Finally, exploring advanced optimizers can enhance model convergence and stability. These enhancements collectively can lead to the development of a more accurate, reliable, and interpretable heart disease prediction model, ultimately contributing to better patient outcomes.

By addressing these areas, the heart disease prediction model can be made more robust, accurate, and applicable in real-world clinical settings, significantly improving patient care and outcomes.

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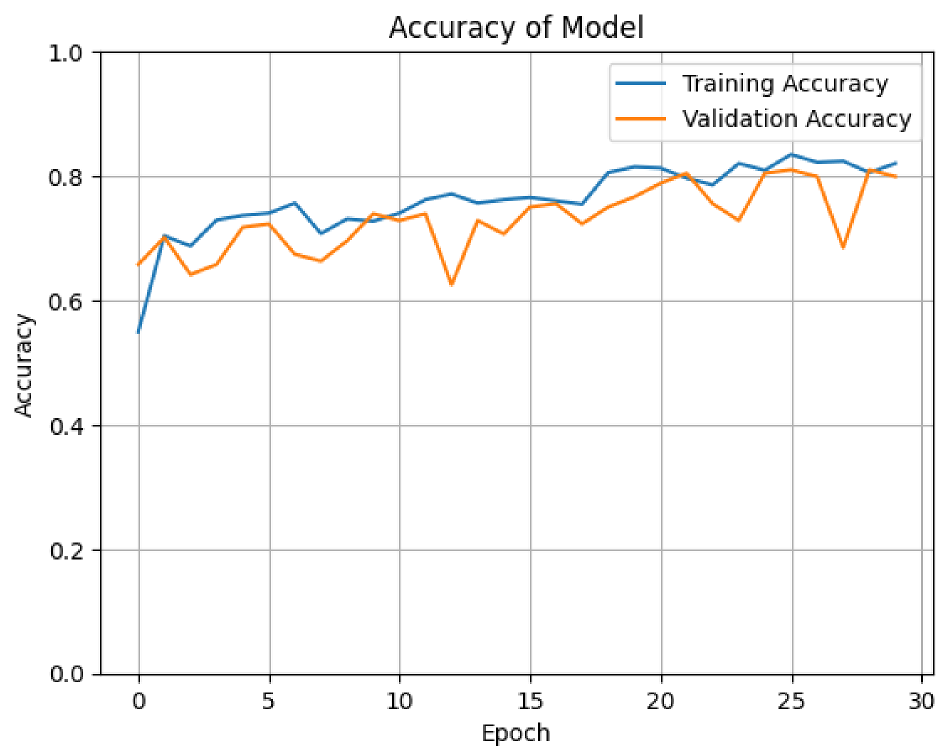
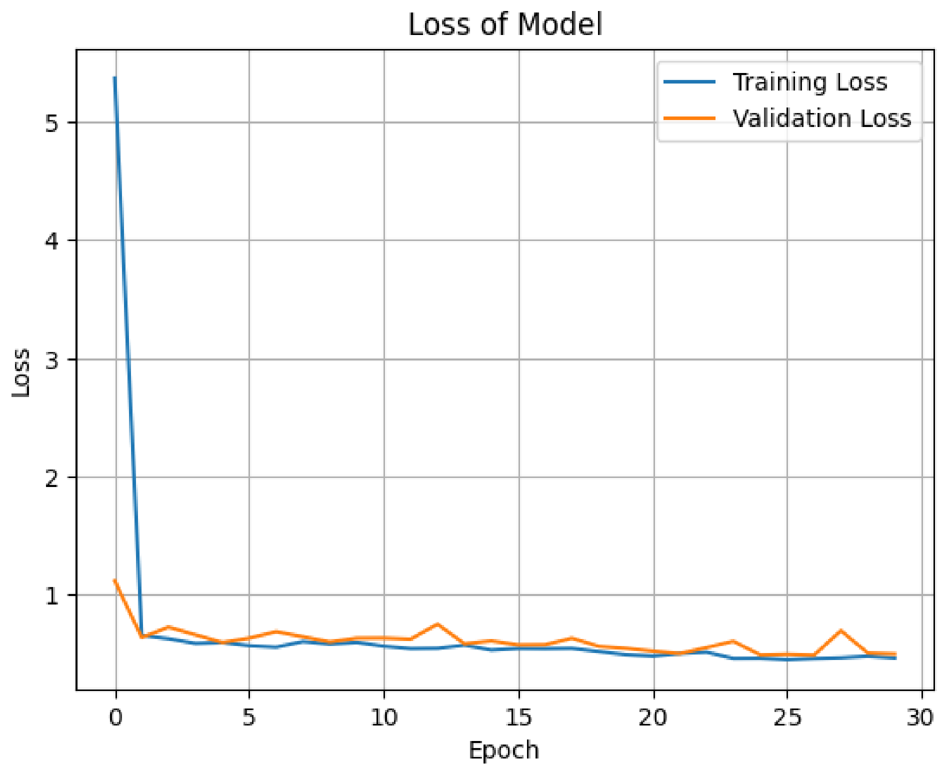
Model 1 Configuration 1

```
REGULARIZATION PARAMETER: 0.001
LEARNING RATE = 0.011
Epoch 1/30
35/35 [==============================] - 0s 5ms/step - loss: 5.3698 - accuracy: 0.5491 - val_loss: 1.11
80 - val_accuracy: 0.6576
Epoch 2/30
35/35 [==============================] - 0s 2ms/step - loss: 0.6565 - accuracy: 0.7036 - val_loss: 0.63
92 - val_accuracy: 0.7011
Epoch 3/30
35/35 [==============================] - 0s 1ms/step - loss: 0.6286 - accuracy: 0.6873 - val_loss: 0.72
61 - val_accuracy: 0.6413
Epoch 4/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5894 - accuracy: 0.7291 - val_loss: 0.66
17 - val_accuracy: 0.6576
Epoch 5/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5965 - accuracy: 0.7364 - val_loss: 0.59
74 - val_accuracy: 0.7174
Epoch 6/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5695 - accuracy: 0.7400 - val_loss: 0.63
37 - val_accuracy: 0.7228
Epoch 7/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5572 - accuracy: 0.7564 - val_loss: 0.68
83 - val_accuracy: 0.6739
Epoch 8/30
35/35 [==============================] - 0s 2ms/step - loss: 0.6046 - accuracy: 0.7073 - val_loss: 0.64
54 - val_accuracy: 0.6630
Epoch 9/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5837 - accuracy: 0.7309 - val_loss: 0.60
23 - val_accuracy: 0.6957
Epoch 10/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5975 - accuracy: 0.7273 - val_loss: 0.63
36 - val_accuracy: 0.7391
Epoch 11/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5651 - accuracy: 0.7400 - val_loss: 0.63
46 - val_accuracy: 0.7283
Epoch 12/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5450 - accuracy: 0.7618 - val_loss: 0.62
51 - val_accuracy: 0.7391
Epoch 13/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5472 - accuracy: 0.7709 - val_loss: 0.75
14 - val_accuracy: 0.6250
Epoch 14/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5740 - accuracy: 0.7564 - val_loss: 0.58
60 - val_accuracy: 0.7283
Epoch 15/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5329 - accuracy: 0.7618 - val_loss: 0.61
02 - val_accuracy: 0.7065
Epoch 16/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5456 - accuracy: 0.7655 - val_loss: 0.57
62 - val_accuracy: 0.7500
```

```
Epoch 17/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5442 - accuracy: 0.7600 - val_loss: 0.57
78 - val_accuracy: 0.7554
Epoch 18/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5466 - accuracy: 0.7545 - val_loss: 0.63
32 - val_accuracy: 0.7228
Epoch 19/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5199 - accuracy: 0.8055 - val_loss: 0.56
40 - val_accuracy: 0.7500
Epoch 20/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4933 - accuracy: 0.8145 - val_loss: 0.54
74 - val_accuracy: 0.7663
Epoch 21/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4817 - accuracy: 0.8127 - val_loss: 0.52
43 - val_accuracy: 0.7880
Epoch 22/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5031 - accuracy: 0.7964 - val_loss: 0.50
26 - val_accuracy: 0.8043
Epoch 23/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5142 - accuracy: 0.7855 - val_loss: 0.55
38 - val_accuracy: 0.7554
Epoch 24/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4621 - accuracy: 0.8200 - val_loss: 0.60
70 - val_accuracy: 0.7283
Epoch 25/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4632 - accuracy: 0.8091 - val_loss: 0.49
12 - val_accuracy: 0.8043
Epoch 26/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4511 - accuracy: 0.8345 - val_loss: 0.49
67 - val_accuracy: 0.8098
Epoch 27/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4607 - accuracy: 0.8218 - val_loss: 0.48
99 - val_accuracy: 0.7989
Epoch 28/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4669 - accuracy: 0.8236 - val_loss: 0.69
66 - val_accuracy: 0.6848
Epoch 29/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4807 - accuracy: 0.8055 - val_loss: 0.50
72 - val_accuracy: 0.8098
Epoch 30/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4655 - accuracy: 0.8200 - val_loss: 0.49
96 - val_accuracy: 0.7989
```





Model Prediction on Test set

```
6/6 [==============================] - 0s 807us/step - loss: 0.4386 - accuracy: 0.8478
6/6 [==============================] - 0s 2ms/step
```

```
Confusion Matrix
[[65 16]
 [12 91]]
          precision    recall  f1-score   support

        0       0.84      0.80      0.82        81
        1       0.85      0.88      0.87       103

   accuracy                           0.85       184
  macro avg       0.85      0.84      0.84       184
weighted avg       0.85      0.85      0.85       184
```

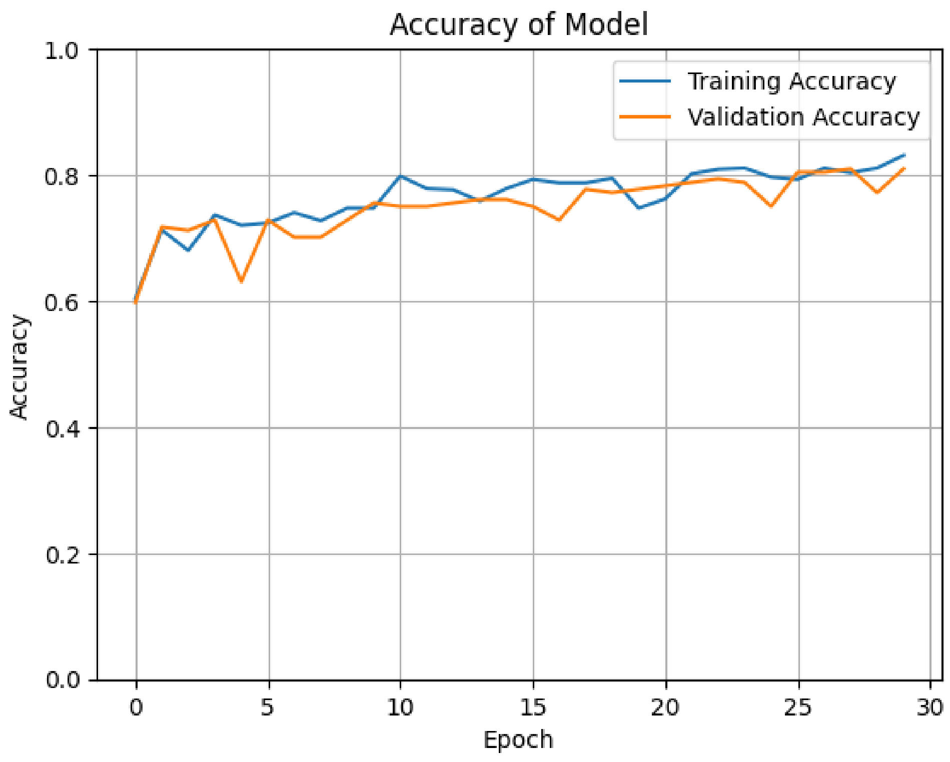
Model 2 Configuration 1

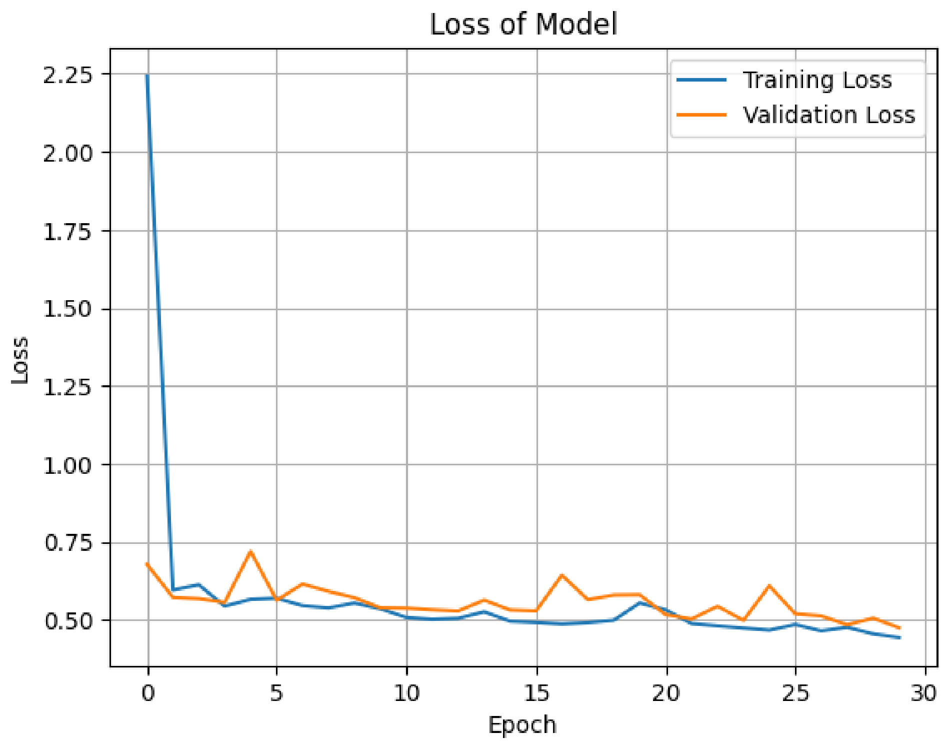
```
REGULARIZATION PARAMETER 0.00026
LEARNING RATE = 0.012
Epoch 1/30
35/35 [==============================] - 0s 4ms/step - loss: 2.2419 - accuracy: 0.6036 - val_loss: 0.67
80 - val_accuracy: 0.5978
Epoch 2/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5955 - accuracy: 0.7127 - val_loss: 0.57
21 - val_accuracy: 0.7174
Epoch 3/30
35/35 [==============================] - 0s 1ms/step - loss: 0.6121 - accuracy: 0.6800 - val_loss: 0.56
80 - val_accuracy: 0.7120
Epoch 4/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5441 - accuracy: 0.7364 - val_loss: 0.55
62 - val_accuracy: 0.7283
Epoch 5/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5658 - accuracy: 0.7200 - val_loss: 0.71
94 - val_accuracy: 0.6304
Epoch 6/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5694 - accuracy: 0.7236 - val_loss: 0.56
30 - val_accuracy: 0.7283
Epoch 7/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5457 - accuracy: 0.7400 - val_loss: 0.61
44 - val_accuracy: 0.7011
Epoch 8/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5385 - accuracy: 0.7273 - val_loss: 0.59
11 - val_accuracy: 0.7011
Epoch 9/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5540 - accuracy: 0.7473 - val_loss: 0.57
12 - val_accuracy: 0.7283
Epoch 10/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5356 - accuracy: 0.7473 - val_loss: 0.53
89 - val_accuracy: 0.7554
Epoch 11/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5079 - accuracy: 0.7982 - val_loss: 0.53
77 - val_accuracy: 0.7500
Epoch 12/30
```

```
35/35 [==============================] - 0s 1ms/step - loss: 0.5017 - accuracy: 0.7782 - val_loss: 0.53
24 - val_accuracy: 0.7500
Epoch 13/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5050 - accuracy: 0.7764 - val_loss: 0.52
83 - val_accuracy: 0.7554
Epoch 14/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5259 - accuracy: 0.7582 - val_loss: 0.56
34 - val_accuracy: 0.7609
Epoch 15/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4956 - accuracy: 0.7782 - val_loss: 0.53
17 - val_accuracy: 0.7609
Epoch 16/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4918 - accuracy: 0.7927 - val_loss: 0.52
86 - val_accuracy: 0.7500
Epoch 17/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4870 - accuracy: 0.7873 - val_loss: 0.64
27 - val_accuracy: 0.7283
Epoch 18/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4912 - accuracy: 0.7873 - val_loss: 0.56
49 - val_accuracy: 0.7772
Epoch 19/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4987 - accuracy: 0.7945 - val_loss: 0.57
95 - val_accuracy: 0.7717
Epoch 20/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5542 - accuracy: 0.7473 - val_loss: 0.58
05 - val_accuracy: 0.7772
Epoch 21/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5321 - accuracy: 0.7618 - val_loss: 0.51
70 - val_accuracy: 0.7826
Epoch 22/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4881 - accuracy: 0.8018 - val_loss: 0.50
30 - val_accuracy: 0.7880
Epoch 23/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4807 - accuracy: 0.8091 - val_loss: 0.54
35 - val_accuracy: 0.7935
Epoch 24/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4738 - accuracy: 0.8109 - val_loss: 0.49
85 - val_accuracy: 0.7880
Epoch 25/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4672 - accuracy: 0.7964 - val_loss: 0.60
88 - val_accuracy: 0.7500
Epoch 26/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4851 - accuracy: 0.7927 - val_loss: 0.51
96 - val_accuracy: 0.8043
Epoch 27/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4647 - accuracy: 0.8109 - val_loss: 0.51
27 - val_accuracy: 0.8043
Epoch 28/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4762 - accuracy: 0.8036 - val_loss: 0.48
43 - val_accuracy: 0.8098
Epoch 29/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4551 - accuracy: 0.8109 - val_loss: 0.50
55 - val_accuracy: 0.7717
Epoch 30/30
```

```
35/35 [==============================] - 0s 1ms/step - loss: 0.4434 - accuracy: 0.8309 - val_loss: 0.47
46 - val_accuracy: 0.8098

Model Prediction on Test set
6/6 [==============================] - 0s 776us/step - loss: 0.4246 - accuracy: 0.8533
```





```
6/6 [==============================] - 0s 0s/step

Confusion Matrix
[[64 17]
 [10 93]]
          precision    recall  f1-score   support

        0      0.86      0.79      0.83        81
        1      0.85      0.90      0.87       103

   accuracy                        0.85       184
  macro avg      0.86      0.85      0.85       184
weighted avg      0.85      0.85      0.85       184
```

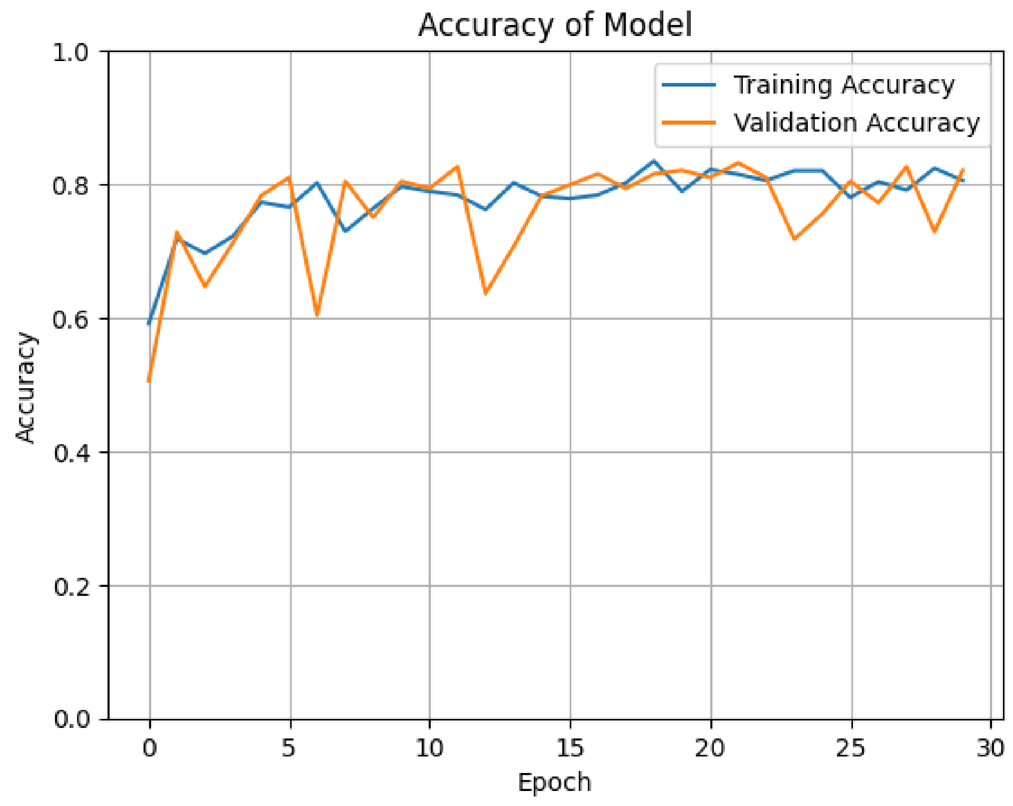
Model 2 Configuration 2

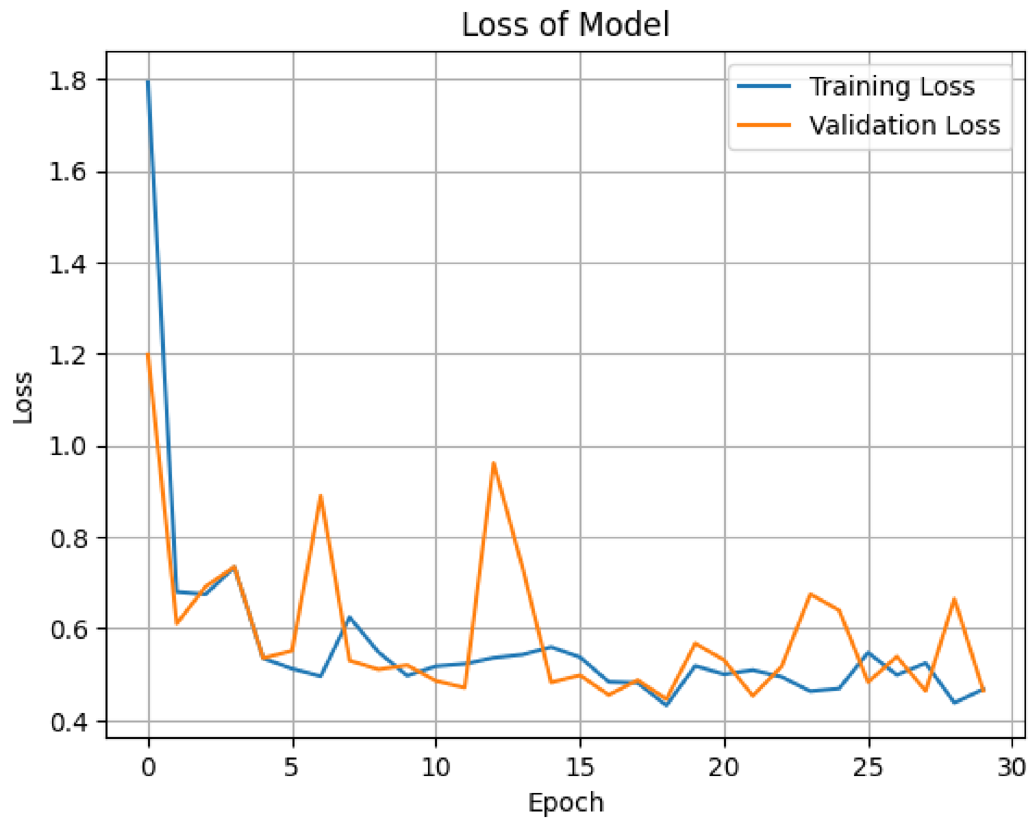
```
REGULARIZATION PARAMETER 0.00067
LEARNING RATE = 0.0063
Epoch 1/30
35/35 [==============================] - 1s 5ms/step - loss: 1.7933 - accuracy: 0.5909 - val_loss: 1.19
82 - val_accuracy: 0.5054
Epoch 2/30
35/35 [==============================] - 0s 2ms/step - loss: 0.6803 - accuracy: 0.7182 - val_loss: 0.61
10 - val_accuracy: 0.7283
Epoch 3/30
35/35 [==============================] - 0s 1ms/step - loss: 0.6751 - accuracy: 0.6964 - val_loss: 0.69
20 - val_accuracy: 0.6467
Epoch 4/30
35/35 [==============================] - 0s 1ms/step - loss: 0.7342 - accuracy: 0.7218 - val_loss: 0.73
51 - val_accuracy: 0.7120
Epoch 5/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5352 - accuracy: 0.7727 - val_loss: 0.53
57 - val_accuracy: 0.7826
Epoch 6/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5127 - accuracy: 0.7655 - val_loss: 0.55
16 - val_accuracy: 0.8098
Epoch 7/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4962 - accuracy: 0.8018 - val_loss: 0.89
02 - val_accuracy: 0.6033
Epoch 8/30
35/35 [==============================] - 0s 1ms/step - loss: 0.6249 - accuracy: 0.7291 - val_loss: 0.53
03 - val_accuracy: 0.8043
Epoch 9/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5488 - accuracy: 0.7636 - val_loss: 0.51
11 - val_accuracy: 0.7500
Epoch 10/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4975 - accuracy: 0.7964 - val_loss: 0.52
02 - val_accuracy: 0.8043
Epoch 11/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5181 - accuracy: 0.7891 - val_loss: 0.48
58 - val_accuracy: 0.7935
Epoch 12/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5231 - accuracy: 0.7836 - val_loss: 0.47
11 - val_accuracy: 0.8261
```

```
Epoch 13/30
35/35 [==============================] - 0s 2ms/step - loss: 0.5364 - accuracy: 0.7618 - val_loss: 0.96
18 - val_accuracy: 0.6359
Epoch 14/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5433 - accuracy: 0.8018 - val_loss: 0.73
47 - val_accuracy: 0.7065
Epoch 15/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5597 - accuracy: 0.7818 - val_loss: 0.48
27 - val_accuracy: 0.7826
Epoch 16/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5377 - accuracy: 0.7782 - val_loss: 0.49
82 - val_accuracy: 0.7989
Epoch 17/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4837 - accuracy: 0.7836 - val_loss: 0.45
50 - val_accuracy: 0.8152
Epoch 18/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4817 - accuracy: 0.8018 - val_loss: 0.48
76 - val_accuracy: 0.7935
Epoch 19/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4322 - accuracy: 0.8345 - val_loss: 0.44
62 - val_accuracy: 0.8152
Epoch 20/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5188 - accuracy: 0.7891 - val_loss: 0.56
75 - val_accuracy: 0.8207
Epoch 21/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5004 - accuracy: 0.8218 - val_loss: 0.53
15 - val_accuracy: 0.8098
Epoch 22/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5096 - accuracy: 0.8145 - val_loss: 0.45
31 - val_accuracy: 0.8315
Epoch 23/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4947 - accuracy: 0.8055 - val_loss: 0.51
76 - val_accuracy: 0.8098
Epoch 24/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4631 - accuracy: 0.8200 - val_loss: 0.67
54 - val_accuracy: 0.7174
Epoch 25/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4693 - accuracy: 0.8200 - val_loss: 0.63
99 - val_accuracy: 0.7554
Epoch 26/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5478 - accuracy: 0.7800 - val_loss: 0.48
31 - val_accuracy: 0.8043
Epoch 27/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4990 - accuracy: 0.8036 - val_loss: 0.53
91 - val_accuracy: 0.7717
Epoch 28/30
35/35 [==============================] - 0s 1ms/step - loss: 0.5247 - accuracy: 0.7909 - val_loss: 0.46
39 - val_accuracy: 0.8261
Epoch 29/30
35/35 [==============================] - 0s 1ms/step - loss: 0.4381 - accuracy: 0.8236 - val_loss: 0.66
53 - val_accuracy: 0.7283
Epoch 30/30
35/35 [==============================] - 0s 2ms/step - loss: 0.4677 - accuracy: 0.8055 - val_loss: 0.46
47 - val_accuracy: 0.8207
```

Model Prediction on Test set

```
6/6 [==============================] - 0s 825us/step - loss: 0.4349 - accuracy: 0.8478
```





```
6/6 [==============================] - 0s 3ms/step

Confusion Matrix
[[67 14]
 [14 89]]
           precision    recall  f1-score   support

         0       0.83      0.83      0.83        81
         1       0.86      0.86      0.86       103

   accuracy                          0.85       184
  macro avg       0.85      0.85      0.85       184
weighted avg       0.85      0.85      0.85       184
```