Predicting In Hospital Mortality

Collaborators

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Problem Statement

Healthcare providers and administrators in New York State aim to improve patient outcomes and reduce in-hospital mortality among pneumonia patients. In-hospital mortality occurs when patients succumb to their condition during their hospital stay, and it is crucial for healthcare providers to predict which patients are at the highest risk of mortality. By identifying these high-risk patients in advance, healthcare providers in New York can implement targeted interventions and allocate resources more effectively to improve patient care and survival rates.

Objectives

The primary objective of using this dataset is to develop a predictive model that can accurately forecast in-hospital mortality among pneumonia patients. By leveraging the detailed information in the dataset, we aim to:

1. Identify High-Risk Populations: Determine demographic and clinical factors associated with higher pneumonia hospitalization rates.
2. Evaluate Quality of Care: Assess metrics such as length of stay, patient disposition, and mortality rates to gauge the quality of pneumonia care.
3. Assess Economic Burden: Investigate the costs associated with pneumonia hospitalizations and identify opportunities for cost reduction.
4. Reduce Readmissions: Identify factors contributing to pneumonia-related readmissions and suggest strategies to minimize them.

Data Understanding

Dataset Overview

The dataset being used for this analysis is the Statewide Planning and Research Cooperative System (SPARCS) Inpatient De-identified dataset. This dataset contains detailed discharge-level information on patient characteristics, diagnoses, treatments, services, charges, and costs for pneumonia patients in New York State from 2009 to 2017. The dataset is de-identified in

compliance with the Health Insurance Portability and Accountability Act (HIPAA), ensuring that the health information is not individually identifiable. Direct identifiers have been redacted, such as removing the day and month portions from dates.

Key Features

- Patient Characteristics: Information about patients such as age, gender, race, and ethnicity.
- Diagnoses: Codes and descriptions of the primary and secondary diagnoses recorded during the hospital stay.
- Treatments and Procedures: Details on the treatments and medical procedures performed on the patients.
- Services: Information on the healthcare services provided during the hospital stay.
- Charges and Costs: Financial data related to the total charges and costs incurred during the hospital stay.

Data Specifics

- Time Period: The dataset spans from 2009 to 2017.
- Geographical Scope: The data covers pneumonia patients in New York State.
- Patient Privacy: All personal identifiers have been removed to protect patient privacy. For example, dates have been modified to exclude the day and month, leaving only the year.

Data Preparation

In the data preparation phase, several steps were undertaken to ensure the dataset's readiness for analysis. These steps included handling missing values using imputation with mean values or a placeholder like 'unknown', removing duplicate records to maintain data integrity, and correcting data entry errors, inconsistencies, or anomalies to ensure accuracy. Additionally, data type inconsistencies were standardized, placeholders were removed or replaced with meaningful values, and numerical features were normalized to a common range. Outliers were identified and appropriately managed to prevent skewing of the analysis, ensuring a robust and accurate dataset for modeling.

1.1 Loading the data

```
# Importing the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import warnings
from scipy import stats
import seaborn as sns
import tensorflow as tf
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from matplotlib.colors import to_hex
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.utils import shuffle
from sklearn.metrics import classification_report, confusion_matrix,
accuracy_score
from sklearn.compose import ColumnTransformer
import shutil
import os
from tensorflow.keras.callbacks import EarlyStopping
from keras_tuner import RandomSearch
from scipy.optimize import minimize
from sklearn.decomposition import PCA
import keras_tuner as kt
from keras.optimizers import Adam
```

```
C:\Users\hp\anaconda3\desktop\envs\learn-env\lib\site-packages\
tensorflow\python\framework\dtypes.py:513: FutureWarning: In the
future `np.object` will be defined as the corresponding NumPy scalar.
  np.object,
```

```
---------------------------------------------------------------------
-----
AttributeError                            Traceback (most recent call
last)
<ipython-input-56-e4c65798e38c> in <module>
      6 from scipy import stats
      7 import seaborn as sns
----> 8 import tensorflow as tf
      9 from tensorflow.keras.models import Sequential
     10 from tensorflow.keras.layers import Dense, Dropout

~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
__init__.py in <module>
     39 import sys as _sys
     40
---> 41 from tensorflow.python.tools import module_util as
_module_util
     42 from tensorflow.python.util.lazy_loader import LazyLoader as
_LazyLoader
     43
```

```
~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
python\__init__.py in <module>
     43
     44 # Bring in subpackages.
---> 45 from tensorflow.python import data
     46 from tensorflow.python import distribute
     47 from tensorflow.python import keras

~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
python\data\__init__.py in <module>
     23
     24 # pylint: disable=unused-import
---> 25 from tensorflow.python.data import experimental
     26 from tensorflow.python.data.ops.dataset_ops import Dataset
     27 from tensorflow.python.data.ops.dataset_ops import INFINITE as
INFINITE_CARDINALITY

~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
python\data\experimental\__init__.py in <module>
     94
     95 # pylint: disable=unused-import
---> 96 from tensorflow.python.data.experimental import service
     97 from tensorflow.python.data.experimental.ops.batching import
dense_to_ragged_batch
     98 from tensorflow.python.data.experimental.ops.batching import
dense_to_sparse_batch

~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
python\data\experimental\service\__init__.py in <module>
     19 from __future__ import print_function
     20
---> 21 from tensorflow.python.data.experimental.ops.data_service_ops
import distribute
     22 from tensorflow.python.data.experimental.service.server_lib
import DispatchServer
     23 from tensorflow.python.data.experimental.service.server_lib
import WorkerServer

~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
python\data\experimental\ops\data_service_ops.py in <module>
     23
     24 from tensorflow.python import tf2
---> 25 from tensorflow.python.data.experimental.ops import
compression_ops
     26 from
tensorflow.python.data.experimental.ops.distribute_options import
AutoShardPolicy
     27 from
tensorflow.python.data.experimental.ops.distribute_options import
```

```
ExternalStatePolicy

~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
python\data\experimental\ops\compression_ops.py in <module>
     18 from __future__ import print_function
     19
---> 20 from tensorflow.python.data.util import structure
     21 from tensorflow.python.ops import gen_experimental_dataset_ops
as ged_ops
     22

~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
python\data\util\structure.py in <module>
     24 import wrapt
     25
---> 26 from tensorflow.python.data.util import nest
     27 from tensorflow.python.framework import composite_tensor
     28 from tensorflow.python.framework import ops

~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
python\data\util\nest.py in <module>
     39
     40 from tensorflow.python import _pywrap_utils
---> 41 from tensorflow.python.framework import sparse_tensor as
_sparse_tensor
     42 from tensorflow.python.util.compat import collections_abc as
_collections_abc
     43

~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
python\framework\sparse_tensor.py in <module>
     27 from tensorflow.python import tf2
     28 from tensorflow.python.framework import composite_tensor
---> 29 from tensorflow.python.framework import constant_op
     30 from tensorflow.python.framework import dtypes
     31 from tensorflow.python.framework import ops

~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
python\framework\constant_op.py in <module>
     27 from tensorflow.core.framework import types_pb2
     28 from tensorflow.python.eager import context
---> 29 from tensorflow.python.eager import execute
     30 from tensorflow.python.framework import dtypes
     31 from tensorflow.python.framework import op_callbacks

~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
python\eager\execute.py in <module>
     25 from tensorflow.python import pywrap_tfe
     26 from tensorflow.python.eager import core
---> 27 from tensorflow.python.framework import dtypes
```

```
     28 from tensorflow.python.framework import ops
     29 from tensorflow.python.framework import tensor_shape

~\anaconda3\desktop\envs\learn-env\lib\site-packages\tensorflow\
python\framework\dtypes.py in <module>
    511     # strings.
    512     types_pb2.DT_STRING:
--> 513         np.object,
    514     types_pb2.DT_COMPLEX64:
    515         np.complex64,

~\anaconda3\desktop\envs\learn-env\lib\site-packages\numpy\__init__.py
in __getattr__(attr)
    303
    304         if attr in __former_attrs__:
--> 305             raise AttributeError(__former_attrs__[attr])
    306
    307         # Importing Tester requires importing all of UnitTest
which is not a

AttributeError: module 'numpy' has no attribute 'object'.
`np.object` was a deprecated alias for the builtin `object`. To avoid
this error in existing code, use `object` by itself. Doing this will
not modify any behavior and is safe.
The aliases was originally deprecated in NumPy 1.20; for more details
and guidance see the original release note at:
    https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
```

```
# Load the CSV file into a DataFrame
df = pd.read_csv('hospital-inpatient-discharges-pneumonia.csv')

# Display the first few rows of the DataFrame
df.head()
```

```
C:\Users\hp\anaconda3\desktop\envs\learn-env\lib\site-packages\
IPython\core\interactiveshell.py:3145: DtypeWarning: Columns
(10,26,27,28,37,38,39,40) have mixed types.Specify dtype option on
import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

```
  Health Service Area Hospital County  Operating Certificate Number  \
0      Capital/Adiron          Albany                       101000.0
1      Capital/Adiron          Albany                       101000.0
2      Capital/Adiron          Albany                       101000.0
3      Capital/Adiron          Albany                       101000.0
4      Capital/Adiron          Albany                       101000.0

   Facility ID                   Facility Name    Age Group  \
0          1.0  Albany Medical Center Hospital  70 or Older
1          1.0  Albany Medical Center Hospital  70 or Older
```

```
2          1.0  Albany Medical Center Hospital     18 to 29
3          1.0  Albany Medical Center Hospital      0 to 17
4          1.0  Albany Medical Center Hospital      0 to 17

  Zip Code - 3 digits Gender        Race          Ethnicity  ...  \
0               105.0      F       White  Not Span/Hispanic  ...
1               105.0      F       White  Not Span/Hispanic  ...
2               109.0      M       White  Not Span/Hispanic  ...
3               112.0      F  Other Race  Not Span/Hispanic  ...
4               120.0      M       White  Not Span/Hispanic  ...

  Abortion Edit Indicator Emergency Department Indicator Total Charges
\
0                       N                              Y      29059.14

1                       N                              Y      15622.27

2                       N                              Y      10190.43

3                       N                              Y      39250.92

4                       N                              N      10578.58


   Total Costs  Payment Typology 1 Payment Topology 2  Payment
Typology 3  \
0      9233.80                 NaN                 NaN
NaN
1      4815.69                 NaN                 NaN
NaN
2      3238.55                 NaN                 NaN
NaN
3     12652.24                 NaN                 NaN
NaN
4      5315.97                 NaN                 NaN
NaN

  Payment Typology 2  Facility Id Ratio of Total Costs to Total
Charges
0                NaN          NaN
NaN
1                NaN          NaN
NaN
2                NaN          NaN
NaN
3                NaN          NaN
NaN
4                NaN          NaN
NaN
```

```
[5 rows x 43 columns]
```

1.2 Data Inspection

```
df.shape
```

```
(379463, 43)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 379463 entries, 0 to 379462
Data columns (total 43 columns):
 #   Column                                 Non-Null Count   Dtype  
---  ------                                 --------------   -----  
 0   Health Service Area                    379454 non-null  object 
 1   Hospital County                        379454 non-null  object 
 2   Operating Certificate Number           379454 non-null  float64
 3   Facility ID                            333778 non-null  float64
 4   Facility Name                          379463 non-null  object 
 5   Age Group                              379463 non-null  object 
 6   Zip Code - 3 digits                    379098 non-null  object 
 7   Gender                                 379463 non-null  object 
 8   Race                                   379463 non-null  object 
 9   Ethnicity                              379463 non-null  object 
 10  Length of Stay                         379463 non-null  object 
 11  Type of Admission                      379463 non-null  object 
 12  Patient Disposition                    379457 non-null  object 
 13  Discharge Year                         379463 non-null  int64  
 14  CCS Diagnosis Code                     379463 non-null  float64
 15  CCS Diagnosis Description              379463 non-null  object 
 16  CCS Procedure Code                     379463 non-null  float64
 17  CCS Procedure Description              379463 non-null  object 
 18  APR DRG Code                           379463 non-null  int64  
 19  APR DRG Description                    379463 non-null  object 
 20  APR MDC Code                           379463 non-null  int64  
 21  APR MDC Description                    379463 non-null  object 
 22  APR Severity of Illness Code           379463 non-null  int64  
 23  APR Severity of Illness Description    379461 non-null  object 
 24  APR Risk of Mortality                  379461 non-null  object 
 25  APR Medical Surgical Description       379463 non-null  object 
 26  Source of Payment 1                    121105 non-null  object 
 27  Source of Payment 2                    89199 non-null   object 
 28  Source of Payment 3                    29840 non-null   object 
 29  Attending Provider License Number      379454 non-null  float64
 30  Operating Provider License Number      202630 non-null  float64
 31  Other Provider License Number          50919 non-null   float64
 32  Birth Weight                           379463 non-null  int64  
 33  Abortion Edit Indicator                379463 non-null  object 
```

```
 34  Emergency Department Indicator          379463 non-null  object
 35  Total Charges                           379463 non-null  float64
 36  Total Costs                             379463 non-null  float64
 37  Payment Typology 1                      258358 non-null  object
 38  Payment Topology 2                      45670 non-null   object
 39  Payment Typology 3                      86509 non-null   object
 40  Payment Typology 2                      147757 non-null  object
 41  Facility Id                             45676 non-null   float64
 42  Ratio of Total Costs to Total Charges  45676 non-null   float64
dtypes: float64(11), int64(5), object(27)
memory usage: 124.5+ MB
```

Before we clean the data we have 379463 rows and 43 columns

2. Data Cleaning

2.1 Dropping unnecessary columns

```
df = df.drop(columns = ['Operating Certificate Number','Facility
ID','Attending Provider License Number',
                        'Operating Provider License Number','Other
Provider License Number', 'Birth Weight',
                        'Abortion Edit Indicator'])
```

The columns above have are not needed for us to carry out our analysis hence us dropping them.

2.2 Handling Missing values

```
# Checking for missing values
df.isnull().sum()
```

```
Health Service Area                       9
Hospital County                           9
Facility Name                             0
Age Group                                 0
Zip Code - 3 digits                     365
Gender                                    0
Race                                      0
Ethnicity                                 0
Length of Stay                            0
Type of Admission                         0
Patient Disposition                       6
Discharge Year                            0
CCS Diagnosis Code                        0
CCS Diagnosis Description                 0
CCS Procedure Code                        0
CCS Procedure Description                 0
APR DRG Code                              0
APR DRG Description                       0
```

```
APR MDC Code                                0
APR MDC Description                         0
APR Severity of Illness Code                0
APR Severity of Illness Description         2
APR Risk of Mortality                       2
APR Medical Surgical Description            0
Source of Payment 1                    258358
Source of Payment 2                    290264
Source of Payment 3                    349623
Emergency Department Indicator              0
Total Charges                               0
Total Costs                                 0
Payment Typology 1                     121105
Payment Topology 2                     333793
Payment Typology 3                     292954
Payment Typology 2                     231706
Facility Id                            333787
Ratio of Total Costs to Total Charges  333787
dtype: int64
```

There are missing values present in some of the columns. To get a better understanding of the missing values we want to investigate the percentage of missing values per column.

```
# Calculate the percentage of missing values for each column
missing_percentage = df.isnull().mean() * 100

# Round the percentages
rounded_missing_percentage = missing_percentage.round()

# Display the rounded percentage of missing values for each column
print("Rounded percentage of missing values for each column:")
print(rounded_missing_percentage)
```

```
Rounded percentage of missing values for each column:
Health Service Area                  0.0
Hospital County                      0.0
Facility Name                        0.0
Age Group                            0.0
Zip Code - 3 digits                  0.0
Gender                               0.0
Race                                 0.0
Ethnicity                            0.0
Length of Stay                       0.0
Type of Admission                    0.0
Patient Disposition                  0.0
Discharge Year                       0.0
CCS Diagnosis Code                   0.0
CCS Diagnosis Description            0.0
CCS Procedure Code                   0.0
```

```
CCS Procedure Description                    0.0
APR DRG Code                                 0.0
APR DRG Description                          0.0
APR MDC Code                                 0.0
APR MDC Description                          0.0
APR Severity of Illness Code                 0.0
APR Severity of Illness Description          0.0
APR Risk of Mortality                        0.0
APR Medical Surgical Description             0.0
Source of Payment 1                         68.0
Source of Payment 2                         76.0
Source of Payment 3                         92.0
Emergency Department Indicator               0.0
Total Charges                                0.0
Total Costs                                  0.0
Payment Typology 1                          32.0
Payment Topology 2                          88.0
Payment Typology 3                          77.0
Payment Typology 2                          61.0
Facility Id                                 88.0
Ratio of Total Costs to Total Charges       88.0
dtype: float64
```

To ensure the quality and reliability of our data analysis, we have decided to drop any columns where the proportion of null values exceeds 40%.

```
# Selecting columns to drop
columns_to_drop =
rounded_missing_percentage[rounded_missing_percentage >= 40].index
df = df.drop(columns=columns_to_drop)

# Display the Missing values after dropping columns
print("\nMissing values after dropping columns with 40% or more
missing values:")
print(df.isnull().sum())
```

```
Missing values after dropping columns with 40% or more missing values:
Health Service Area                          9
Hospital County                              9
Facility Name                                0
Age Group                                    0
Zip Code - 3 digits                        365
Gender                                       0
Race                                         0
Ethnicity                                    0
Length of Stay                               0
Type of Admission                            0
Patient Disposition                          6
```

```
Discharge Year                              0
CCS Diagnosis Code                          0
CCS Diagnosis Description                   0
CCS Procedure Code                          0
CCS Procedure Description                   0
APR DRG Code                                0
APR DRG Description                         0
APR MDC Code                                0
APR MDC Description                         0
APR Severity of Illness Code                0
APR Severity of Illness Description         2
APR Risk of Mortality                       2
APR Medical Surgical Description            0
Emergency Department Indicator              0
Total Charges                               0
Total Costs                                 0
Payment Typology 1                     121105
dtype: int64
```

After removing columns with more than 40% missing values, some missing values still remain in the dataset. For cases where the number of missing values is fewer than 9, we will proceed by dropping the affected rows.

```
# Dropping the rows where missing values are less than 10
df = df.dropna(subset=['Health Service Area'])
df = df.dropna(subset=['Patient Disposition'])
df = df.dropna(subset=['APR Severity of Illness Description'])
df.isnull().sum()
```

```
Health Service Area                         0
Hospital County                             0
Facility Name                               0
Age Group                                   0
Zip Code - 3 digits                       360
Gender                                      0
Race                                        0
Ethnicity                                   0
Length of Stay                              0
Type of Admission                           0
Patient Disposition                         0
Discharge Year                              0
CCS Diagnosis Code                          0
CCS Diagnosis Description                   0
CCS Procedure Code                          0
CCS Procedure Description                   0
APR DRG Code                                0
APR DRG Description                         0
APR MDC Code                                0
APR MDC Description                         0
```

```
APR Severity of Illness Code                0
APR Severity of Illness Description         0
APR Risk of Mortality                       0
APR Medical Surgical Description            0
Emergency Department Indicator              0
Total Charges                               0
Total Costs                                 0
Payment Typology 1                     121092
dtype: int64
```

For the 'Payment typology 1' column, we will replace missing values with the placeholder 'unknown'.

```
# Replacing the missing values with unknown
df['Payment Typology 1'].fillna('unknown', inplace=True)

# Checking the missing values
df.isnull().sum()
```

```
Health Service Area                     0
Hospital County                         0
Facility Name                           0
Age Group                               0
Zip Code - 3 digits                   360
Gender                                  0
Race                                    0
Ethnicity                               0
Length of Stay                          0
Type of Admission                       0
Patient Disposition                     0
Discharge Year                          0
CCS Diagnosis Code                      0
CCS Diagnosis Description               0
CCS Procedure Code                      0
CCS Procedure Description               0
APR DRG Code                            0
APR DRG Description                     0
APR MDC Code                            0
APR MDC Description                     0
APR Severity of Illness Code            0
APR Severity of Illness Description     0
APR Risk of Mortality                   0
APR Medical Surgical Description        0
Emergency Department Indicator          0
Total Charges                           0
Total Costs                             0
Payment Typology 1                      0
dtype: int64
```

Upon inspecting the data, we found that the 'Zip Code' column corresponds to the hospital county. Based on this relationship, we will identify counties with missing values and replace them with the appropriate zip codes corresponding to those counties.

```
# Filter rows where 'Zip Code' is missing
missing_zip_df = df[df['Zip Code - 3 digits'].isnull()]

# Get unique counties with missing zip codes
counties_with_missing_zip = missing_zip_df['Hospital
County'].drop_duplicates().tolist()

print("Counties with missing zip codes:")
print(counties_with_missing_zip)
```

```
Counties with missing zip codes:
['Clinton', 'Oneida', 'Rensselaer', 'Bronx', 'Manhattan', 'Queens',
'Chemung', 'Jefferson', 'Nassau', 'Onondaga', 'Otsego', 'Rockland',
'Westchester', 'Richmond', 'Steuben', 'Broome', 'Cortland', 'Lewis',
'Tompkins', 'Kings', 'Putnam', 'Suffolk', 'Chautauqua', 'Ontario',
'Albany', 'Saratoga', 'Franklin']
```

The output displays counties with missing zip codes. To ensure consistency with the existing data format, we researched the zip codes for these counties and used only the first three digits. This approach aligns with the format used in the dataset.

```
# Mapping of counties to their respective three-digit zip codes
county_to_zip_prefix = {
    'Albany': '122','Bronx': '104','Brooklyn': '112','Broome':
'139','Chemung': '149','Chautauqua': '147','Clinton':
'129','Cortland': '130',
    'Franklin': '129','Jefferson': '136','Kings': '112','Lewis':
'133','Manhattan': '100','Nassau': '115','Oneida': '134',
    'Onondaga': '132','Ontario': '144','Otsego': '138','Putnam':
'105','Queens': '111','Rensselaer': '121','Richmond': '103',
    'Rockland': '109','Saratoga': '128','Steuben': '148','Suffolk':
'117','Tompkins': '148','Westchester': '105'
}

# Function to replace missing zip codes based on county
def fill_zip_code(row):
    if pd.isnull(row['Zip Code - 3 digits']):
        return county_to_zip_prefix.get(row['Hospital County'], None)
    return row['Zip Code - 3 digits']

# Apply the function to fill missing values
df['Zip Code - 3 digits'] = df.apply(fill_zip_code, axis=1)

# Checking the missing values
df.isnull().sum()
```

```
Health Service Area                         0
Hospital County                             0
Facility Name                               0
Age Group                                   0
Zip Code - 3 digits                         0
Gender                                      0
Race                                        0
Ethnicity                                   0
Length of Stay                              0
Type of Admission                           0
Patient Disposition                         0
Discharge Year                              0
CCS Diagnosis Code                          0
CCS Diagnosis Description                   0
CCS Procedure Code                          0
CCS Procedure Description                   0
APR DRG Code                                0
APR DRG Description                         0
APR MDC Code                                0
APR MDC Description                         0
APR Severity of Illness Code                0
APR Severity of Illness Description         0
APR Risk of Mortality                       0
APR Medical Surgical Description            0
Emergency Department Indicator              0
Total Charges                               0
Total Costs                                 0
Payment Typology 1                          0
dtype: int64
```

All the missing values have been taken care of.

2.3 Checking for Duplicates

```
# Checking for duplicates
df.duplicated().sum()
```

```
406
```

There are 406 duplicates in our data, we decided to drop them because removing the entries ensures data integrity, accuracy, and efficiency by eliminating redundancy and preventing bias in analysis.

```
# Dropping duplicates
df = df.drop_duplicates()

# Checking for duplicate after being dropped
df.duplicated().sum()
```

```
0
```

We have removed all the duplicated values

2.4 Checking Invalid Entries

```
# Define common placeholders
placeholders = ["N/A", "NA", "null", "None", "undefined", "", 'nan']

# Initialize a dictionary to hold placeholder counts
placeholder_counts = {placeholder: 0 for placeholder in placeholders}

# Loop through each placeholder and count its occurrences
for placeholder in placeholders:
    # Use case-insensitive comparison and strip leading/trailing
spaces
    placeholder_count = (df.applymap(lambda x: str(x).strip().lower())
== placeholder.lower()).sum().sum()
    if placeholder_count > 0:
        placeholder_counts[placeholder] = placeholder_count

# Print the counts of each placeholder
for placeholder, count in placeholder_counts.items():
    if count >= 0:
        print(f"Found {count} occurrences of placeholder
'{placeholder}'")
```

```
Found 0 occurrences of placeholder 'N/A'
Found 0 occurrences of placeholder 'NA'
Found 0 occurrences of placeholder 'null'
Found 0 occurrences of placeholder 'None'
Found 0 occurrences of placeholder 'undefined'
Found 0 occurrences of placeholder ''
Found 0 occurrences of placeholder 'nan'
```

This code counts occurrences of common placeholder values representing missing or undefined data in the dataset to help assess and address data quality issues. From the output there arent any invalid entries in the data set.

Upon inspection of the Zip code column we noticed a place holder value OOS. In order to understand this we want to check the counties that have this place holder

```
# Filter the DataFrame to find rows where Zip Code is 'OOS'
oos_counties = df[df['Zip Code - 3 digits'].str.strip().str.upper() ==
'OOS']

# Get the unique counties with 'OOS' in Zip Code
oos_county_list = oos_counties['Hospital County'].unique()

# Display the counties
print("Counties with 'OOS' in Zip Code:")
for county in oos_county_list:
    print(county)
```

```
Counties with 'OOS' in Zip Code:
Albany
Allegany
Broome
Cattaraugus
Cayuga
Chautauqua
Chemung
Clinton
Cortland
Delaware
Dutchess
Erie
Suffolk
Essex
Franklin
Jefferson
Lewis
Livingston
Madison
Monroe
Montgomery
Nassau
Niagara
Oneida
Onondaga
Ontario
Orange
Orleans
Oswego
Otsego
Putnam
Rensselaer
Rockland
St Lawrence
Saratoga
Schenectady
Schoharie
Steuben
Sullivan
Tompkins
Ulster
Warren
Wayne
Westchester
Wyoming
Bronx
Kings
Manhattan
Queens
```

```
Richmond
Chenango
Genesee
Yates
Herkimer
Columbia
Fulton
Schuyler
```

To take care of the place holders, we will filter the DataFrame to exclude rows where the zip code is 'OOS', then create a dictionary mapping each hospital county to its corresponding zip code by selecting the first valid zip code for each county.

```
# Filter the DataFrame to get rows where Zip Code is not 'OOS'
valid_zip_codes_df = df[df['Zip Code - 3
digits'].str.strip().str.upper() != 'OOS']

# Create a dictionary mapping counties to zip codes
zip_code_mapping = valid_zip_codes_df[['Hospital County', 'Zip Code -
3 digits']].drop_duplicates()
zip_code_mapping = zip_code_mapping.dropna()
zip_code_mapping = zip_code_mapping.groupby('Hospital County')['Zip
Code - 3 digits'].first().to_dict()

# Print the zip code mapping for verification
print("Zip Code Mapping from Existing Data:")
for county, zip_code in zip_code_mapping.items():
    print(f"{county}: {zip_code}")
```

```
Zip Code Mapping from Existing Data:
Albany: 105.0
Allegany: 145
Bronx: 100
Broome: 120
Cattaraugus: 140
Cayuga: 121
Chautauqua: 140
Chemung: 130
Chenango: 133
Clinton: 121
Columbia: 120
Cortland: 109
Delaware: 117
Dutchess: 104
Erie: 140
Essex: 128
Franklin: 120
Fulton: 120
Genesee: 140
```

```
Herkimer: 133
Jefferson: 131
Kings: 100
Lewis: 109
Livingston: 144
Madison: 130
Manhattan: 100
Monroe: 117
Montgomery: 120
Nassau: 110
Niagara: 130
Oneida: 120
Onondaga: 130
Ontario: 131
Orange: 100
Orleans: 140
Oswego: 130
Otsego: 120
Putnam: 105
Queens: 100
Rensselaer: 120
Richmond: 103
Rockland: 109
Saratoga: 104
Schenectady: 100
Schoharie: 120
Schuyler: 145
St Lawrence: 136
Steuben: 144
Suffolk: 109
Sullivan: 113
Tompkins: 112
Ulster: 100
Warren: 103
Wayne: 131
Westchester: 104
Wyoming: 140
Yates: 131

# Replace 'OOS' with the correct zip code based on the county
df['Zip Code - 3 digits'] = df.apply(
    lambda row: zip_code_mapping.get(row['Hospital County'], row['Zip
Code - 3 digits'])
    if row['Zip Code - 3 digits'].strip().upper() == 'OOS' else
row['Zip Code - 3 digits'],
    axis=1
)

# Count occurrences of 'OOS' in the Zip Code - 3 digits column
oos_count = df[df['Zip Code - 3 digits'].str.strip().str.upper() ==
```

```
'OOS'].shape[0]

# Print the number of occurrences
print(f"Number of 'OOS' still present in Zip Code - 3 digits column:
{oos_count}")
```

```
Number of 'OOS' still present in Zip Code - 3 digits column: 0
```

All the place holders have been removed.

2.5 Checking Data Types

```
# Checking the data types
df.dtypes
```

```
Health Service Area                    object
Hospital County                        object
Facility Name                          object
Age Group                              object
Zip Code - 3 digits                    object
Gender                                 object
Race                                   object
Ethnicity                              object
Length of Stay                         object
Type of Admission                      object
Patient Disposition                    object
Discharge Year                          int64
CCS Diagnosis Code                    float64
CCS Diagnosis Description              object
CCS Procedure Code                    float64
CCS Procedure Description              object
APR DRG Code                            int64
APR DRG Description                    object
APR MDC Code                            int64
APR MDC Description                    object
APR Severity of Illness Code            int64
APR Severity of Illness Description    object
APR Risk of Mortality                  object
APR Medical Surgical Description       object
Emergency Department Indicator         object
Total Charges                         float64
Total Costs                           float64
Payment Typology 1                     object
dtype: object
```

There are two columns that do not have an appropriate data type Zip Code and Length of Stay.

- Some zip code values in our dataset were represented as floats. Zip codes are generally whole numbers, so these float representations were not appropriate for our analysis.

- The 'Length of Stay' column is currently saved as an object data type, whereas it should be numeric. To understand the reason for this, we will examine the unique values in this column.

```
# Convert all values to numeric, forcing errors to NaN
df['Zip Code - 3 digits'] = pd.to_numeric(df['Zip Code - 3 digits'],
errors='coerce')

# Round off zip code values to the nearest whole number and convert to
integer
df['Zip Code - 3 digits'] = df['Zip Code - 3
digits'].round().astype(int)

# Checking if the conversion caused NA values
df.isnull().sum()
```

```
Health Service Area                     0
Hospital County                         0
Facility Name                           0
Age Group                               0
Zip Code - 3 digits                     0
Gender                                  0
Race                                    0
Ethnicity                               0
Length of Stay                          0
Type of Admission                       0
Patient Disposition                     0
Discharge Year                          0
CCS Diagnosis Code                      0
CCS Diagnosis Description               0
CCS Procedure Code                      0
CCS Procedure Description               0
APR DRG Code                            0
APR DRG Description                     0
APR MDC Code                            0
APR MDC Description                     0
APR Severity of Illness Code            0
APR Severity of Illness Description     0
APR Risk of Mortality                   0
APR Medical Surgical Description        0
Emergency Department Indicator          0
Total Charges                           0
Total Costs                             0
Payment Typology 1                      0
dtype: int64
```

```
# Checking if the column is no longer a float
df['Zip Code - 3 digits'].dtypes
```

```
dtype('int32')
```

The data type has been sucessfuly changed.

```
unique_values = df['Length of Stay'].unique()

# Print the unique values
print(unique_values)
```

```
['6' '3' '2' '5' '9' '1' '20' '4' '37' '8' '27' '21' '23' '7' '31'
'14'
 '11' '46' '18' '28' '10' '15' '17' '32' '13' '24' '22' '12' '33' '26'
 '19' '16' '34' '58' '39' '40' '29' '25' '38' '35' '100' '30' '72'
'36'
 '110' '96' '63' '43' '44' '75' '57' '62' '42' '115' '87' '120 +' '73'
 '69' '59' '76' '81' '86' '52' '118' '78' '88' '54' '47' '61' '66'
'94'
 '41' '45' '112' '82' '64' '77' '60' '53' '56' '49' '98' '70' '97'
'90'
 '51' '50' '65' '84' '89' '55' '48' '71' '92' '79' '109' '80' '83'
'67'
 '111' '95' '91' '68' '74' '101' '117' '85' '103' '104' '102' '108'
'114'
 '106' '107' '116' '113' '119' '93' '105' 6 4 9 3 5 8 2 14 15 20 21 13
1
 11 7 55 48 26 12 10 58 23 28 16 18 37 19 29 30 31 49 50 75 25 43 17
35 22
 27 41 51 32 24 34 42 33 44 47 68 53 40 39 94 118 46 45 38 105 70 64
36 76
 88 72 '99']
```

Looking at the unique values there are numbers that have quotes this shows that the numbers are saved as strings. Additionally there are values that have a plus sign. Firstly we want to see how many 120+ days are there in the data.

```
# Count occurrences of '120+'
count_120_plus = df['Length of Stay'].str.contains('120\ +',
regex=True).sum()

print(f"Number of entries with '120 +': {count_120_plus}")
```

```
Number of entries with '120 +': 124
```

We have identified 124 patients who stayed for more than 120 days, and we will retain the "120+" values for our analysis as they are crucial. To handle this, we will separate the 'Length of Stay' column into two cases: one with "120+" and the other with numeric and string values. We will convert the numeric and string values into numeric format while preserving the "120+" values. After processing, the 'Length of Stay' column will remain as an object data type due to the presence of "120+".

```
# Separate rows with special cases (e.g., values containing '+')
special_cases = df['Length of Stay'].str.contains(r'\+', na=False)
special_values = df[special_cases]
remaining_values = df[~special_cases]

# Function to check for non-numeric values
def check_non_numeric(value):
    try:
        pd.to_numeric(value, errors='raise')
        return None  # Value is numeric
    except (ValueError, TypeError):
        return value  # Value is not numeric

# Function to clean and convert remaining values to numeric, errors
are coerced to NaN
def convert_to_numeric(value):
    try:
        return pd.to_numeric(value, errors='coerce')  # Convert to
numeric or NaN if conversion fails
    except ValueError:
        return None

# Apply the function to remaining values
remaining_values['Length of Stay'] = remaining_values['Length of
Stay'].apply(convert_to_numeric)

# Recombine with special values
df_cleaned = pd.concat([remaining_values, special_values],
ignore_index=True)

# Ensure that the Length of Stay column in df is properly formatted
df['Length of Stay'] = df_cleaned['Length of Stay']

print("Unique values in the Length of Stay column after recombining:")
print(df['Length of Stay'].unique())
print(f"Number of missing values: {df['Length of
Stay'].isnull().sum()}")
```

```
<ipython-input-82-f4c6d733533a>:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  remaining_values['Length of Stay'] = remaining_values['Length of
Stay'].apply(convert_to_numeric)

Unique values in the Length of Stay column after recombining:
[6 3 2 5 9 1 20 4 37 8 27 21 23 7 31 14 11 46 18 28 10 15 17 32 13 24
22
```

```
 12 33 19 16 34 26 58 39 40 29 25 38 35 100 30 72 36 110 96 63 43 44
75 57
 42 115 87 73 69 59 76 81 86 52 118 78 88 54 47 61 66 94 41 45 112 82
64
 77 60 53 56 49 98 70 97 90 51 62 50 65 84 89 55 48 71 92 79 109 80 83
67
 111 95 91 68 74 101 117 85 103 104 102 108 114 106 107 116 113 119 93
105
 99 '120 +' nan]
Number of missing values: 423
```

The conversion has created 423 missing values. We will treat these missing values using forward fill because it allows us to use preceding data points to fill in gaps, which is particularly useful when earlier values are expected to be similar to subsequent values.

```
# Perform backward fill
df['Length of Stay'] = df['Length of Stay'].fillna(method='ffill')

# Checking if the conversion created any missing values
df.isnull().sum()
```

```
Health Service Area                     0
Hospital County                         0
Facility Name                           0
Age Group                               0
Zip Code - 3 digits                     0
Gender                                  0
Race                                    0
Ethnicity                               0
Length of Stay                          0
Type of Admission                       0
Patient Disposition                     0
Discharge Year                          0
CCS Diagnosis Code                      0
CCS Diagnosis Description               0
CCS Procedure Code                      0
CCS Procedure Description               0
APR DRG Code                            0
APR DRG Description                     0
APR MDC Code                            0
APR MDC Description                     0
APR Severity of Illness Code            0
APR Severity of Illness Description     0
APR Risk of Mortality                   0
APR Medical Surgical Description        0
Emergency Department Indicator          0
Total Charges                           0
Total Costs                             0
```

```
Payment Typology 1                        0
dtype: int64
```

The missing values have been taken care of.

```
# Checking the data types after the conversion
df.dtypes
```

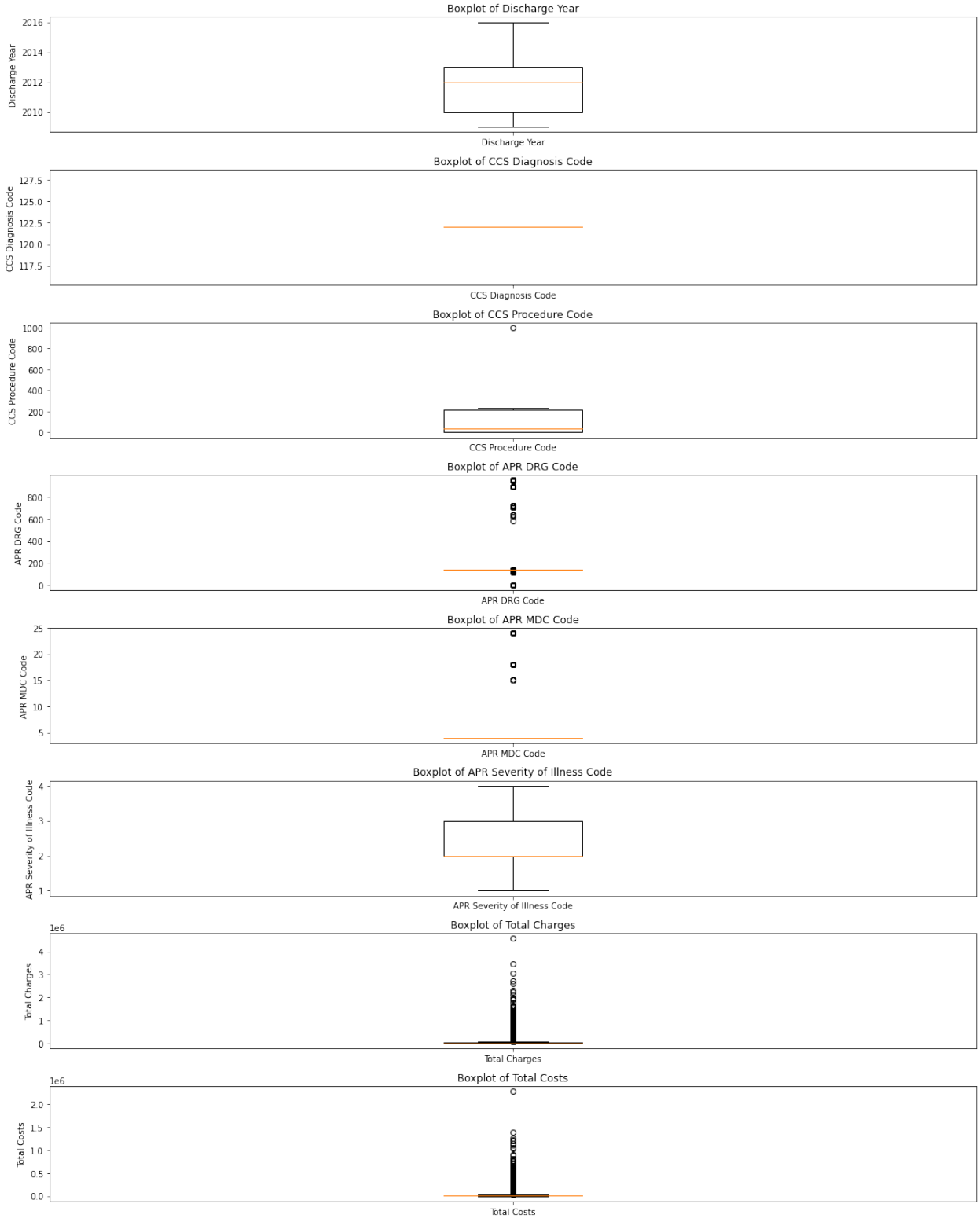
```
Health Service Area                      object
Hospital County                          object
Facility Name                            object
Age Group                                object
Zip Code - 3 digits                       int32
Gender                                   object
Race                                     object
Ethnicity                                object
Length of Stay                           object
Type of Admission                        object
Patient Disposition                      object
Discharge Year                            int64
CCS Diagnosis Code                      float64
CCS Diagnosis Description                object
CCS Procedure Code                      float64
CCS Procedure Description                object
APR DRG Code                              int64
APR DRG Description                      object
APR MDC Code                              int64
APR MDC Description                      object
APR Severity of Illness Code              int64
APR Severity of Illness Description      object
APR Risk of Mortality                    object
APR Medical Surgical Description         object
Emergency Department Indicator           object
Total Charges                           float64
Total Costs                             float64
Payment Typology 1                       object
dtype: object
```

The 'Length of Stay' column has been maintained as an object type as intended. This is acceptable because it allows us to retain the "120+" values that are essential for our analysis

2.6 Handling Outliers

```
# Creating boxplots for numeric columns

# Filter numerical columns
numerical_cols = df.select_dtypes(include=['float64',
'int64']).columns

# Create boxplots for each numerical column
```

```
plt.figure(figsize=(16, 20))  # Increase size to accommodate more
plots
for i, col in enumerate(numerical_cols, 1):
    plt.subplot(len(numerical_cols), 1, i)  # Number of rows = number
of numerical columns
    plt.boxplot(df[col].dropna())  # Drop NaN values for the boxplot
    plt.title(f'Boxplot of {col}')
    plt.ylabel(col)
    plt.xticks([1], [col])  # Set x-tick labels

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



Justification for Keeping Outliers:

1. APR MDC Code and APR DRG Code: These codes categorize medical diagnoses and treatments. Outliers in these codes might represent rare or unusual cases that are

crucial for a complete analysis of the patient population. Excluding them could lead to a biased understanding of the diagnosis and treatment distributions.

2. Total Charges: Outliers in total charges can indicate exceptionally high-cost cases, such as complex or prolonged hospitalizations. Retaining these outliers is important for accurately assessing the full range of charges.

3. Total Costs: Similarly, outliers in total costs may reflect extreme cases with unusually high or low costs. Including these outliers ensures a thorough evaluation of cost patterns and helps in identifying factors that contribute to significant cost variations.

2.7 Reviewing the Cleaned Data

```
# Shape of the data
df.shape
```

```
(379040, 28)
```

Our cleaned data has 379,040 rows and 29 columns

```
# Checking the columns
df.columns
```

```
Index(['Health Service Area', 'Hospital County', 'Facility Name', 'Age
Group',
       'Zip Code - 3 digits', 'Gender', 'Race', 'Ethnicity', 'Length
of Stay',
       'Type of Admission', 'Patient Disposition', 'Discharge Year',
       'CCS Diagnosis Code', 'CCS Diagnosis Description', 'CCS
Procedure Code',
       'CCS Procedure Description', 'APR DRG Code', 'APR DRG
Description',
       'APR MDC Code', 'APR MDC Description', 'APR Severity of Illness
Code',
       'APR Severity of Illness Description', 'APR Risk of Mortality',
       'APR Medical Surgical Description', 'Emergency Department
Indicator',
       'Total Charges', 'Total Costs', 'Payment Typology 1'],
      dtype='object')
```

```
# The data types
print("\nData types of the columns:")
print(df.dtypes)
```

```

Data types of the columns:
Health Service Area                     object
Hospital County                         object
Facility Name                           object
```

```
Age Group                              object
Zip Code - 3 digits                     int32
Gender                                 object
Race                                   object
Ethnicity                              object
Length of Stay                         object
Type of Admission                      object
Patient Disposition                    object
Discharge Year                          int64
CCS Diagnosis Code                    float64
CCS Diagnosis Description              object
CCS Procedure Code                    float64
CCS Procedure Description              object
APR DRG Code                            int64
APR DRG Description                    object
APR MDC Code                            int64
APR MDC Description                    object
APR Severity of Illness Code            int64
APR Severity of Illness Description    object
APR Risk of Mortality                  object
APR Medical Surgical Description       object
Emergency Department Indicator         object
Total Charges                         float64
Total Costs                           float64
Payment Typology 1                     object
dtype: object
```

```
# Sample of the data
print("\nRandom sample of the cleaned data:")
print(df.sample(5))
```

```
Random sample of the cleaned data:
       Health Service Area Hospital County  \
284584         Long Island         Suffolk
27247        Southern Tier     St Lawrence
208839       New York City           Bronx
214279       New York City           Kings
198579      Capital/Adiron        Saratoga

                                           Facility Name    Age Group
\
284584    Brookhaven Memorial Hospital Medical Center Inc  70 or Older

27247                           Massena Memorial Hospital  70 or Older

208839  Bronx-Lebanon Hospital Center - Concourse Divi...     30 to 49

214279                   Kingsbrook Jewish Medical Center  70 or Older
```

```
198579                                    Saratoga Hospital  70 or Older


        Zip Code - 3 digits Gender                     Race
Ethnicity  \
284584                   117      M                    White  Not
Span/Hispanic
27247                    129      M                    White  Not
Span/Hispanic
208839                   104      F  Black/African American  Not
Span/Hispanic
214279                   112      M               Other Race  Not
Span/Hispanic
198579                   128      F                    White
Unknown

       Length of Stay Type of Admission  ... APR MDC Code  \
284584              6         Emergency  ...            4
27247               1         Emergency  ...            4
208839              2         Emergency  ...            4
214279             11         Emergency  ...            4
198579             11         Emergency  ...            4

                                    APR MDC Description  \
284584  Diseases and Disorders of the Respiratory System
27247   Diseases and Disorders of the Respiratory System
208839  Diseases and Disorders of the Respiratory System
214279  Diseases and Disorders of the Respiratory System
198579  Diseases and Disorders of the Respiratory System

        APR Severity of Illness Code APR Severity of Illness
Description  \
284584                              3
Major
27247                               2
Moderate
208839                              2
Moderate
214279                              4
Extreme
198579                              3
Major

        APR Risk of Mortality APR Medical Surgical Description  \
284584                  Major                          Medical
27247                   Minor                          Medical
208839               Moderate                          Medical
214279                Extreme                          Medical
198579                  Major                          Medical
```

```
        Emergency Department Indicator Total Charges  Total Costs  \
284584                                Y     140619.59     27513.55
27247                                 Y       4568.76      2623.22
208839                                Y       6900.41      8465.63
214279                                Y     142492.00     32994.96
198579                                Y      12957.23      4011.63

       Payment Typology 1
284584           Medicare
27247             unknown
208839           Medicaid
214279           Medicare
198579           Medicare

[5 rows x 28 columns]
```

3. Exploratory Data Analysis

3.1 Univariate Analysis

Descriptive Statistics

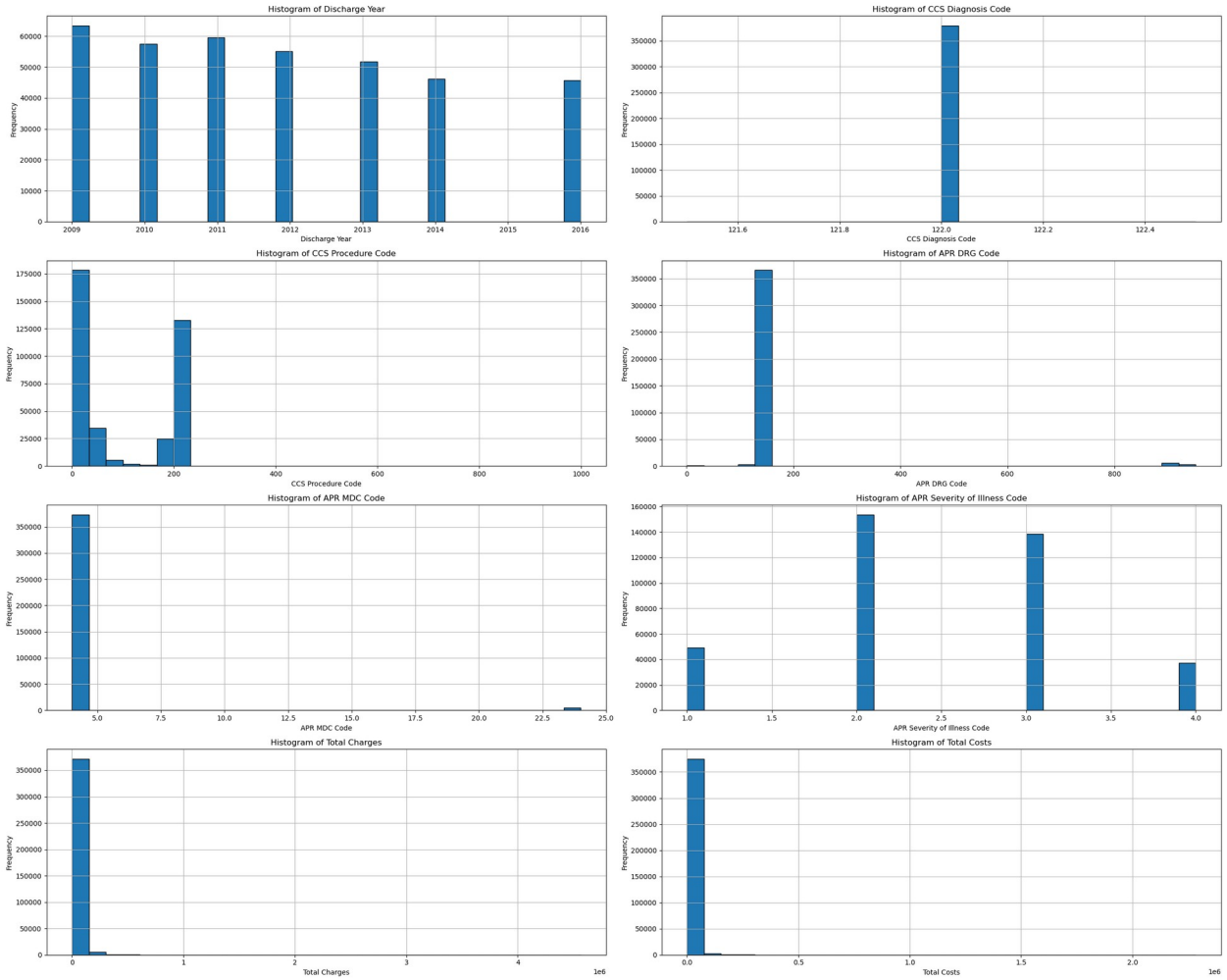
```
# Descriptive Statistics
df.describe()
```

```
       Zip Code - 3 digits  Discharge Year  CCS Diagnosis Code  \
count        379040.000000   379040.000000            379040.0
mean            119.360345     2011.900251               122.0
std              14.188260        2.192895                 0.0
min             100.000000     2009.000000               122.0
25%             109.000000     2010.000000               122.0
50%             115.000000     2012.000000               122.0
75%             130.000000     2013.000000               122.0
max             149.000000     2016.000000               122.0

       CCS Procedure Code   APR DRG Code   APR MDC Code  \
count       379040.000000  379040.000000  379040.000000
mean            97.007661     155.498185       4.296570
std            104.304281     115.154542       2.411541
min              0.000000       1.000000       4.000000
25%              0.000000     139.000000       4.000000
50%             39.000000     139.000000       4.000000
75%            217.000000     139.000000       4.000000
max            999.000000     952.000000      24.000000

       APR Severity of Illness Code  Total Charges   Total Costs
count                 379040.000000   3.790400e+05  3.790400e+05
```

```
mean                          2.433157   3.171435e+04  1.144247e+04
std                           0.838668   4.983998e+04  1.934008e+04
min                           1.000000   2.000000e-02  0.000000e+00
25%                           2.000000   1.055899e+04  4.276148e+03
50%                           2.000000   1.907150e+04  6.996460e+03
75%                           3.000000   3.540068e+04  1.217406e+04
max                           4.000000   4.563146e+06  2.284311e+06
```

Histograms for numeric columns

```
# Plot histograms for all numeric columns
numeric_cols = df.select_dtypes(include=['float64', 'int64']).columns

# Determine grid size (rows x columns)
n_cols = 2  # Number of columns for the grid
n_rows = -(-len(numeric_cols) // n_cols)  # Number of rows needed

plt.figure(figsize=(25, 5 * n_rows))
for i, col in enumerate(numeric_cols):
    plt.subplot(n_rows, n_cols, i + 1)
    df[col].hist(bins=30, edgecolor='black')
    plt.title(f'Histogram of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



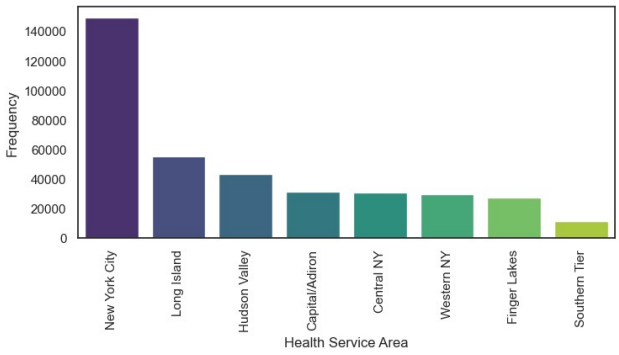
The histograms of the numeric columns reveal varying distributions. Some columns exhibit skewed distributions, indicating that data is not evenly spread and may be concentrated towards one end of the range. Other columns show more symmetric distributions, suggesting a more uniform spread of values.

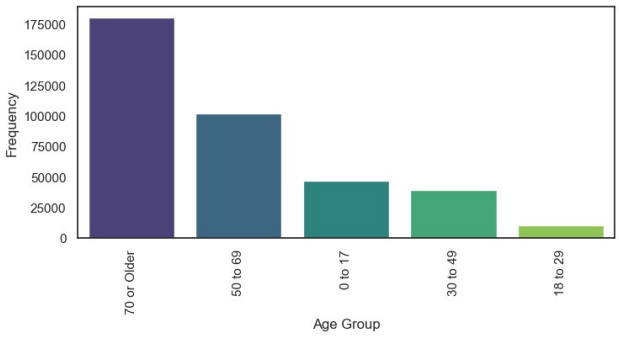
Count Plots for categorical variables

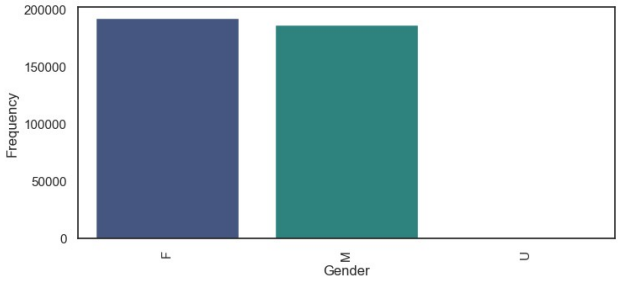
```
df.select_dtypes(include=['object', 'category']).columns.tolist()
```

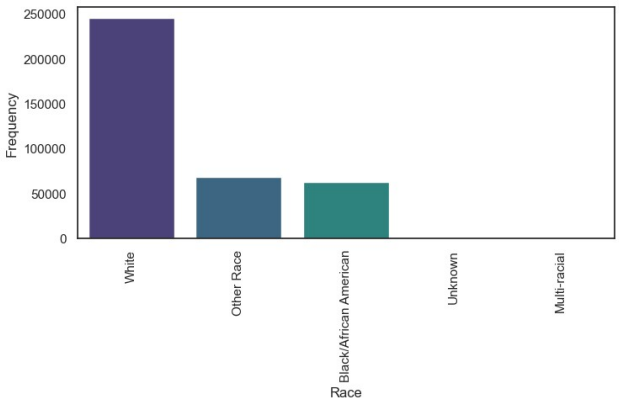
```
['Health Service Area',
 'Hospital County',
 'Facility Name',
 'Age Group',
 'Gender',
 'Race',
 'Ethnicity',
 'Length of Stay',
 'Type of Admission',
 'Patient Disposition',
 'CCS Diagnosis Description',
```

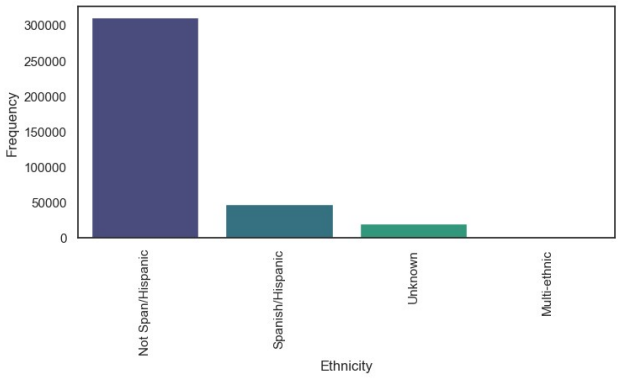
```
 'CCS Procedure Description',
 'APR DRG Description',
 'APR MDC Description',
 'APR Severity of Illness Description',
 'APR Risk of Mortality',
 'APR Medical Surgical Description',
 'Emergency Department Indicator',
 'Payment Typology 1']

cat_cols = ['Health Service Area','Age
Group','Gender','Race','Ethnicity','Type of Admission','Patient
Disposition',
          'APR Severity of Illness Description','APR Risk of
Mortality',
          'APR Medical Surgical Description','Payment Typology
1','Emergency Department Indicator']

rows = 7
columns = 2
index = 1
plt.figure(figsize=(15,40))
sns.set(style='white')
for i in cat_cols:
    plt.subplot(rows,columns,index)
    sns.countplot(x=df[i],order =
df[i].value_counts().index,palette="viridis")
    plt.ylabel('Frequency')
    plt.xticks(rotation=90)
    index +=1
plt.tight_layout()
plt.show()
```

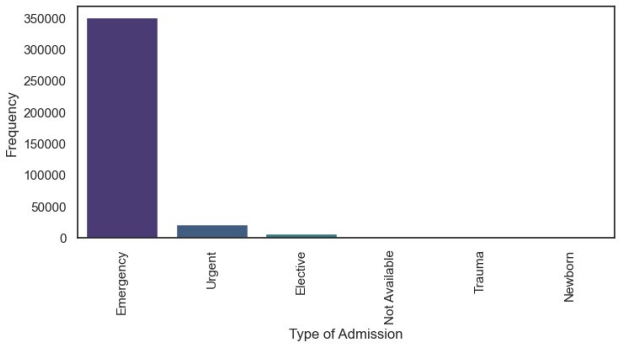

Frequency
0
20000
40000
60000
80000
100000
120000
140000
New York City
Long Island
Hudson Valley
Capital/Adiron
Central NY
Western NY
Finger Lakes
Southern Tier
Health Service Area


Frequency
0
25000
50000
75000
100000
125000
150000
175000
70 or Older
50 to 69
0 to 17
30 to 49
18 to 29
Age Group


Frequency
0
50000
100000
150000
200000
F
M
U
Gender


Frequency
0
50000
100000
150000
200000
250000
White
Other Race
Black/African American
Unknown
Multi-racial
Race


Frequency
0
50000
100000
150000
200000
250000
300000
Not Span/Hispanic
Spanish/Hispanic
Unknown
Multi-ethnic
Ethnicity


Frequency
0
50000
100000
150000
200000
250000
300000
350000
Emergency
Urgent
Elective
Not Available
Trauma
Newborn
Type of Admission


Frequency
100000
150000
200000


Frequency
50000
75000
100000
125000
150000

Interpretation

No of patients are quietly more in New York city than other cities.

More number of patients fall in the age category 70 years or older.

Female patients are more in number as comapre to male patients.

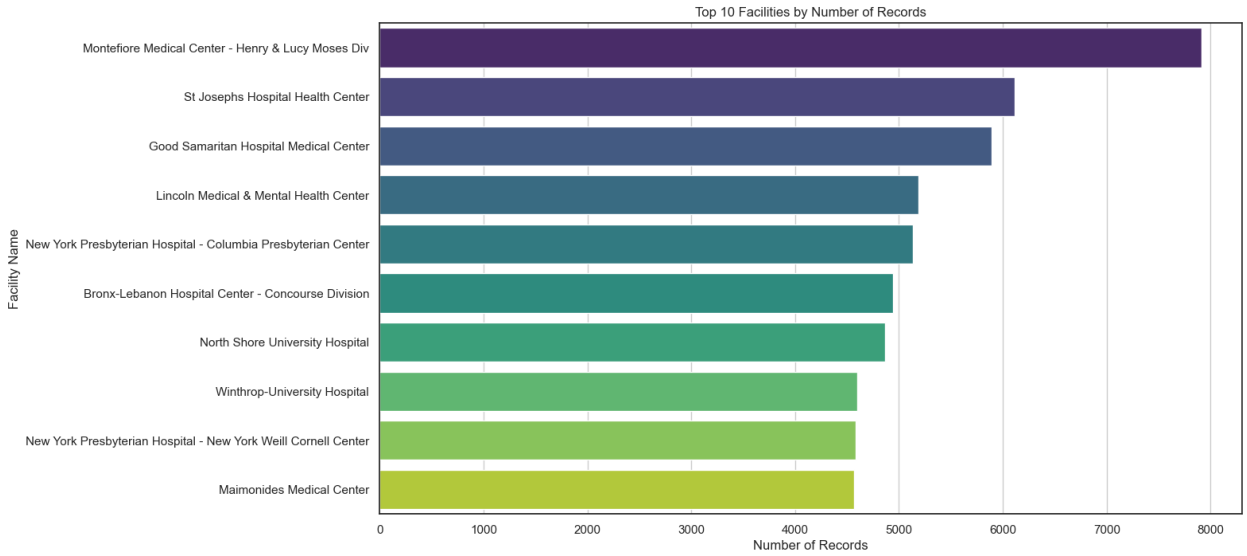
Patients enrolled in Emergency are huge in number.

Patient Disposition i.e. patients destination after discharge, mostly are in Home or Self Care prescription.

Mostly patients have Minor Risk of Mortality.

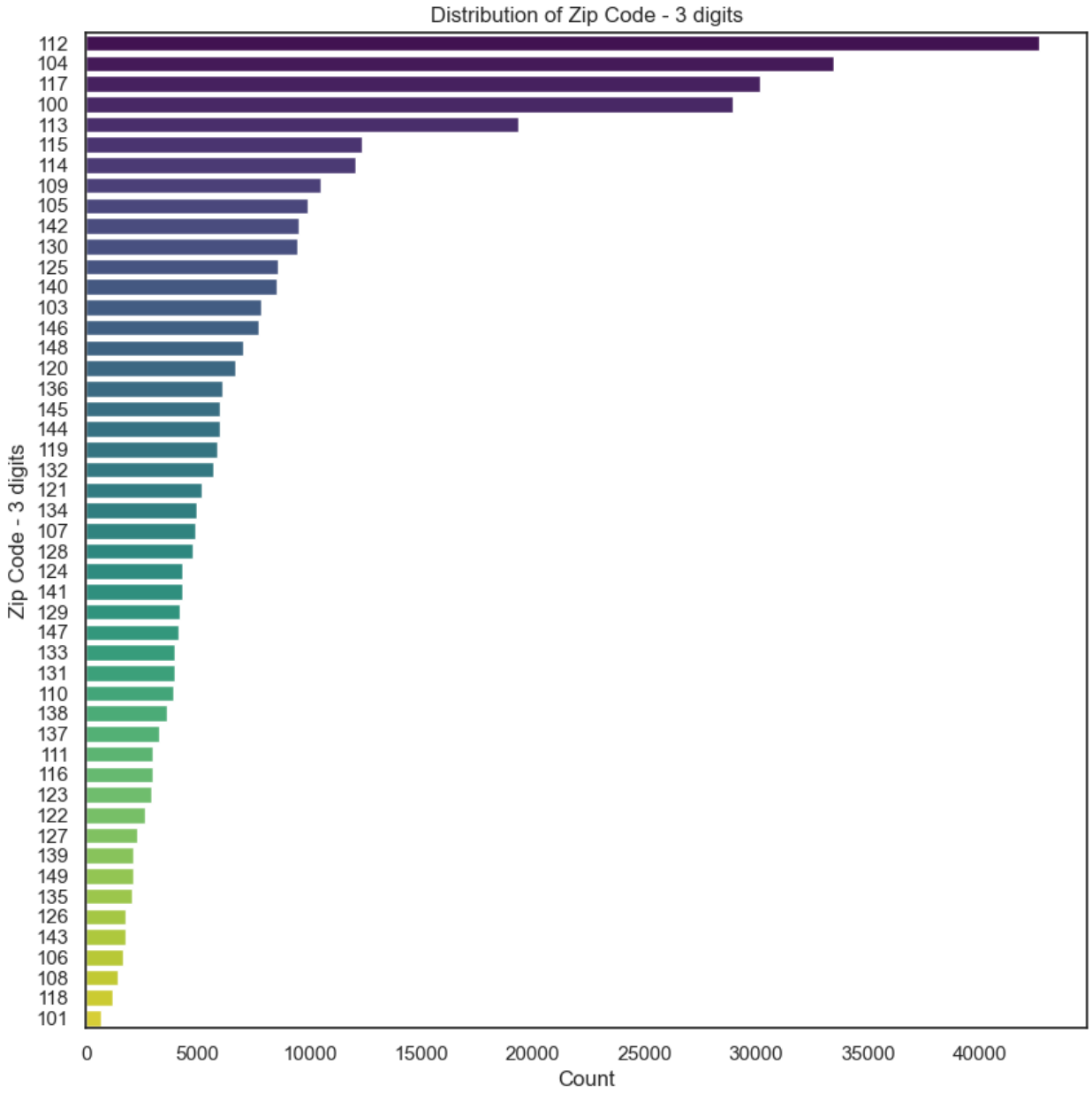
Patients have Medicare payment typology more

```
# Count the number of records per Facility Name
facility_counts = df['Facility Name'].value_counts()

# Create a DataFrame for plotting
facility_df = pd.DataFrame({'Facility Name': facility_counts.index,
'Count': facility_counts.values})

top_n = facility_df.head(10)

# Plot the bar plot
plt.figure(figsize=(14, 8))
sns.barplot(x='Count', y='Facility Name', data=top_n,
palette='viridis')
plt.title(f'Top 10 Facilities by Number of Records')
plt.xlabel('Number of Records')
plt.ylabel('Facility Name')
plt.grid(axis='x')
plt.show()
```



The graph shows the top 10 facilities based on the number of records, with Montefiore Medical Center having the highest number of records.

```
# Zip Code distribution
plt.figure(figsize=(10, 10))
sns.countplot(y=df['Zip Code - 3 digits'], order=df['Zip Code - 3
digits'].value_counts().index, palette='viridis')
plt.title('Distribution of Zip Code - 3 digits')
plt.xlabel('Count')
plt.ylabel('Zip Code - 3 digits')
plt.show()
```



The most prevelant Zip Code is 122

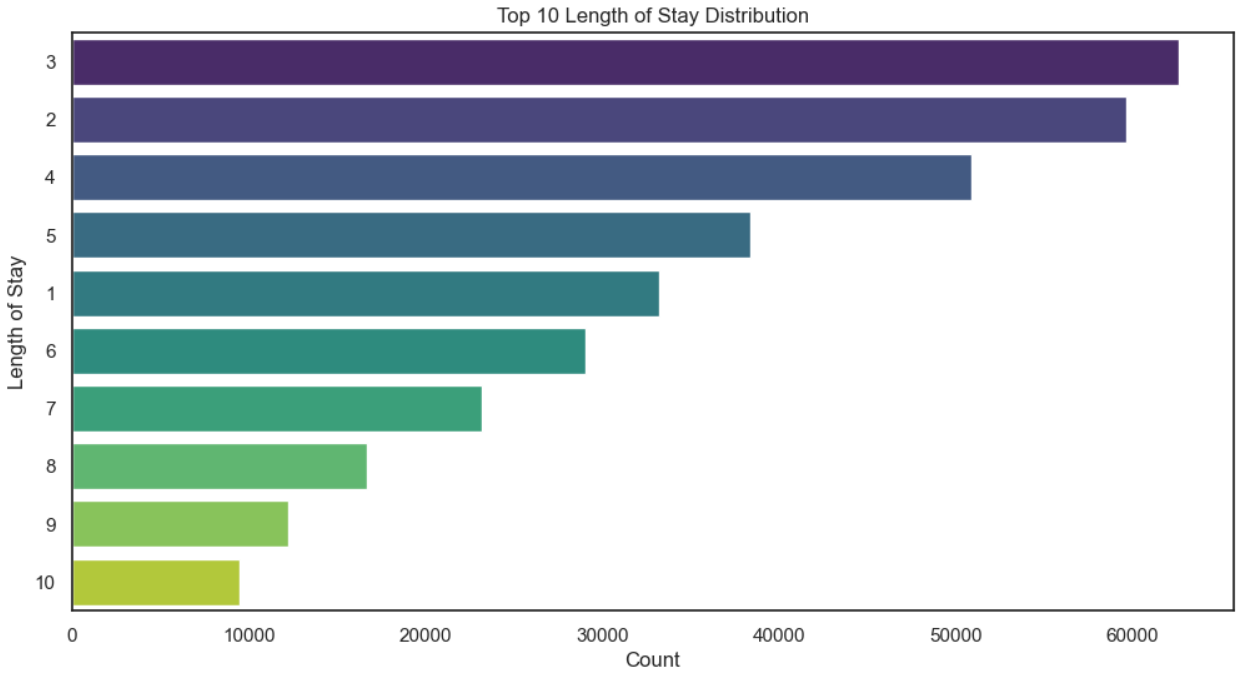
```
# Extract the top 10 and bottom 10 Length of Stay values
top_10_los = df['Length of Stay'].value_counts().nlargest(10).index
bottom_10_los = df['Length of
Stay'].value_counts().nsmallest(10).index

# Print Top 10 Length of Stay values
print("Top 10 Length of Stay Values and Their Counts:")
top_10_counts = df['Length of Stay'].value_counts().loc[top_10_los]
print(top_10_counts)
```

```
# Print Bottom 10 Length of Stay values
print("\nBottom 10 Length of Stay Values and Their Counts:")
bottom_10_counts = df['Length of
Stay'].value_counts().loc[bottom_10_los]
print(bottom_10_counts)
```

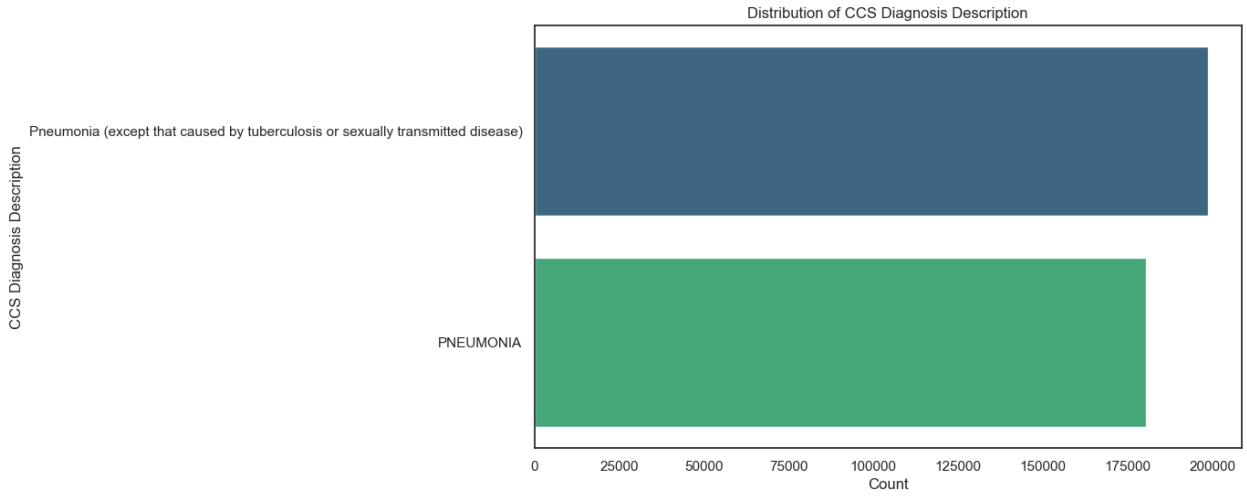
```
Top 10 Length of Stay Values and Their Counts:
Length of Stay
3     62614
2     59645
4     50945
5     38431
1     33253
6     29048
7     23189
8     16728
9     12231
10     9487
Name: count, dtype: int64

Bottom 10 Length of Stay Values and Their Counts:
Length of Stay
106    1
116    1
119    1
93     1
99     1
108    1
112    2
107    2
113    2
105    2
Name: count, dtype: int64
```

The top 10 lengths of stay predominantly range from 1 to 10 days, with shorter stays being much more common. In contrast, the bottom 10 lengths of stay, which are significantly longer, are rare, indicating that extended stays are exceptional in the dataset.

```
# Filter the DataFrame to include only top 10 lengths of stay
top_10_df = df[df['Length of Stay'].isin(top_10_los)]

# Plot for Top 10 Length of Stay
plt.figure(figsize=(12, 6))
sns.countplot(y='Length of Stay', data=top_10_df, order=top_10_los,
palette="viridis")
plt.title('Top 10 Length of Stay Distribution')
plt.xlabel('Count')
plt.ylabel('Length of Stay')
plt.show()
```




```
# Distribution of CCS Diagnosis Description
plt.figure(figsize=(10, 6))
sns.countplot(y=df['CCS Diagnosis Description'], order=df['CCS
Diagnosis Description'].value_counts().index, palette="viridis")
plt.title('Distribution of CCS Diagnosis Description')
plt.xlabel('Count')
plt.ylabel('CCS Diagnosis Description')
plt.show()
```



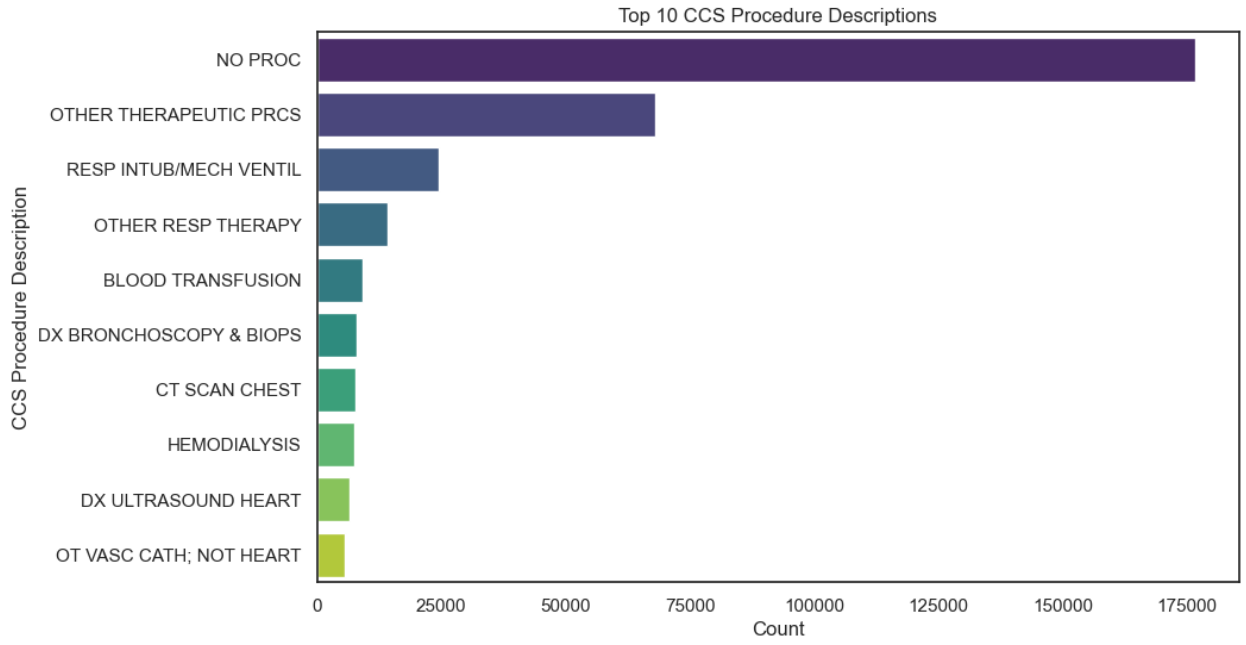
The most dominant CCS diagnosis is Pneumonia that is either caused by tuberculosis or sexually transmitted diseases

```python
# Get the top 10 and bottom 10 CCS Procedure Descriptions
top_10_ccs = df['CCS Procedure
Description'].value_counts().head(10).index
bottom_10_ccs = df['CCS Procedure
Description'].value_counts().tail(10).index

# Filter the DataFrame for the top 10 CCS Procedure Descriptions
top_10_df = df[df['CCS Procedure Description'].isin(top_10_ccs)]

# Get the count of each CCS Procedure Description in the top 10
top_10_counts = top_10_df['CCS Procedure Description'].value_counts()

# Print the top 10 CCS Procedure Descriptions and their counts
print("Top 10 CCS Procedure Descriptions and Their Counts:")
print(top_10_counts)

# Filter the DataFrame for the bottom 10 CCS Procedure Descriptions
bottom_10_df = df[df['CCS Procedure Description'].isin(bottom_10_ccs)]

# Get the count of each CCS Procedure Description in the bottom 10
bottom_10_counts = bottom_10_df['CCS Procedure
Description'].value_counts()

# Print the bottom 10 CCS Procedure Descriptions and their counts
print("\nBottom 10 CCS Procedure Descriptions and Their Counts:")
print(bottom_10_counts)
```

```
Top 10 CCS Procedure Descriptions and Their Counts:
CCS Procedure Description
NO PROC                     176546
OTHER THERAPEUTIC PRCS       68144
RESP INTUB/MECH VENTIL       24430
OTHER RESP THERAPY           14283
BLOOD TRANSFUSION             9114
DX BRONCHOSCOPY & BIOPS       7971
CT SCAN CHEST                 7673
HEMODIALYSIS                  7547
DX ULTRASOUND HEART           6646
OT VASC CATH; NOT HEART       5529
Name: count, dtype: int64

Bottom 10 CCS Procedure Descriptions and Their Counts:
CCS Procedure Description
MYELOGRAM                   1
LOC EXC LRG INTEST LESN     1
VARI VEIN STRIP;LOW LMB     1
REPAIR RETINAL TEAR         1
FETAL MONITORING            1
MASTECTOMY                  1
HYSTERECTOMY; AB/VAG        1
```

```
EXC OF SEMI CART KNEE      1
OT PRCS TO ASSIST DELIV    1
UNGROUPABLE                1
Name: count, dtype: int64
```

```
# Plot the top 10 CCS Procedure Descriptions
plt.figure(figsize=(10, 6))
sns.countplot(y=df['CCS Procedure Description'], order=top_10_ccs,
palette="viridis")
plt.title('Top 10 CCS Procedure Descriptions')
plt.xlabel('Count')
plt.ylabel('CCS Procedure Description')
plt.show()
```



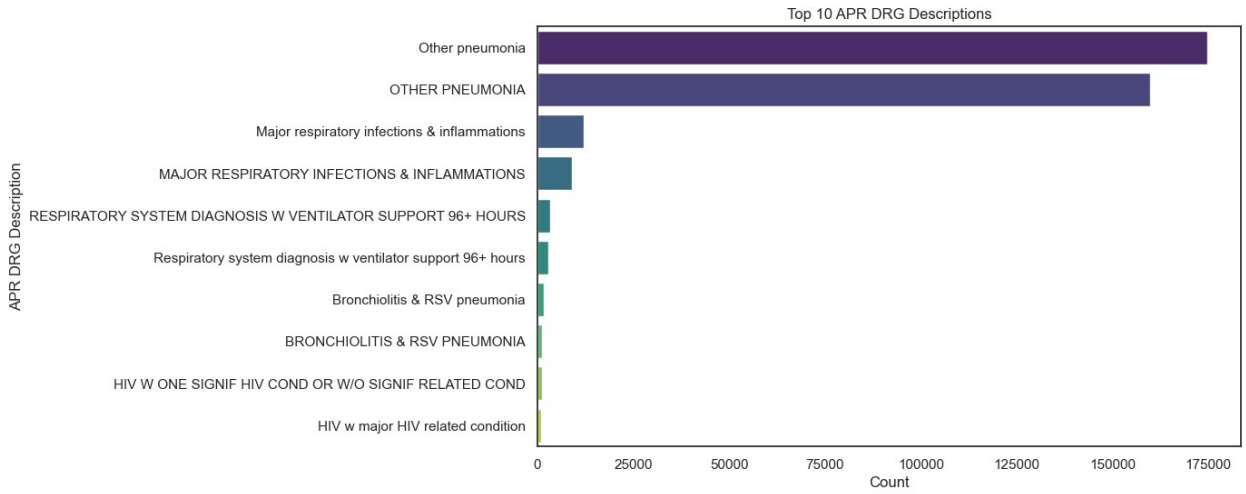
In the dataset, "NO PROC" is the most common CCS Procedure Description, indicating that no procedure was performed in these cases. In contrast, the least common descriptions, each with only one occurrence, include rare or less frequently performed procedures.

```
# Get the top 10 most frequent APR DRG Descriptions
top_10_apr_drg = df['APR DRG
Description'].value_counts().head(10).index

# Filter the DataFrame for the top 10 APR DRG Descriptions
top_10_df = df[df['APR DRG Description'].isin(top_10_apr_drg)]

# Get the bottom 10 least frequent APR DRG Descriptions
bottom_10_apr_drg = df['APR DRG
Description'].value_counts().tail(10).index

# Filter the DataFrame for the bottom 10 APR DRG Descriptions
```

```
bottom_10_df = df[df['APR DRG Description'].isin(bottom_10_apr_drg)]

# Print the top 10 APR DRG Descriptions and their counts
print("Top 10 APR DRG Descriptions and Their Counts:")
print(top_10_df['APR DRG Description'].value_counts())

# Print the bottom 10 APR DRG Descriptions and their counts
print("\nBottom 10 APR DRG Descriptions and Their Counts:")
print(bottom_10_df['APR DRG Description'].value_counts())
```

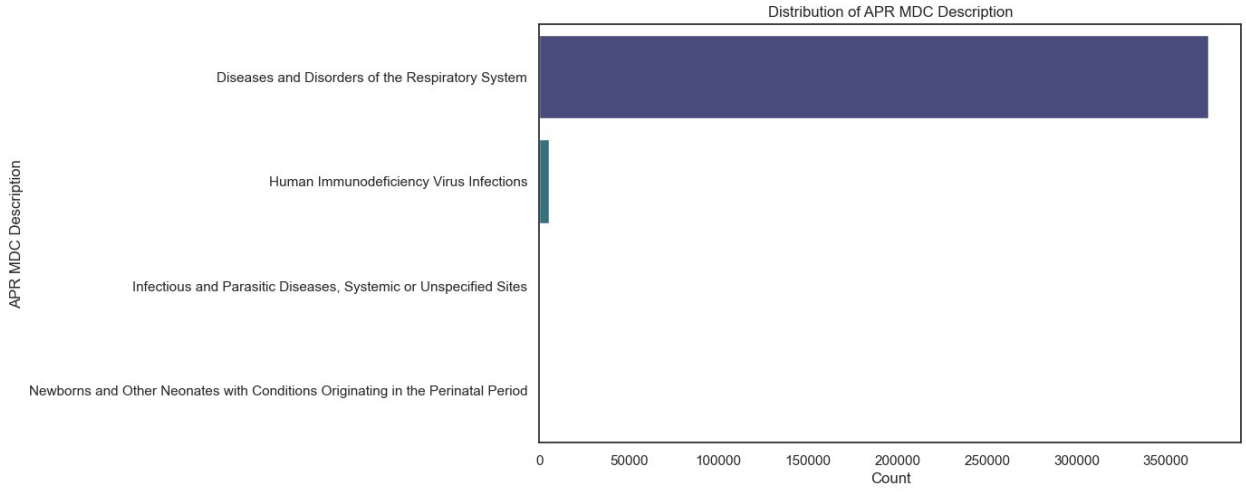
```
Top 10 APR DRG Descriptions and Their Counts:
APR DRG Description
Other pneumonia                                                  174769
OTHER PNEUMONIA                                                  159696
Major respiratory infections & inflammations                      12011
MAJOR RESPIRATORY INFECTIONS & INFLAMMATIONS                       8961
RESPIRATORY SYSTEM DIAGNOSIS W VENTILATOR SUPPORT 96+ HOURS        3334
Respiratory system diagnosis w ventilator support 96+ hours        2796
Bronchiolitis & RSV pneumonia                                      1668
BRONCHIOLITIS & RSV PNEUMONIA                                      1227
HIV W ONE SIGNIF HIV COND OR W/O SIGNIF RELATED COND               1131
HIV w major HIV related condition                                   888
Name: count, dtype: int64

Bottom 10 APR DRG Descriptions and Their Counts:
APR DRG Description
Other infectious & parasitic diseases                              7
BONE MARROW TRANSPLANT                                             2
NEONATE, BIRTHWT >2499G W RESP DIST SYND/OTH MAJ RESP COND         2
HEART &/OR LUNG TRANSPLANT                                         2
Neonate, birthwt >2499g w resp dist synd/oth maj resp cond         2
Bone marrow transplant                                             2
Heart &/or lung transplant                                         2
NEONATE BWT 2000-2499G W RESP DIST SYND/OTH MAJ RESP COND          1
LIVER TRANSPLANT &/OR INTESTINAL TRANSPLANT                        1
Neonate, transferred <5 days old, not born here                    1
Name: count, dtype: int64
```

```
# Plot for the top 10 APR DRG Descriptions
plt.figure(figsize=(10, 6))
sns.countplot(y=top_10_df['APR DRG Description'],
order=top_10_apr_drg, palette="viridis")
plt.title('Top 10 APR DRG Descriptions')
plt.xlabel('Count')
plt.ylabel('APR DRG Description')
plt.show()
```



The top 10 APR DRG descriptions primarily focus on pneumonia and respiratory conditions, with "Other pneumonia" and "OTHER PNEUMONIA" being the most common. Conversely, the bottom 10 descriptions are rare and involve specific or complex procedures such as bone marrow and heart transplants, with counts as low as 1 or 2.

```
# Distribution of APR MDC Description
plt.figure(figsize=(10, 6))
sns.countplot(y=df['APR MDC Description'], order=df['APR MDC
Description'].value_counts().index, palette="viridis")
plt.title('Distribution of APR MDC Description')
plt.xlabel('Count')
plt.ylabel('APR MDC Description')
plt.show()
```

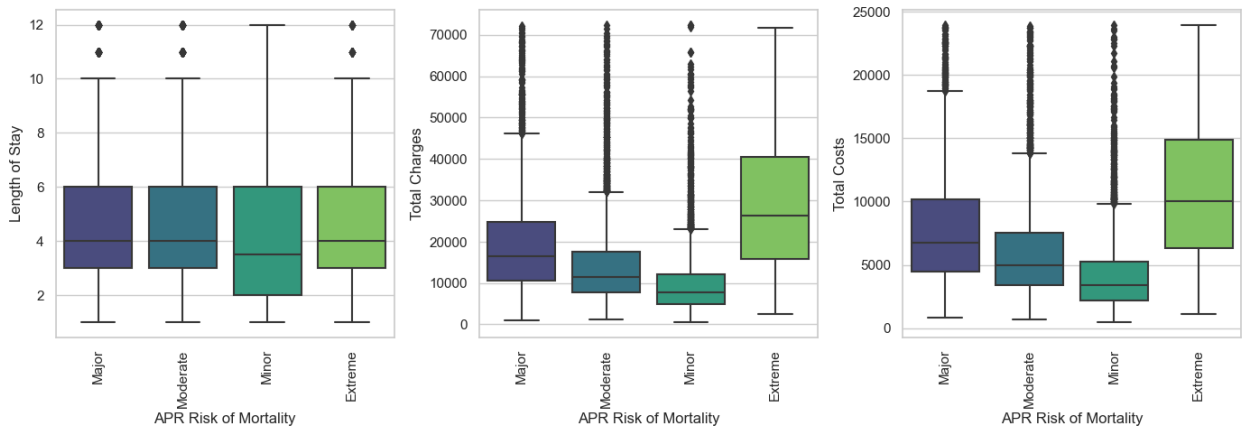


The most dominant APR MDC Description is Diseases and Disorders of the Respiratory System

3.2 Bivariate Analysis

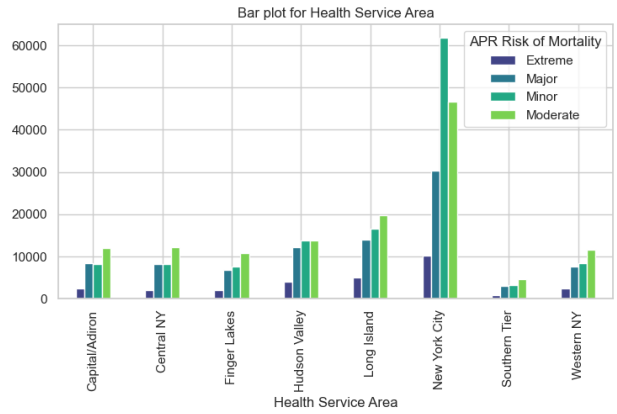
Variables vs Target Variable

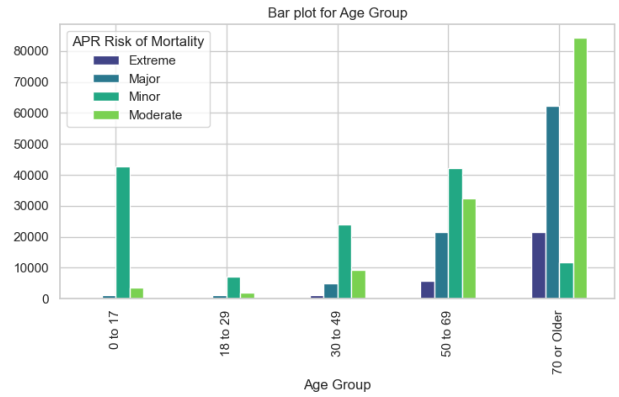
```
df['Length of Stay'] = df['Length of Stay'].replace('120 +',
130).astype(float)

rows = 1
columns = 3
index = 1
plt.figure(figsize = (14,5))
sns.set_style('whitegrid')
for i in ['Length of Stay','Total Charges','Total Costs']:
    plt.subplot(rows,columns,index)
    q1=df[i].quantile(.25)
    q3=df[i].quantile(.75)
    iqr=q3-q1
    sns.boxplot(x='APR Risk of Mortality',y=i,palette="viridis",
                data=df[df[i]<q3+1.5*iqr][0:10000])
    plt.xticks(rotation = 90)
    index +=1
plt.tight_layout()
plt.show()
```

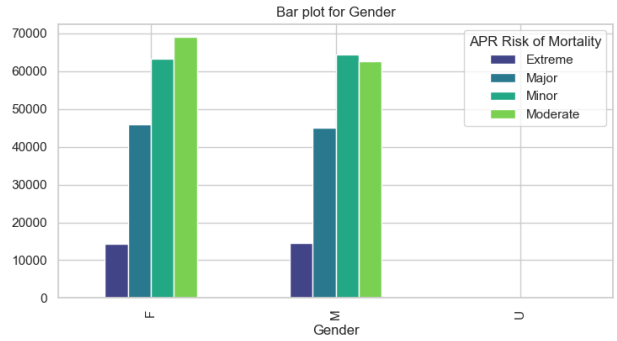


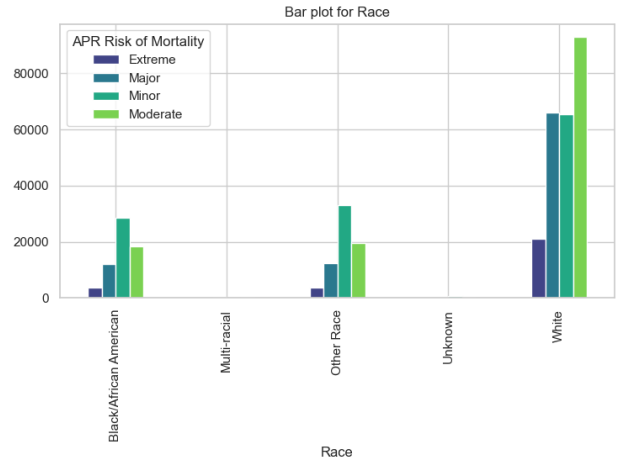

```
rows = 7
cols = 2
index = 1

# Create a figure with specified size
plt.figure(figsize=(15, 45))

# Define a custom color palette
palette = sns.color_palette("viridis", n_colors=len(df['APR Risk of
Mortality'].unique()))

# Loop through categorical columns and create subplots
```

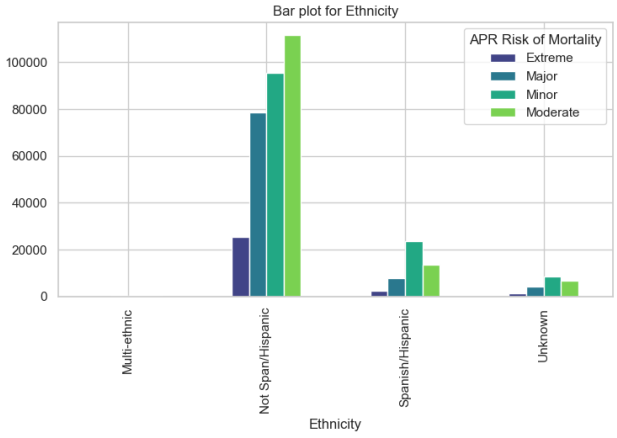
```
for i in cat_cols:
    if index > rows * cols:
        break
    ax = plt.subplot(rows, cols, index)

    # Create crosstab and plot
    crosstab = pd.crosstab(df[i], df['APR Risk of Mortality'])
    crosstab.plot.bar(ax=ax, color=palette)

    ax.set_title(f'Bar plot for {i}')
    index += 1

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

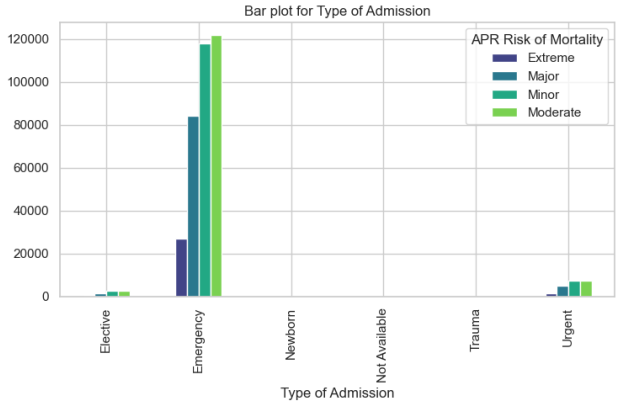

Bar plot for Health Service Area
APR Risk of Mortality
Extreme
Major
Minor
Moderate
0
10000
20000
30000
40000
50000
60000
Capital/Adiron
Central NY
Finger Lakes
Hudson Valley
Long Island
New York City
Southern Tier
Western NY
Health Service Area


Bar plot for Age Group
APR Risk of Mortality
Extreme
Major
Minor
Moderate
0
10000
20000
30000
40000
50000
60000
70000
80000
0 to 17
18 to 29
30 to 49
50 to 69
70 or Older
Age Group


Bar plot for Gender
APR Risk of Mortality
Extreme
Major
Minor
Moderate
0
10000
20000
30000
40000
50000
60000
70000
F
M
U
Gender

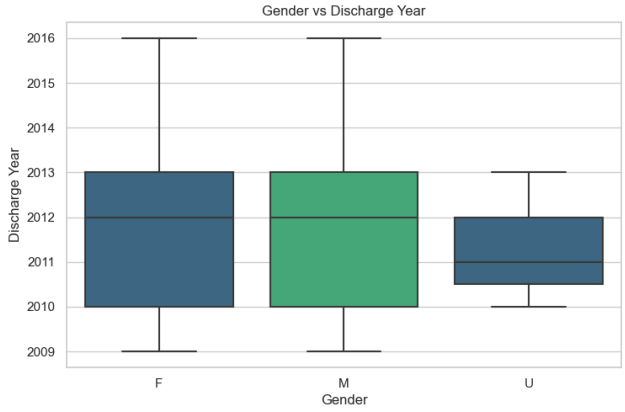

Bar plot for Race
APR Risk of Mortality
Extreme
Major
Minor
Moderate
0
20000
40000
60000
80000
Black/African American
Multi-racial
Other Race
Unknown
White
Race

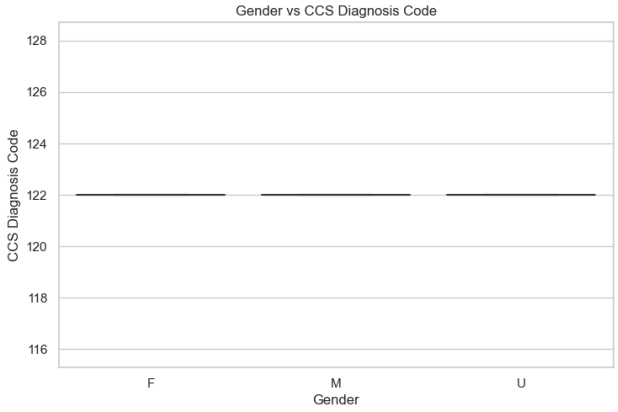

Bar plot for Ethnicity
APR Risk of Mortality
Extreme
Major
Minor
Moderate
0
20000
40000
60000
80000
100000
Multi-ethnic
Not Span/Hispanic
Spanish/Hispanic
Unknown
Ethnicity

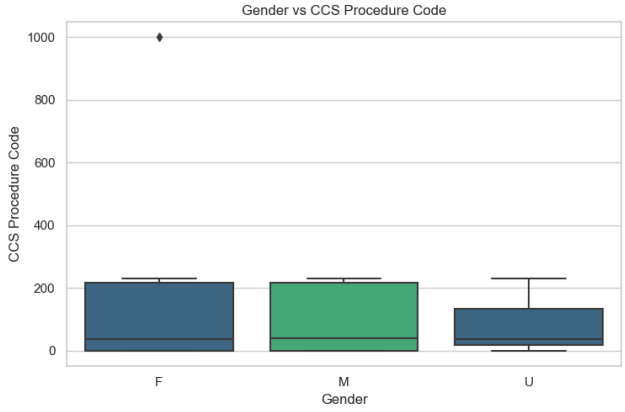

Bar plot for Type of Admission
APR Risk of Mortality
Extreme
Major
Minor
Moderate
0
20000
40000
60000
80000
100000
120000
Elective
Emergency
Newborn
Not Available
Trauma
Urgent
Type of Admission

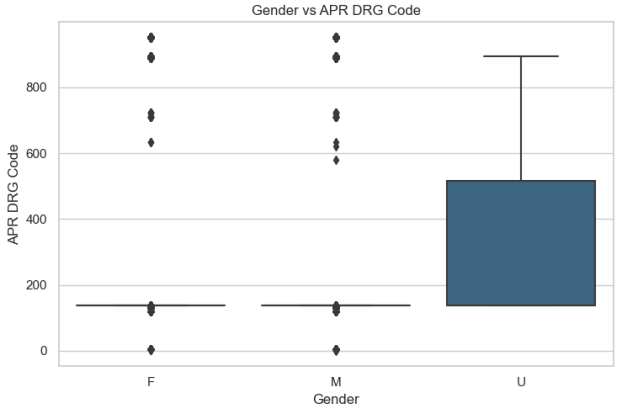
Gender Vs Other Features

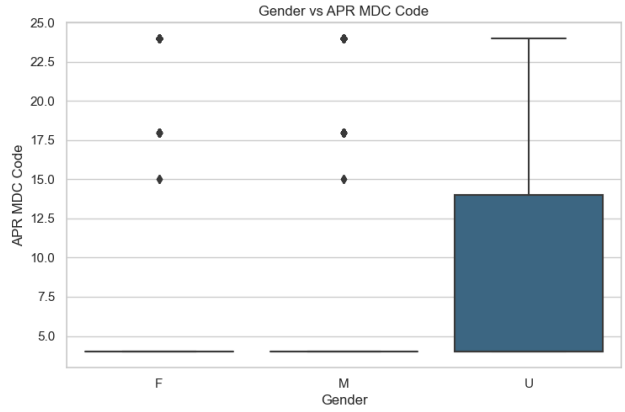
```
# Set up the figure with enough rows to accommodate all plots
rows = (len(numerical_cols) + 1) // 2  # Ensure enough rows for all plots
fig, axes = plt.subplots(nrows=rows, ncols=2, figsize=(15, rows * 5))

# Set the color palette as a list of colors
palette = sns.color_palette("viridis", n_colors=2)  # 2 colors for the Gender categories

# Plot numerical columns
for i, col in enumerate(numerical_cols):
    ax = axes[i // 2, i % 2]  # Correctly index the axes
    sns.boxplot(x='Gender', y=col, data=df, ax=ax, palette=palette)
    ax.set_title(f'Gender vs {col}')

# Remove any unused subplots (if the number of plots is less than total subplots)
for j in range(len(numerical_cols), rows * 2):
    fig.delaxes(axes[j // 2, j % 2])

# Adjust layout
plt.tight_layout()
plt.show()
```

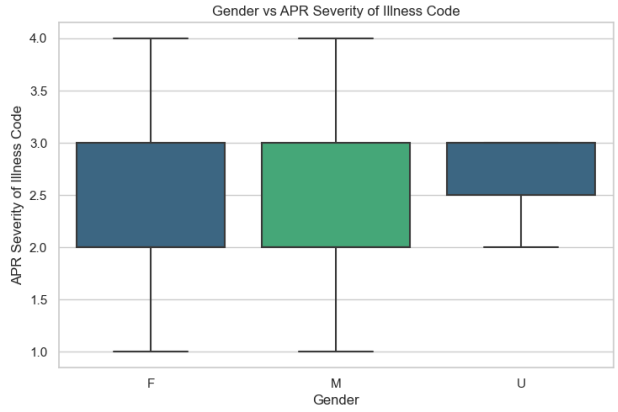

Gender vs Discharge Year
Discharge Year
2016
2015
2014
2013
2012
2011
2010
2009
F
M
U
Gender

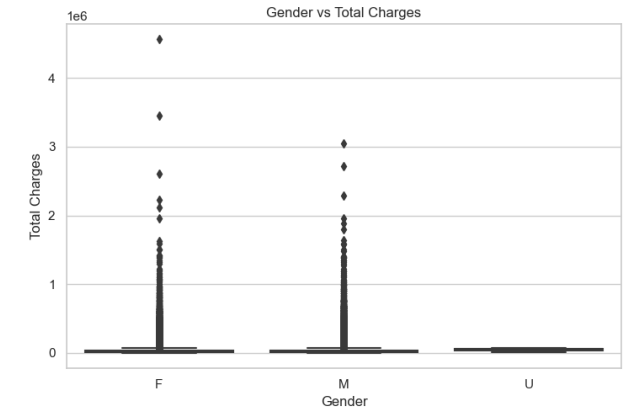

Gender vs CCS Diagnosis Code
CCS Diagnosis Code
128
126
124
122
120
118
116
F
M
U
Gender

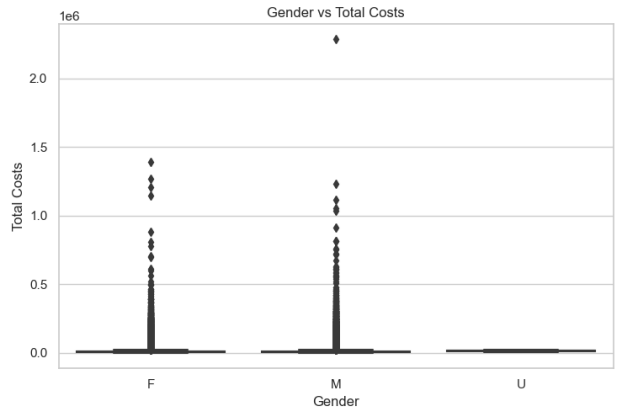

Gender vs CCS Procedure Code
CCS Procedure Code
1000
800
600
400
200
0
F
M
U
Gender


Gender vs APR DRG Code
APR DRG Code
800
600
400
200
0
F
M
U
Gender

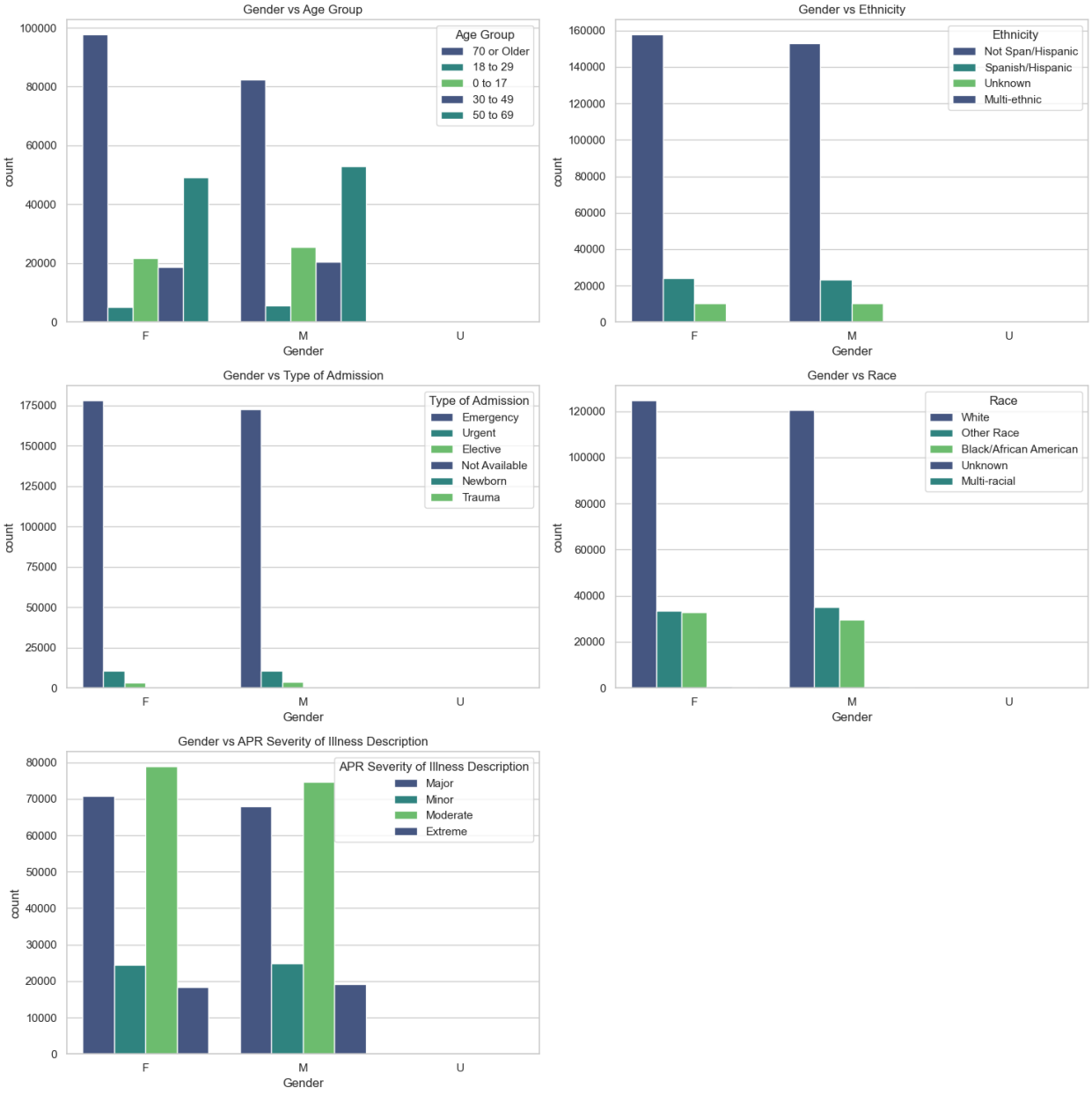

Gender vs APR MDC Code
APR MDC Code
25.0
22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
F
M
U
Gender


Gender vs APR Severity of Illness Code
APR Severity of Illness Code
4.0
3.5
3.0
2.5
2.0
1.5
1.0
F
M
U
Gender


Gender vs Total Charges
1e6
Total Charges
4
3
2
1
0
F
M
U
Gender


Gender vs Total Costs
1e6
Total Costs
2.0
1.5
1.0
0.5
0.0
F
M
U
Gender

```
# Define the list of categorical columns to plot
categorical_cols = ['Age Group', 'Ethnicity', 'Type of Admission',
'Race', 'APR Severity of Illness Description']

# Calculate the number of rows needed
n_rows = (len(categorical_cols) + 1) // 2

# Set up the figure with the calculated number of rows
fig, axes = plt.subplots(nrows=n_rows, ncols=2, figsize=(15, n_rows *
5))

# Set the color palette
palette = sns.color_palette("viridis",
n_colors=len(df['Gender'].unique()))  # Adjust the number of colors
based on unique values in 'Gender'

# Plot categorical columns
for i, col in enumerate(categorical_cols):
    sns.countplot(x='Gender', hue=col, data=df, ax=axes[i // 2, i %
2], palette=palette)
    axes[i // 2, i % 2].set_title(f'Gender vs {col}')

# Remove any unused subplots
for j in range(len(categorical_cols), n_rows * 2):
    fig.delaxes(axes[j // 2, j % 2])

# Adjust layout
plt.tight_layout()
plt.show()
```

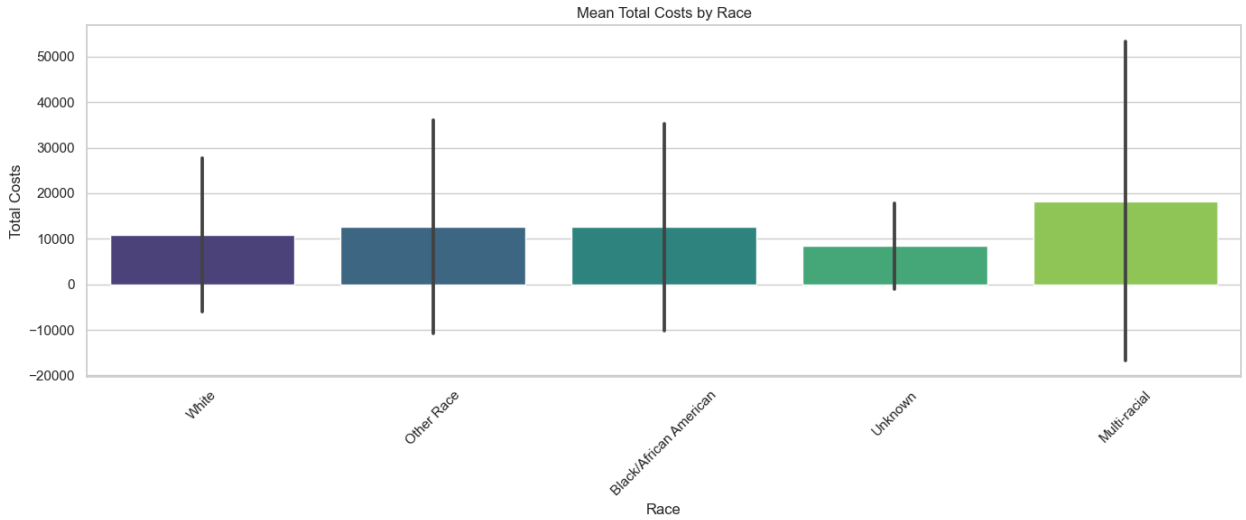


Total Costs Vs Other features

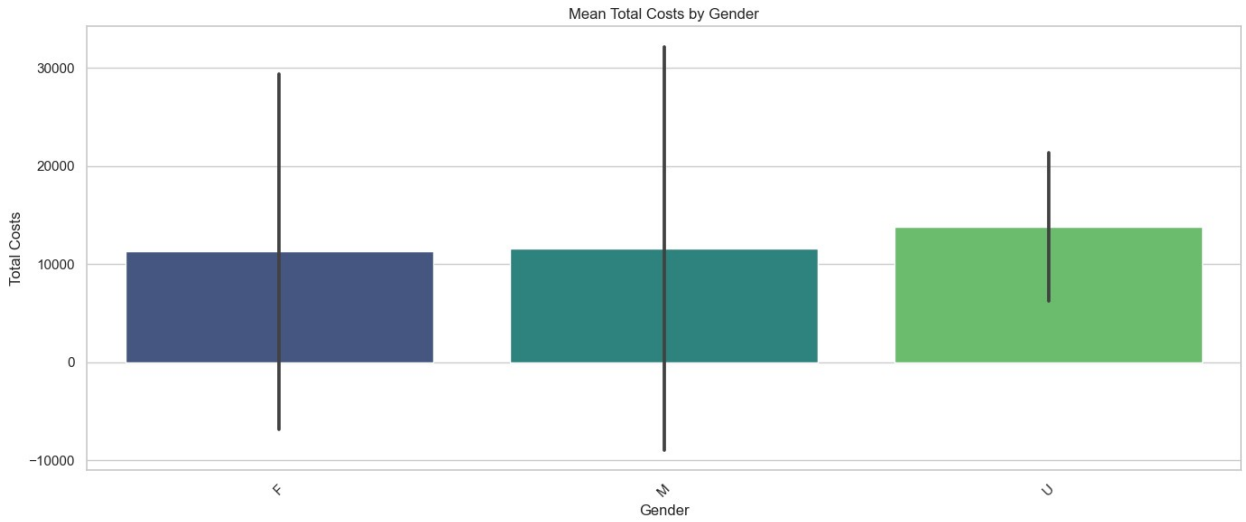
```
# Define a list of categorical features to plot against Total Costs
categorical_features = ['Race', 'Gender', 'Age Group', 'Type of
Admission', 'APR Severity of Illness Description',
                        'Ethnicity']

# Function to plot mean total costs by categorical feature
def plot_mean_total_costs_by_feature(feature):
    plt.figure(figsize=(14, 6))
    sns.barplot(x=feature, y='Total Costs', data=df, estimator='mean',
ci='sd', palette='viridis')
    plt.title(f'Mean Total Costs by {feature}')
```

```
    plt.xlabel(feature)
    plt.ylabel('Total Costs')
    plt.xticks(rotation=45)
    plt.tight_layout()  # Adjusts plot to make sure everything fits
without overlap
    plt.show()

# Plot for each feature
for feature in categorical_features:
    plot_mean_total_costs_by_feature(feature)
```

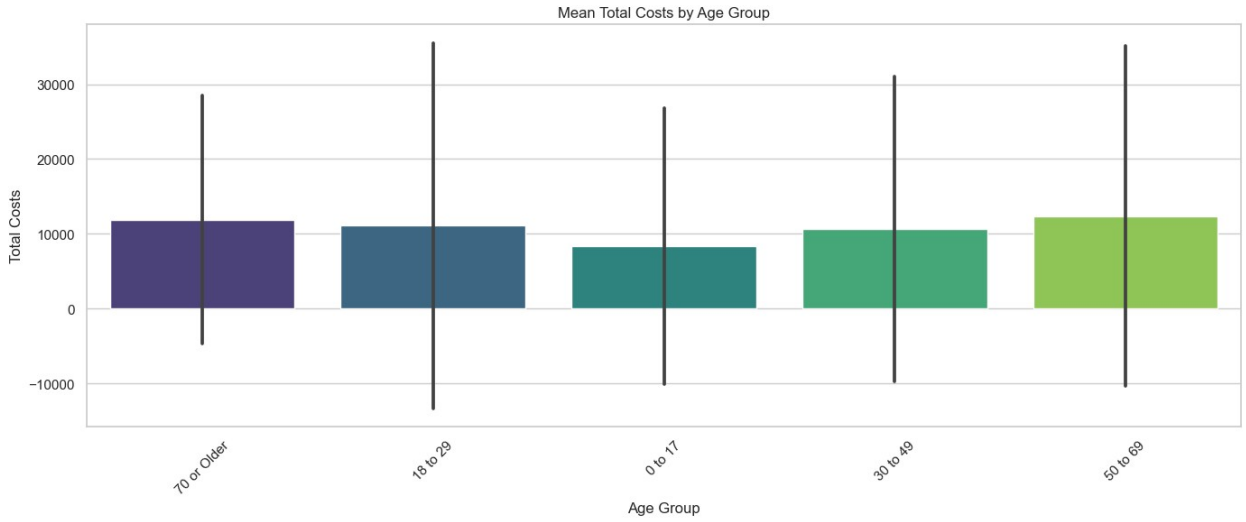
```
C:\Users\lydia\AppData\Local\Temp\ipykernel_10920\2456152702.py:8:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same
effect.

  sns.barplot(x=feature, y='Total Costs', data=df, estimator='mean',
ci='sd', palette='viridis')
```



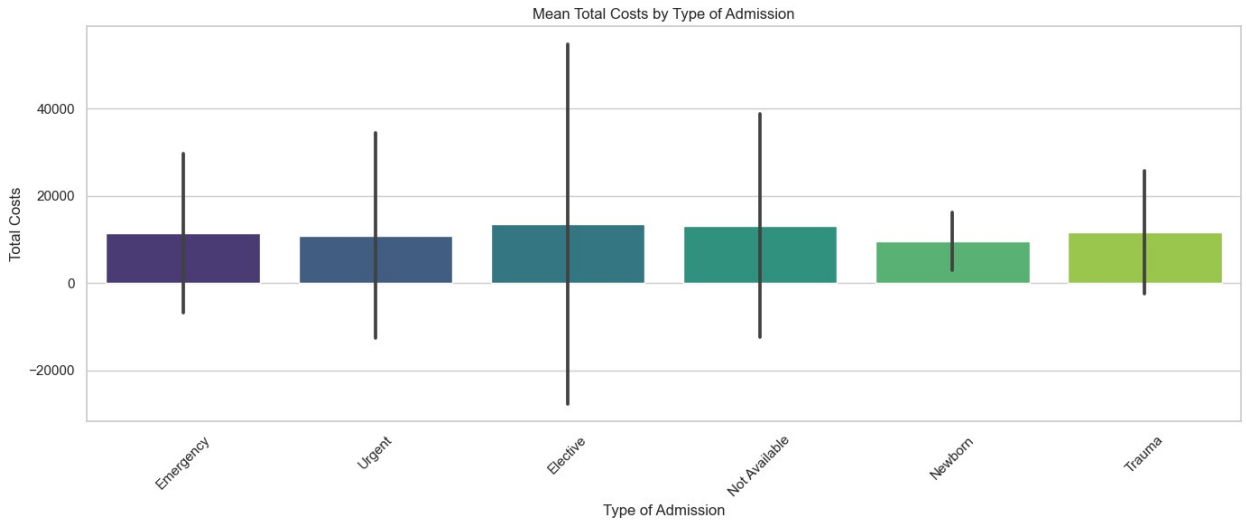

```
C:\Users\lydia\AppData\Local\Temp\ipykernel_10920\2456152702.py:8:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same
effect.

  sns.barplot(x=feature, y='Total Costs', data=df, estimator='mean',
ci='sd', palette='viridis')
```



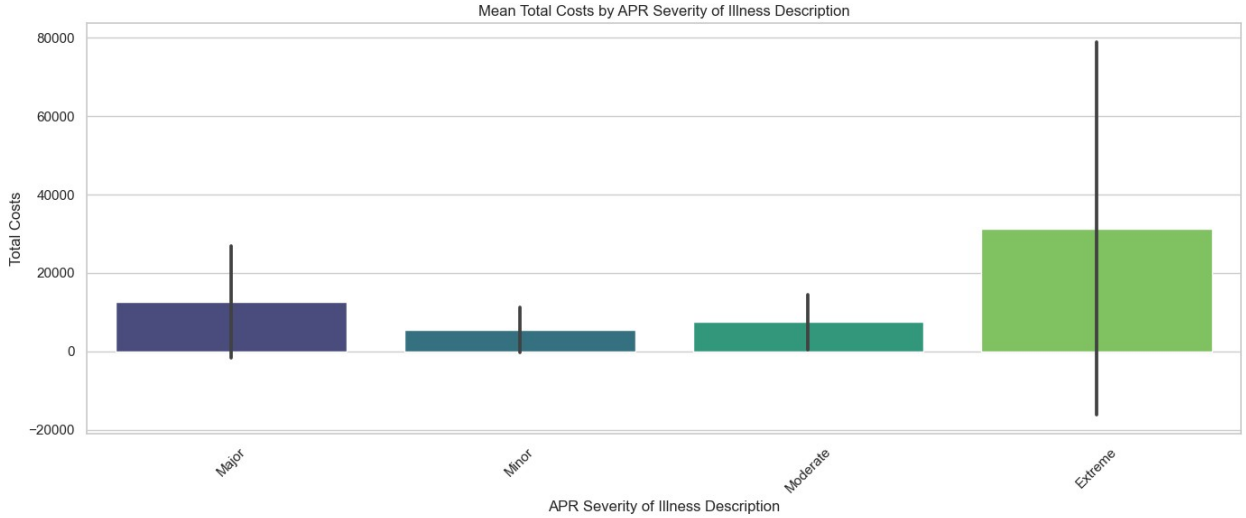

```
C:\Users\lydia\AppData\Local\Temp\ipykernel_10920\2456152702.py:8:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same
effect.

  sns.barplot(x=feature, y='Total Costs', data=df, estimator='mean',
ci='sd', palette='viridis')
```



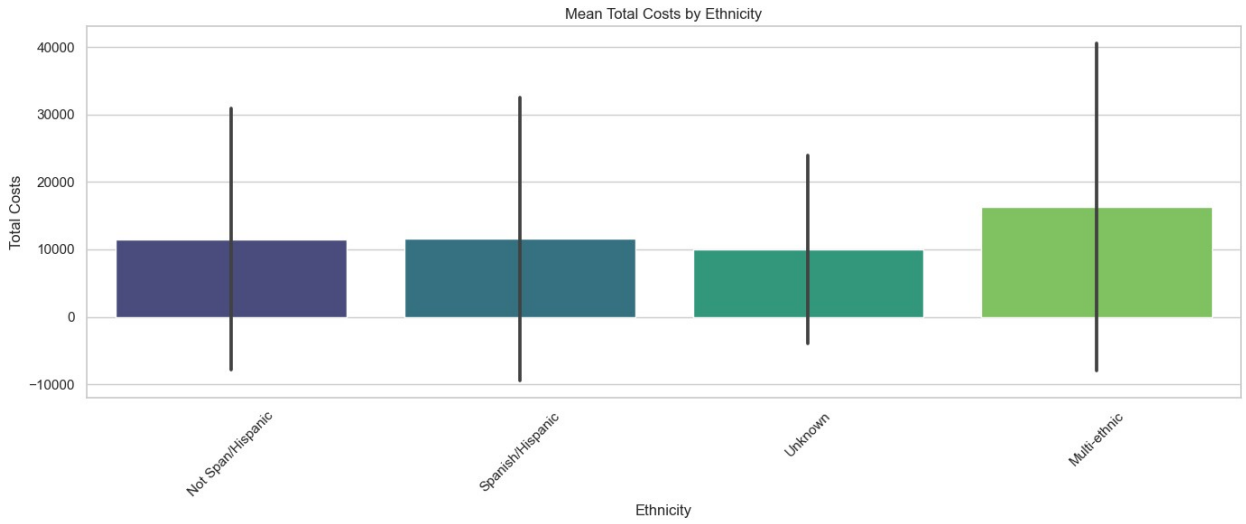

```
C:\Users\lydia\AppData\Local\Temp\ipykernel_10920\2456152702.py:8:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same
effect.

  sns.barplot(x=feature, y='Total Costs', data=df, estimator='mean',
ci='sd', palette='viridis')
```




```
C:\Users\lydia\AppData\Local\Temp\ipykernel_10920\2456152702.py:8:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same
effect.

  sns.barplot(x=feature, y='Total Costs', data=df, estimator='mean',
ci='sd', palette='viridis')
```



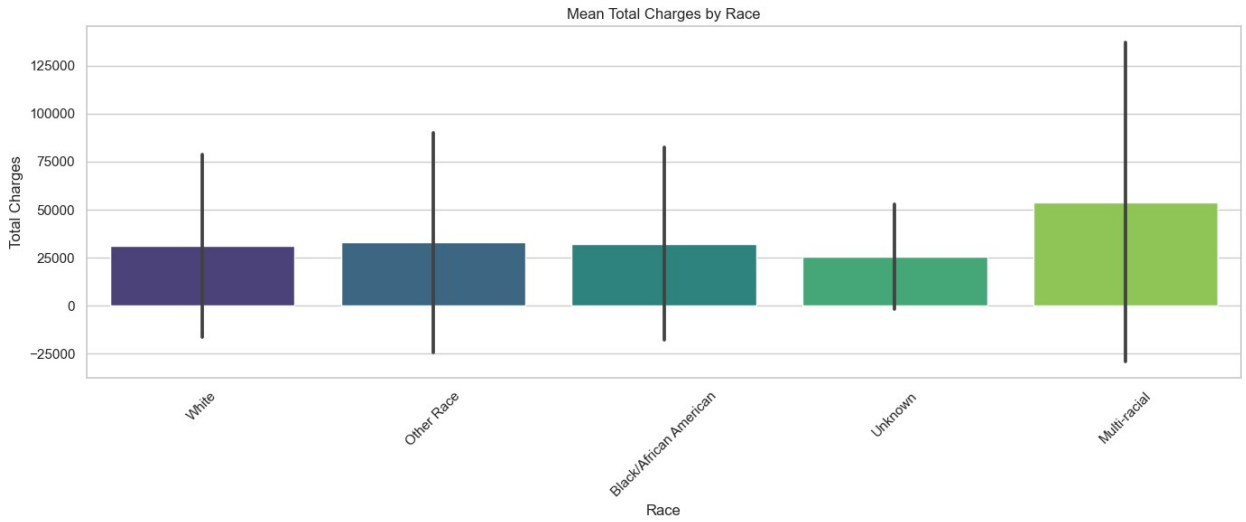

```
C:\Users\lydia\AppData\Local\Temp\ipykernel_10920\2456152702.py:8:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same
effect.

  sns.barplot(x=feature, y='Total Costs', data=df, estimator='mean',
ci='sd', palette='viridis')
```



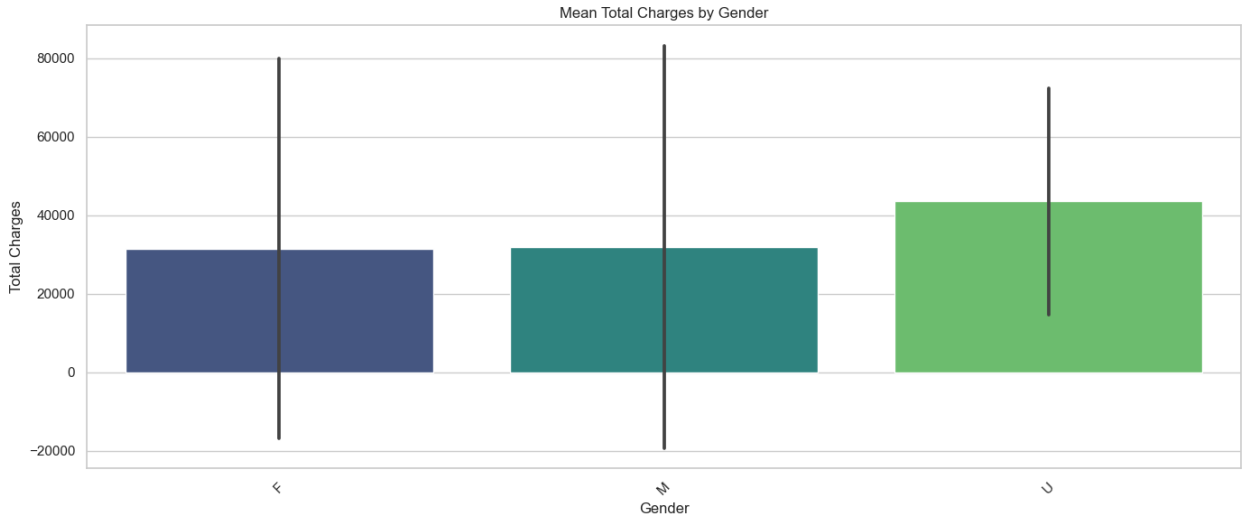
Total Charges Vs Other features

```
# Define a list of categorical features to plot against Total Charges
categorical_features = ['Race', 'Gender', 'Age Group', 'Type of
Admission', 'APR Severity of Illness Description',
                        'Ethnicity']

# Function to plot mean total charges by categorical feature
def plot_mean_total_charges_by_feature(feature):
    plt.figure(figsize=(14, 6))
    sns.barplot(x=feature, y='Total Charges', data=df,
estimator='mean', ci='sd', palette='viridis')
    plt.title(f'Mean Total Charges by {feature}')
    plt.xlabel(feature)
    plt.ylabel('Total Charges')
    plt.xticks(rotation=45)
    plt.tight_layout()  # Adjusts plot to make sure everything fits
without overlap
    plt.show()

# Plot for each feature
for feature in categorical_features:
    plot_mean_total_charges_by_feature(feature)
```

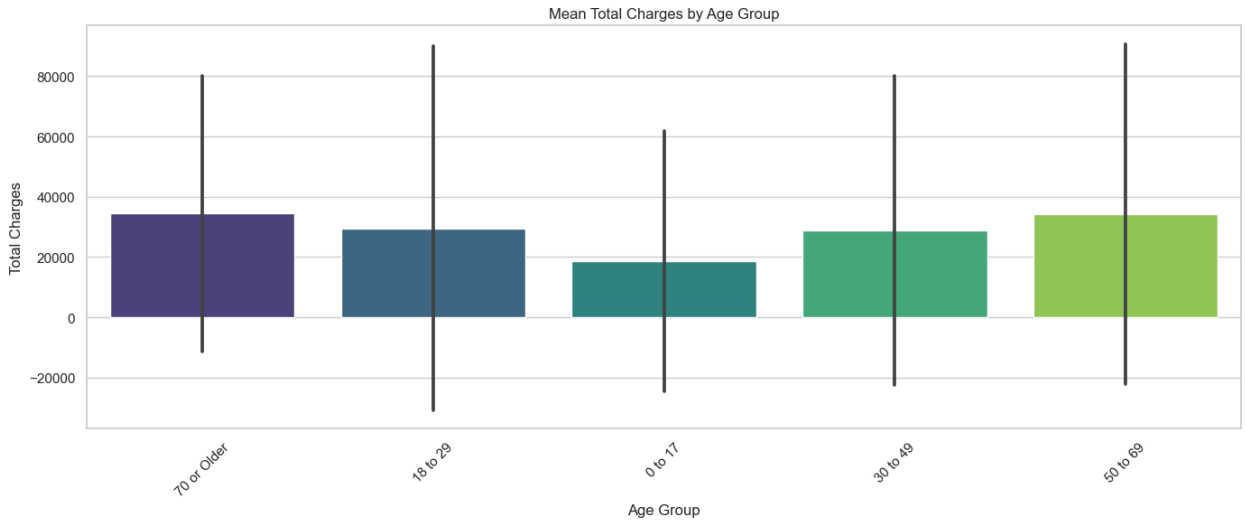
```
C:\Users\lydia\AppData\Local\Temp\ipykernel_10920\1388394571.py:8:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same
effect.

  sns.barplot(x=feature, y='Total Charges', data=df, estimator='mean',
ci='sd', palette='viridis')
```



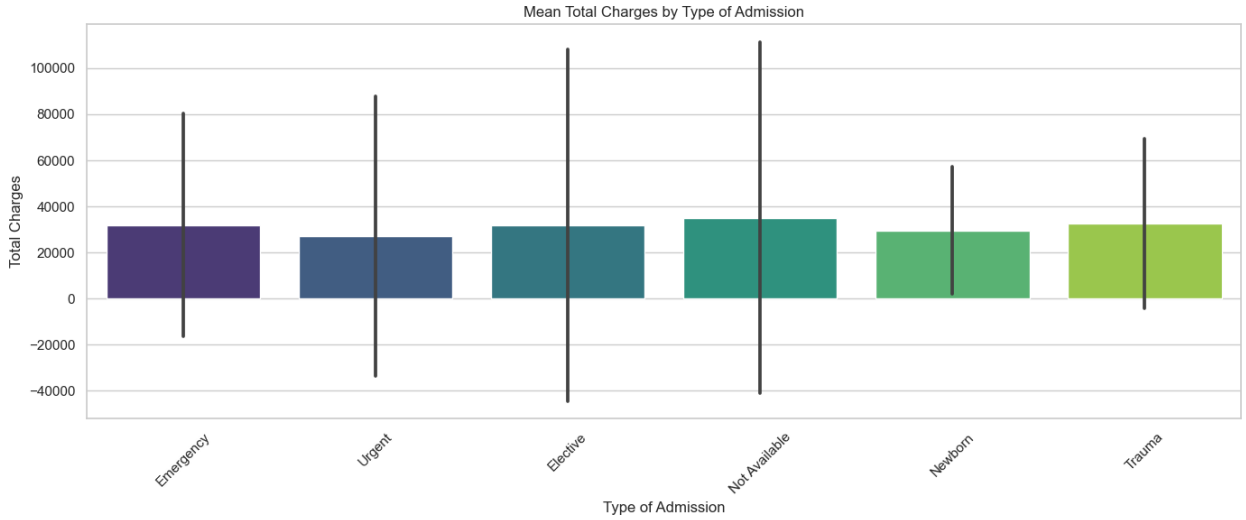

```
C:\Users\lydia\AppData\Local\Temp\ipykernel_10920\1388394571.py:8:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same
effect.

  sns.barplot(x=feature, y='Total Charges', data=df, estimator='mean',
ci='sd', palette='viridis')
```




```
C:\Users\lydia\AppData\Local\Temp\ipykernel_10920\1388394571.py:8:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same
effect.

  sns.barplot(x=feature, y='Total Charges', data=df, estimator='mean',
ci='sd', palette='viridis')
```

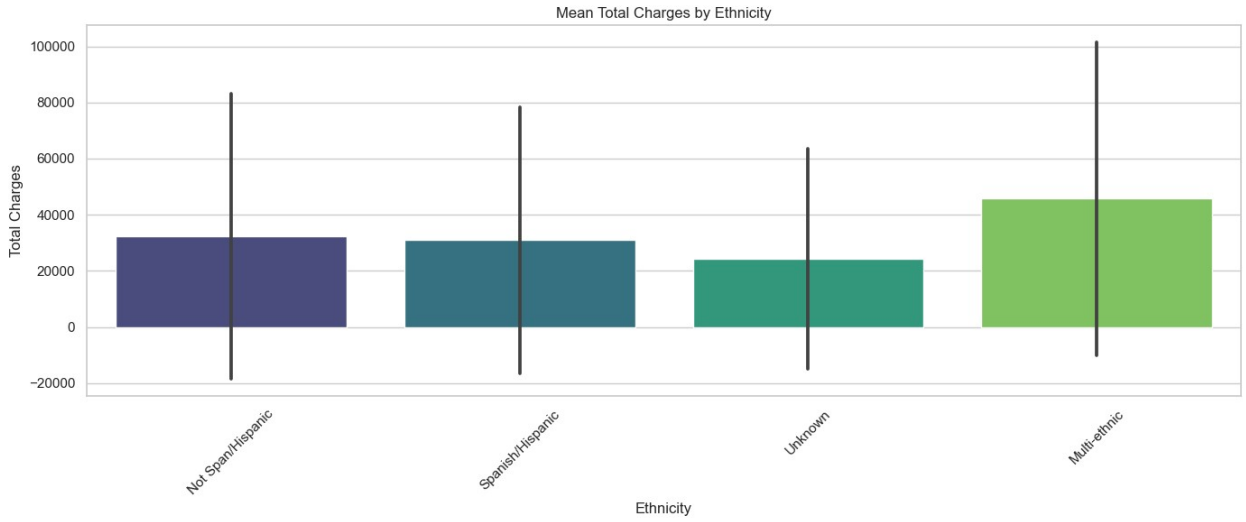



```
C:\Users\lydia\AppData\Local\Temp\ipykernel_10920\1388394571.py:8:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same
effect.

  sns.barplot(x=feature, y='Total Charges', data=df, estimator='mean',
ci='sd', palette='viridis')
```




```
C:\Users\lydia\AppData\Local\Temp\ipykernel_10920\1388394571.py:8:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same
effect.

  sns.barplot(x=feature, y='Total Charges', data=df, estimator='mean',
ci='sd', palette='viridis')
```


```
C:\Users\lydia\AppData\Local\Temp\ipykernel_10920\1388394571.py:8:
FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same
effect.

  sns.barplot(x=feature, y='Total Charges', data=df, estimator='mean',
ci='sd', palette='viridis')
```



3.3 Multivariate Analysis

Severity of Illness by Gender and Race

```
# Create the contingency table
contingency_table_severity_gender_race = pd.crosstab(index=[df['APR
Severity of Illness Description'], df['Race']], columns=df['Gender'])
```

```
# Print the contingency table
print(contingency_table_severity_gender_race)
```

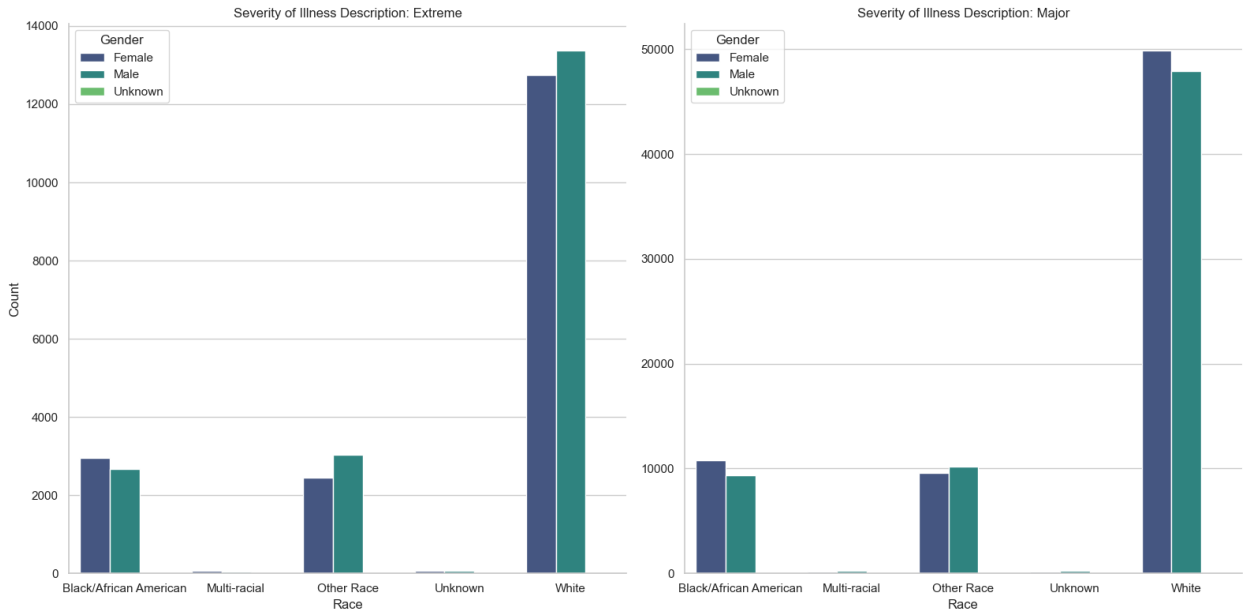
```
Gender                                                          F
M  U
APR Severity of Illness Description Race

Extreme                              Black/African American   2951
2664  0
                                     Multi-racial               62
54  0
                                     Other Race               2440
3031  0
                                     Unknown                    64
57  0
                                     White                   12747
13382  0
Major                                Black/African American  10774
9384  2
                                     Multi-racial              200
208  0
                                     Other Race               9620
10163  0
                                     Unknown                   200
233  0
                                     White                   49905
47907  0
Minor                                Black/African American   5005
4990  0
                                     Multi-racial               45
42  0
                                     Other Race               6766
7073  0
                                     Unknown                   134
141  0
                                     White                   12584
12536  0
Moderate                             Black/African American  14252
12676  0
                                     Multi-racial              184
191  0
                                     Other Race              14725
14878  0
                                     Unknown                   320
301  0
                                     White                   49478
46670  1
```

```
# Create the contingency table
contingency_table_severity_gender_race = pd.crosstab(
```

```
    [df['APR Severity of Illness Description'], df['Race']],
    df['Gender'],
    margins=False
).reset_index()

# Rename columns for clarity
contingency_table_severity_gender_race.columns.name = None  # Remove
the name of the columns
contingency_table_severity_gender_race =
contingency_table_severity_gender_race.rename(columns={'U':
'Unknown'})

# Melt the data for plotting
severity_gender_race_df = pd.melt(
    contingency_table_severity_gender_race,
    id_vars=['APR Severity of Illness Description', 'Race'],
    value_vars=['F', 'M', 'Unknown'],
    var_name='Gender',
    value_name='Count'
)

# Filter data for the first two severity descriptions
severity_descriptions_first_half = ['Extreme', 'Major']
subset_data_first_half =
severity_gender_race_df[severity_gender_race_df['APR Severity of
Illness Description'].isin(severity_descriptions_first_half)]

# Create a discrete palette from the viridis colormap
num_colors = len(subset_data_first_half['Gender'].unique())
viridis_palette = sns.color_palette("viridis", num_colors)

# Convert the viridis color palette to hex
viridis_palette_hex = [to_hex(color) for color in viridis_palette]

# Plot the FacetGrid for the first two severity descriptions
g1 = sns.FacetGrid(subset_data_first_half, col='APR Severity of
Illness Description', col_wrap=2, height=8, sharey=False)
g1.map(sns.barplot, 'Race', 'Count', 'Gender',
palette=viridis_palette_hex)

# Modify legend
for ax in g1.axes.flat:
    handles, labels = ax.get_legend_handles_labels()
    # Update legend labels
    new_labels = ['Female', 'Male', 'Unknown']
    ax.legend(handles=handles, labels=new_labels, title='Gender')

# Set axis labels and titles
g1.set_axis_labels('Race', 'Count')
g1.set_titles(col_template='Severity of Illness Description:
```

```
{col_name}')

plt.show()
```

```
C:\Users\lydia\anaconda3\Lib\site-packages\seaborn\axisgrid.py:712:
UserWarning: Using the barplot function without specifying `order` is
likely to produce an incorrect plot.
  warnings.warn(warning)
C:\Users\lydia\anaconda3\Lib\site-packages\seaborn\axisgrid.py:717:
UserWarning: Using the barplot function without specifying `hue_order`
is likely to produce an incorrect plot.
  warnings.warn(warning)
C:\Users\lydia\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```

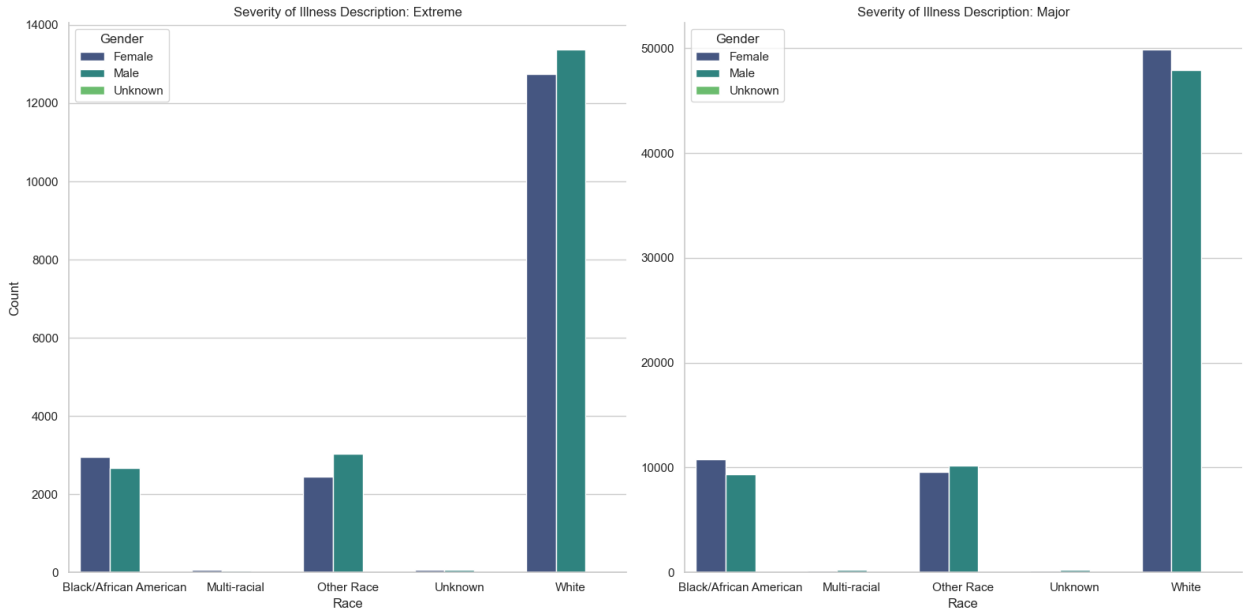


- Severity Distribution: Females generally have higher counts in the major and moderate severity categories, while males have slightly higher counts in the extreme severity category.
- Gender Distribution: For all severity levels, the number of cases with unknown gender is very low, indicating that the majority of cases have well-documented gender information.
- Comparative Insight: Most severity levels show more cases for females compared to males, except for extreme severity, where males slightly outnumber females.

```
# Filter data for the first two severity descriptions
severity_descriptions_second_half = ['Minor', 'Moderate']
subset_data_second_half =
severity_gender_race_df[severity_gender_race_df['APR Severity of
Illness Description'].isin(severity_descriptions_first_half)]
```

```
# Create a discrete palette from the viridis colormap
num_colors = len(subset_data_first_half['Gender'].unique())
viridis_palette = sns.color_palette("viridis", num_colors)

# Convert the viridis color palette to hex
viridis_palette_hex = [to_hex(color) for color in viridis_palette]

# Plot the FacetGrid for the first two severity descriptions
g1 = sns.FacetGrid(subset_data_second_half, col='APR Severity of
Illness Description', col_wrap=2, height=8, sharey=False)
g1.map(sns.barplot, 'Race', 'Count', 'Gender',
palette=viridis_palette_hex)

# Modify legend
for ax in g1.axes.flat:
    handles, labels = ax.get_legend_handles_labels()
    # Update legend labels
    new_labels = ['Female', 'Male', 'Unknown']
    ax.legend(handles=handles, labels=new_labels, title='Gender')

# Set axis labels and titles
g1.set_axis_labels('Race', 'Count')
g1.set_titles(col_template='Severity of Illness Description:
{col_name}')

plt.show()
```

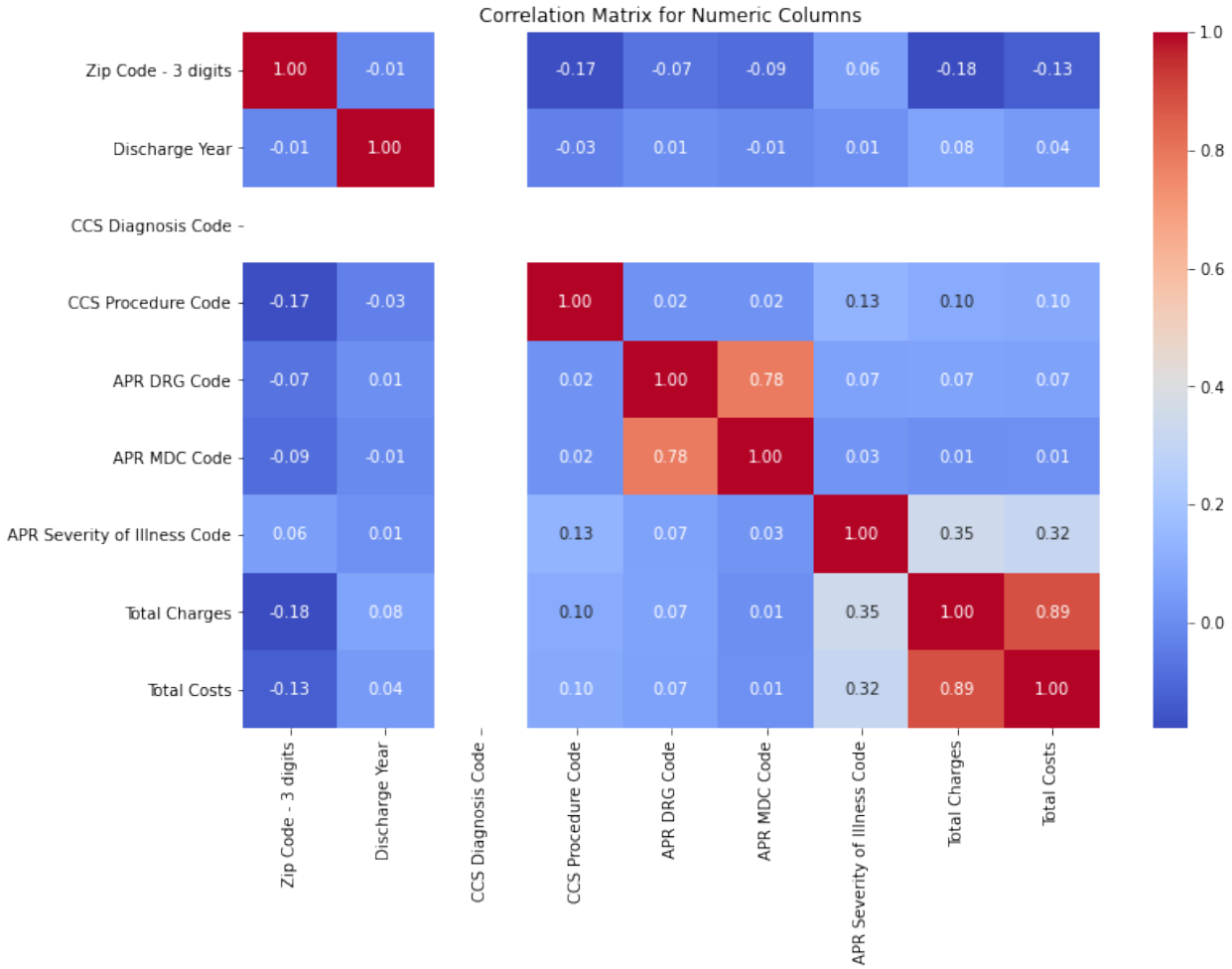
```
C:\Users\lydia\anaconda3\Lib\site-packages\seaborn\axisgrid.py:712:
UserWarning: Using the barplot function without specifying `order` is
likely to produce an incorrect plot.
  warnings.warn(warning)
C:\Users\lydia\anaconda3\Lib\site-packages\seaborn\axisgrid.py:717:
UserWarning: Using the barplot function without specifying `hue_order`
is likely to produce an incorrect plot.
  warnings.warn(warning)
C:\Users\lydia\anaconda3\Lib\site-packages\seaborn\axisgrid.py:118:
UserWarning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```



Data Preparation.

Correlation Matrix

```
numeric_df = df.select_dtypes(include=['number'])

# Calculate the correlation matrix
corr_matrix = numeric_df.corr()

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix for Numeric Columns')
plt.show()
```



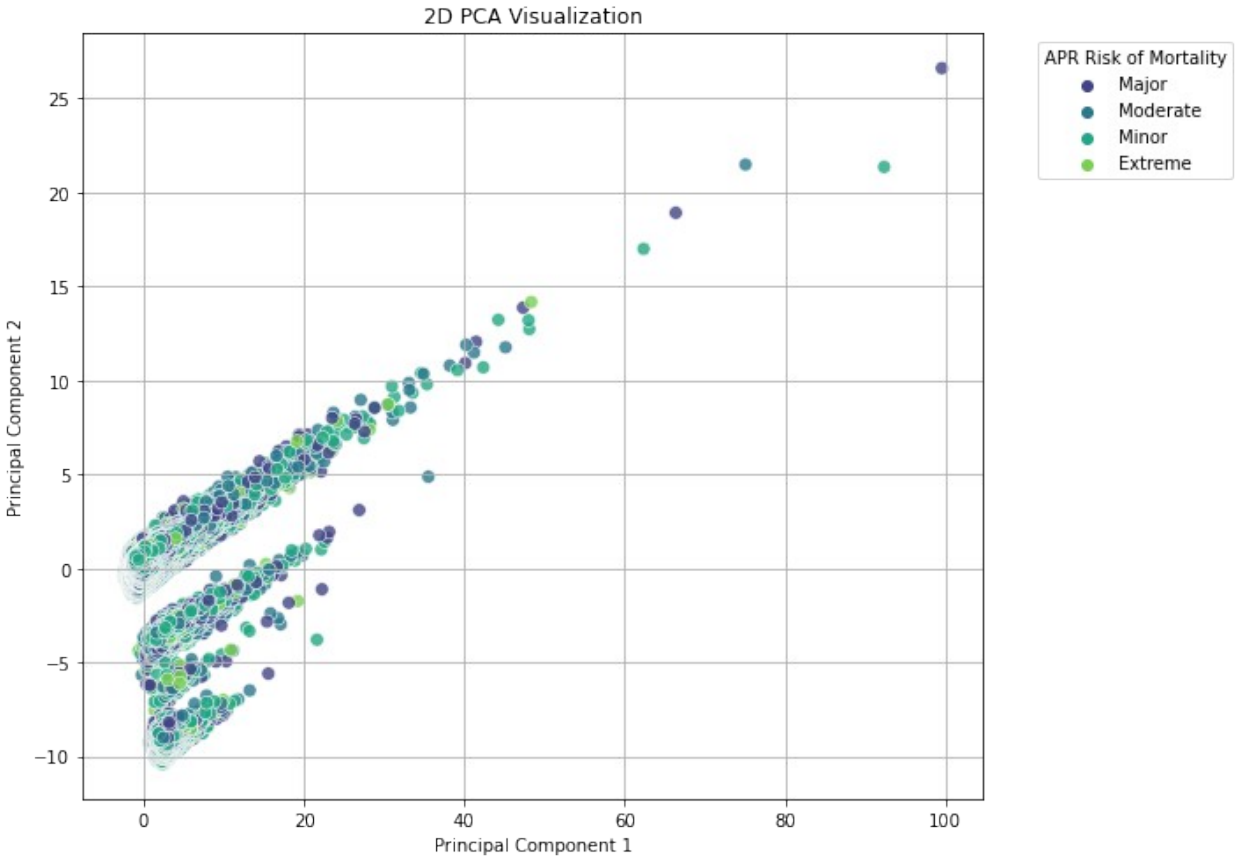
From the correlation matrix, Total charges and Total cost seem to have multicolinearity. Lets handle it with PCA.

PCA

```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report
import matplotlib.pyplot as plt
import seaborn as sns
target = 'APR Risk of Mortality'

# Identify numeric and categorical columns
numeric_features =
df.select_dtypes(include=[np.number]).columns.tolist()
categorical_features =
```

```
df.select_dtypes(exclude=[np.number]).columns.tolist()

# Remove target variable from the features lists
if target in numeric_features:
    numeric_features.remove(target)
if target in categorical_features:
    categorical_features.remove(target)

# Encode categorical variables
df_encoded = pd.get_dummies(df, columns=categorical_features,
drop_first=True)

# Standardize the numeric features
scaler = StandardScaler()
df_encoded[numeric_features] =
scaler.fit_transform(df_encoded[numeric_features])

# Perform PCA
pca = PCA(n_components=2)
principalComponents =
pca.fit_transform(df_encoded.drop(columns=[target]).values)

# Create a DataFrame with the principal components
principalDf = pd.DataFrame(data=principalComponents,
columns=['Principal Component 1', 'Principal Component 2'])

# Include the target variable in the DataFrame
finalDf = pd.concat([principalDf, df[[target]]], axis=1)

# Plotting the PCA results
plt.figure(figsize=(10, 7))

# Scatter plot
sns.scatterplot(
    x='Principal Component 1',
    y='Principal Component 2',
    hue=target,  # Use the target variable for coloring
    palette='viridis',
    data=finalDf,
    s=60,
    alpha=0.8
)

plt.title('2D PCA Visualization')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')

# Move the legend to the top-right corner
plt.legend(title=target, bbox_to_anchor=(1.05, 1), loc='upper left')
```

```
plt.grid(True)
plt.tight_layout()  # Adjust layout to fit legend

plt.show()
```



PCA reduces the variables into principal components that reduces multicolinearity

4. Modelling

4.1 Modelling Processing

We explored both traditional machine learning models and deep learning models to predict the target variable, which is a multi-class classification problem with four distinct classes.

Machine Learning Models

- Logistic Regression Model(Baseline)
- Decision Tree
- XG Boost

Deep Learning Models For deep learning models, we employed several architectures to leverage their capacity to learn complex patterns from data:

- Feedforward Neural Network (FNN)
- Multilayer Perceptron (MLP)
- Artificial Neural Network (ANN)
- Ensemble Methods (DNN, ANN, and MLP)

Optimizer and Loss Function

Optimizer: Adam

The Adam optimizer was chosen for training our deep learning models. Adam is an adaptive learning rate optimization algorithm that combines the advantages of two other popular methods: AdaGrad and RMSProp. It is well-suited for handling sparse gradients on noisy data. Its key features include:

- Adaptive Learning Rates: Adam adjusts the learning rate for each parameter individually, which is beneficial for models with complex parameter spaces.
- Efficient: Requires less memory and is computationally efficient.
- Robust: Works well in practice for a wide range of deep learning architectures and problems.

Loss Function: Sparse Categorical Crossentropy

We used sparse_categorical_crossentropy as the loss function for our multi-class classification task. The reasons for choosing this loss function include:

- Efficient for Multi-Class Problems: Specifically designed for multi-class classification where the target variable can belong to one of several classes.
- Minimizes the Log Loss: Encourages the model to produce probabilities close to 1 for the true class and close to 0 for other classes, optimizing classification accuracy.

4. 2 Evaluation Metrics

For evaluating the performance of our models, we will focus primarily on recall and precision, while also considering f1 score, confusion matrix and ROC Curve as supplementary metrics.

Primary Metrics

Recall:

Recall is crucial in predicting "APR Risk of Mortality" because it measures the model's ability to correctly identify high-risk patients. Given the serious consequences of missing a high-risk case (false negative) in a healthcare setting, our goal is to achieve a recall of 85%. This target will serve as the benchmark for determining whether the model performs well in capturing true positive cases.

Precision:

Precision indicates the model’s ability to provide accurate predictions and minimize false positives. In healthcare, high precision ensures that when the model identifies a patient as high-risk, there is a strong likelihood that the patient is indeed high-risk. While our primary focus is on

achieving a recall of 85%, maintaining high precision is also important to avoid unnecessary interventions or treatments.

Balance between Recall and Precision

Achieving a balance between recall and precision is essential. Our goal is to maximize recall while maintaining acceptable precision, thereby minimizing both false negatives (missed high-risk cases) and false positives (incorrectly classified low-risk cases).

Additional Metrics

Confusion Matrix:

The confusion matrix will provide detailed insights into the types of errors the model makes. It will help us understand where the model struggles and which classes are often confused with each other, guiding further improvements. Our target recall of 85% will serve as the baseline for assessing the model's performance, with other metrics providing additional context and insights.

ROC Curve

It's an essential tool for evaluating the performance of classification models. It provides a comprehensive view of a model's ability to distinguish between different classes and helps in making informed decisions about threshold selection and model improvements.The model with the highest AUC is the best model to use for feature importance.

Feature Importance

With the highest performing model, we were able to conduct feature importance and identify the most important features that predict In hospital mortality for pneumonia patients.

4.3 Data Preprocessing

Feature Selection and Target Variable

Features: We used the principal components to train our machine learning models as it takes a shorter time. All columns from the dataset were used as features to build our deep learning models. This is because the deep learning models could handle the large dataset and gave us the best results.

Target Variable: The target variable for our classification task is the "APR Risk of Mortality," which is a multi-class variable with four distinct classes representing different levels of mortality risk.

Data Usage Strategy

Due to the large size of our dataset, we adopted different data usage strategies for different models:

Logistic Regression, Decision Trees and XG Boost:

For this models, we used PCA to obtain principal componenets then trained our data on this using this models. This approach was chosen to manage computational resources efficiently, as decision trees can be memory-intensive and computationally expensive when trained on very large datasets.

Other Models (XG Boost, FNN, MLP, ANN, Ensemble Methods):

For these models, we utilized the entire dataset. The full dataset allows these models to fully capture the patterns and complexities present in the data. Deep learning models, in particular, benefit from larger datasets due to their capacity to learn intricate patterns and dependencies. XG Boost was identified as the best model from the ROC Curve, we then trained it using the entire dataset and then used it for feature importance.

Logistic Regression

```
# Split the dataset
X = principalDf
y = df[target]
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Logistic Regression Model
log_reg_model = LogisticRegression()
log_reg_model.fit(X_train, y_train)
y_pred_log_reg = log_reg_model.predict(X_test)
print("Logistic Regression Model")
print("Accuracy:", accuracy_score(y_test, y_pred_log_reg))
print("Classification Report:\n", classification_report(y_test,
y_pred_log_reg))
```

```
Logistic Regression Model
Accuracy: 0.5086666314900802
Classification Report:
              precision    recall  f1-score   support

     Extreme       0.57      0.12      0.19      5748
       Major       0.47      0.41      0.44     18160
       Minor       0.61      0.69      0.65     25492
    Moderate       0.43      0.49      0.46     26408

    accuracy                           0.51     75808
   macro avg       0.52      0.43      0.43     75808
weighted avg       0.51      0.51      0.50     75808
```

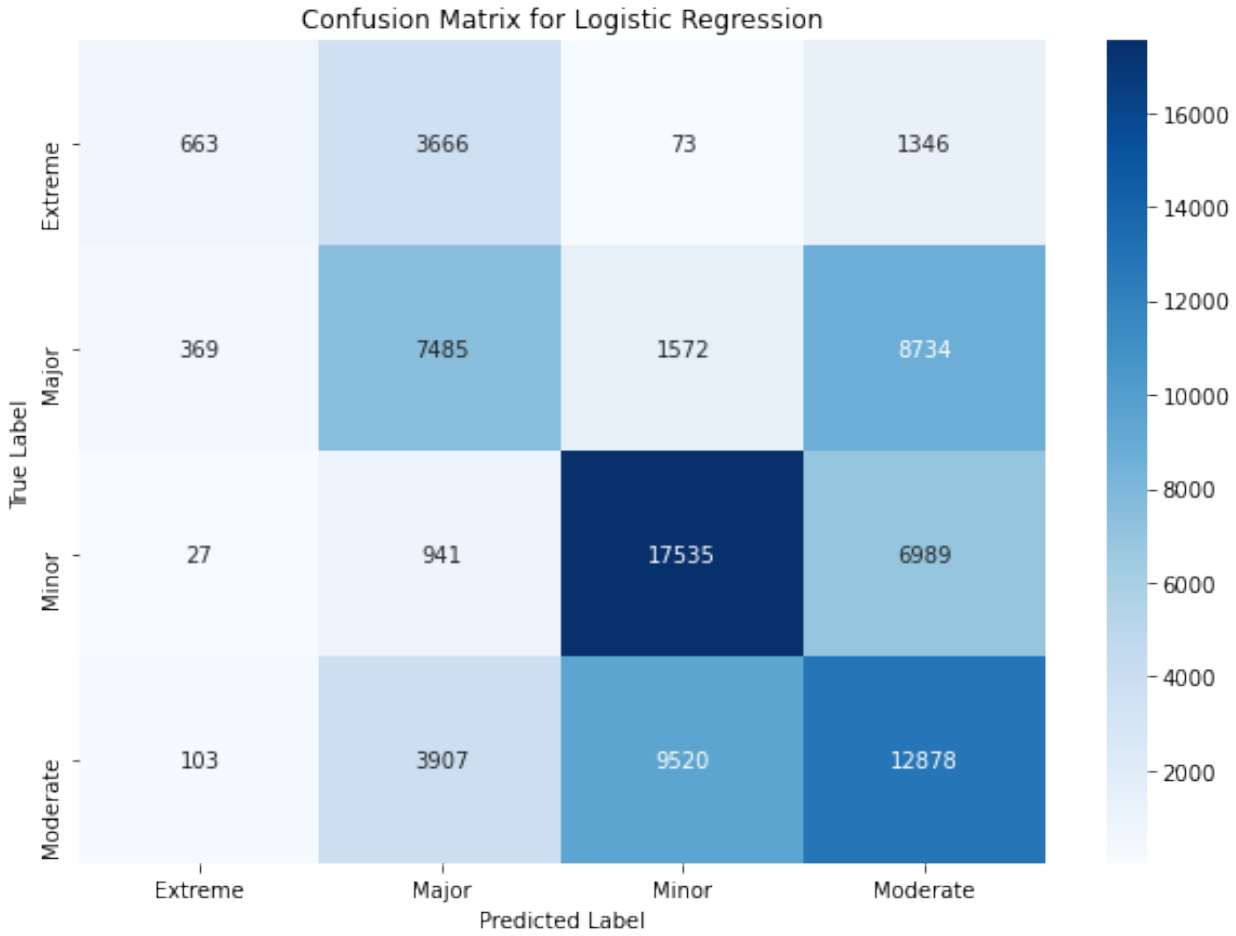
1) For the Extreme class, the model has a relatively higher precision but very low recall. This indicates that when the model predicts the Extreme class, it is correct 57% of the time, but it only identifies 12% of the true Extreme cases.

2) The Major class has moderate precision and recall, meaning that the model predicts this class with some degree of accuracy but still misses a considerable number of actual cases.

3)The Minor class has the highest precision, recall, and F1-score among all classes, indicating that the model performs best in predicting this class.

4) For the Moderate class, the precision and recall are slightly below average, suggesting that the model has difficulty distinguishing this class from other

```
from sklearn.metrics import confusion_matrix
# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred_log_reg,
labels=log_reg_model.classes_)

# Plot confusion matrix
plt.figure(figsize=(10,7))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=log_reg_model.classes_,
yticklabels=log_reg_model.classes_)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix for Logistic Regression')
plt.show()
```



Decision Tree

```
# Decision Tree Model
dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train, y_train)
y_pred_dt = dt_model.predict(X_test)
print("Decision Tree Model")
print("Accuracy:", accuracy_score(y_test, y_pred_dt))
print("Classification Report:\n", classification_report(y_test,
y_pred_dt))
```

```
Decision Tree Model
Accuracy: 0.4378033980582524
Classification Report:
              precision    recall  f1-score   support

     Extreme       0.26      0.27      0.26      5748
       Major       0.38      0.38      0.38     18160
       Minor       0.55      0.56      0.56     25492
    Moderate       0.40      0.40      0.40     26408

    accuracy                           0.44     75808
   macro avg       0.40      0.40      0.40     75808
weighted avg       0.44      0.44      0.44     75808
```

The overall accuracy of the decision tree model is 43.78%, meaning the model correctly classified approximately 44% of the samples.

1) Out of all predictions made for the "Extreme" class, only 26% were correct. This indicates a relatively high number of false positives. Of all actual "Extreme" instances, the model correctly identified 27%. This reflects a considerable number of false negatives.

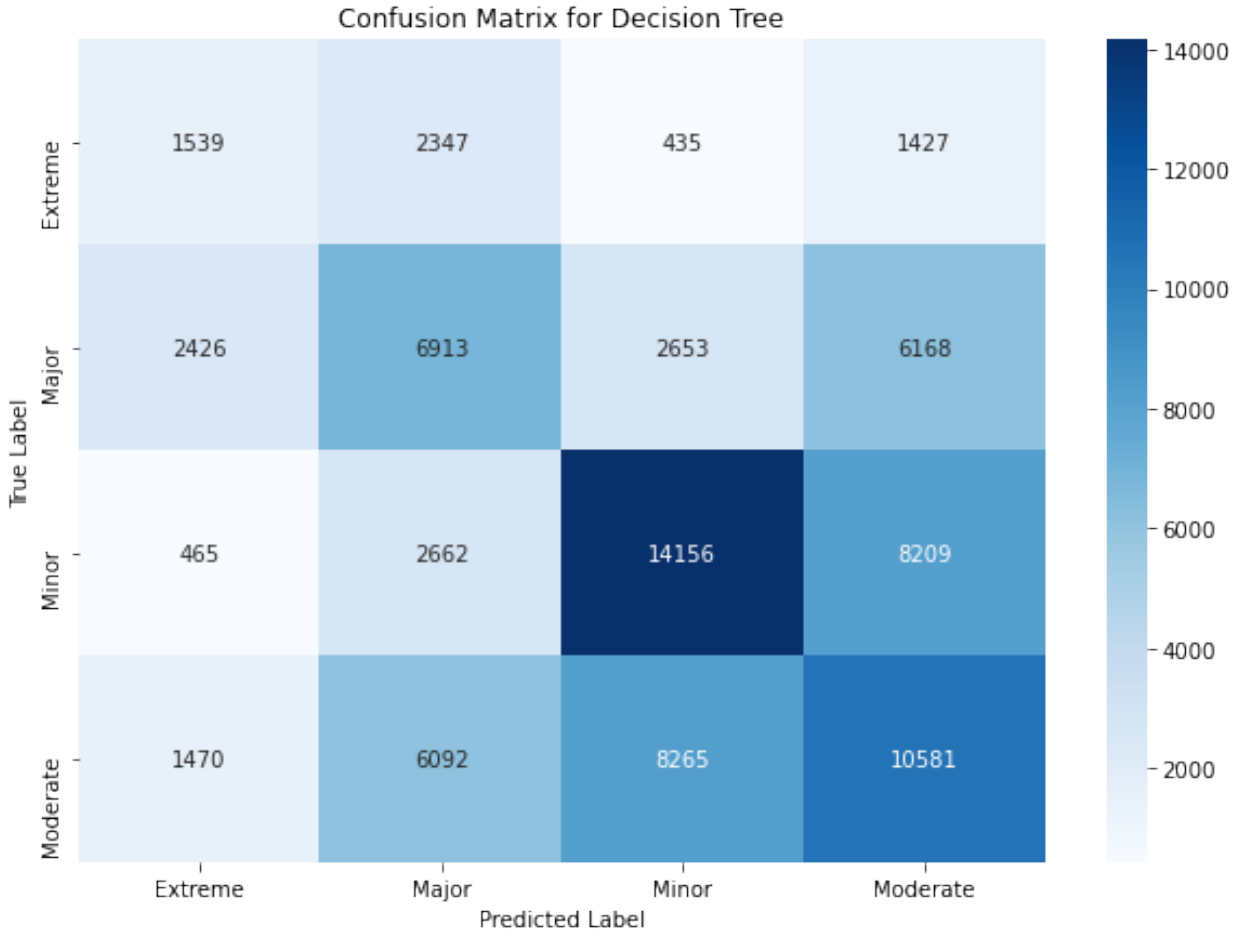
2)The model's precision for the "Major" class is 38%, showing a high number of false positives.The recall is 38%, indicating a significant number of false negatives.

3)For the "Minor" class, 55% of the predictions were accurate. This is the highest precision among the classes. The model correctly identified 56% of the actual "Minor" cases, which is comparatively better than other classes.

4)The precision for the "Moderate" class is 40%, showing room for improvement. The recall is 40%, indicating a need to reduce false negatives.

```
from sklearn.metrics import confusion_matrix
# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred_dt, labels=dt_model.classes_)

# Plot the confusion matrix
plt.figure(figsize=(10,7))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
xticklabels=dt_model.classes_, yticklabels=dt_model.classes_)
```

```
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix for Decision Tree')
plt.show()
```



XG Boost

```
# Initialize the XGBoost model
import xgboost as xgb
from sklearn.metrics import accuracy_score, classification_report,
roc_curve, roc_auc_score
import matplotlib.pyplot as plt
xg_boost_model = xgb.XGBClassifier(random_state=42)

# Fit the model
xg_boost_model.fit(X_train, y_train)

# Make predictions
y_pred_xgb = xg_boost_model.predict(X_test)
y_probs_xgb = xg_boost_model.predict_proba(X_test)[:, 1]  # For binary
classification
```

```
# Print accuracy and classification report
print("XGBoost Model")
print("Accuracy:", accuracy_score(y_test, y_pred_xgb))
print("Classification Report:\n", classification_report(y_test,
y_pred_xgb))
```

```
XGBoost Model
Accuracy: 0.5377005065428451
Classification Report:
              precision    recall  f1-score   support

     Extreme       0.50      0.20      0.29      5748
       Major       0.49      0.51      0.50     18160
       Minor       0.63      0.71      0.67     25492
    Moderate       0.47      0.46      0.47     26408

    accuracy                           0.54     75808
   macro avg       0.52      0.47      0.48     75808
weighted avg       0.53      0.54      0.53     75808
```

1) Out of all predictions made for the "Extreme" class, 50% were correct. This indicates that half of the positive predictions are true positives. For Recall, the model correctly identified only 20% of the actual "Extreme" instances, which means there are a significant number of false negatives.

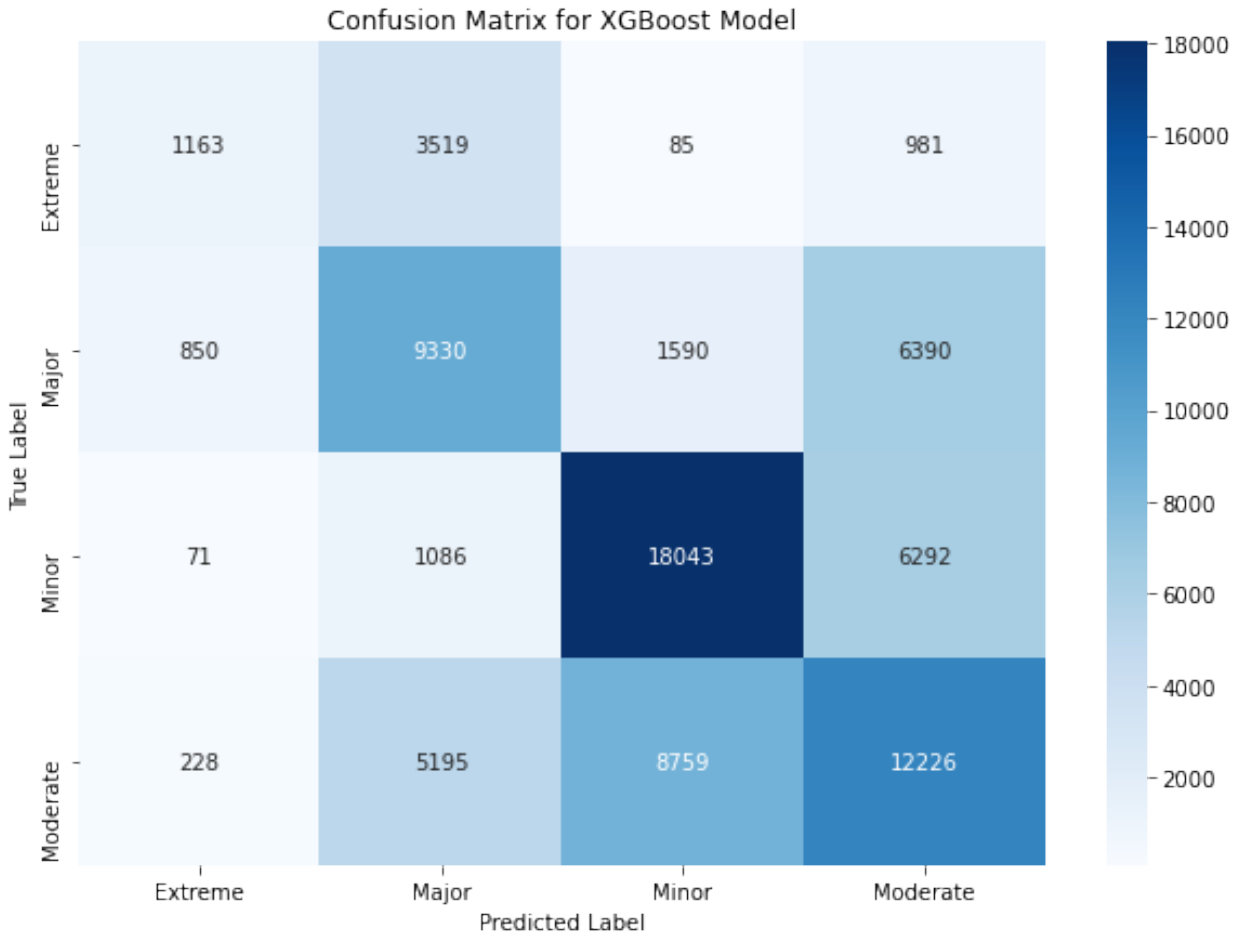
2)The model's precision for the "Major" class is 49%, showing a moderate number of false positives.The recall is 51%, indicating the model captures slightly more than half of the actual "Major" cases.

3)For the "Minor" class, 63% of the predictions were accurate, making this the class with the highest precision. The model correctly identified 71% of the actual "Minor" cases, demonstrating strong recall performance.

4)The precision for the "Moderate" class is 47%, showing that there are some false positives. The recall is 46%, suggesting a number of false negatives.

```
from sklearn.metrics import confusion_matrix
import seaborn as sns

# Make predictions
y_pred_xgb = xg_boost_model.predict(X_test)

# Compute confusion matrix
cm_xgb = confusion_matrix(y_test, y_pred_xgb,
labels=xg_boost_model.classes_)

# Plot confusion matrix
plt.figure(figsize=(10,7))
```

```
sns.heatmap(cm_xgb, annot=True, fmt='d', cmap='Blues',
xticklabels=xg_boost_model.classes_,
yticklabels=xg_boost_model.classes_)
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.title('Confusion Matrix for XGBoost Model')
plt.show()
```



DEEP LEARNING MODELS

Feed Forward Neural Network

```
# Defining the FFNN Model
model = Sequential([
    Dense(128, input_shape=(902,), activation='relu'),  # Ensure the
input shape matches
    Dense(64, activation='relu'),
    Dense(4, activation='softmax')  # Assuming 4 classes for the
target
])
```

```
# Compile the model
model.compile(optimizer='adam',
loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Train the model
history = model.fit(x_train, y_train, epochs=20, batch_size=32,
validation_split=0.2, verbose=1)
```

```
---------------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
<ipython-input-114-ae7ea78f17e7> in <module>
      1 # Defining the FFNN Model
----> 2 model = Sequential([
      3     Dense(128, input_shape=(902,), activation='relu'),  #
Ensure the input shape matches
      4     Dense(64, activation='relu'),
      5     Dense(4, activation='softmax')  # Assuming 4 classes for
the target

NameError: name 'Sequential' is not defined
```

Evaluation

```
# Make predictions
y_pred = model.predict(x_test)
y_pred_classes = y_pred.argmax(axis=1)

# Classification report
print('Classification report')
print(classification_report(y_test, y_pred_classes))
```

```
2369/2369 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step
Classification report
              precision    recall  f1-score   support

           0       0.68      0.61      0.64      5748
           1       0.59      0.59      0.59     18160
           2       0.64      0.66      0.65     26408
           3       0.84      0.84      0.84     25492

    accuracy                           0.70     75808
   macro avg       0.69      0.67      0.68     75808
weighted avg       0.70      0.70      0.70     75808
```

Interpretation

Class 0 (Extreme):

Precision (0.68): Of all instances predicted as Class 0, 68% are actually Class 0.

Recall (0.57): Of all actual Class 0 instances, 57% are correctly identified as Class 0.

F1-Score (0.62): Balances precision and recall for Class 0.

Class 0 has moderate precision but lower recall. This indicates that while the predictions for Class 0 are reasonably accurate, the model misses a significant number of true Class 0 instances. The F1-Score reflects this balance, showing that improvements could be made in correctly identifying more Class 0 instances.

Class 1 (Major):

Precision (0.60): Of all instances predicted as Class 1, 60% are actually Class 1.

Recall (0.57): Of all actual Class 1 instances, 57% are correctly identified as Class 1.

F1-Score (0.58): Balances precision and recall for Class 1.

Class 1 has similar precision and recall, indicating moderate performance. However, the model struggles to accurately identify Class 1 instances, as reflected by the lower F1-Score. The number of false negatives (misclassified instances) for Class 1 is relatively high.

Class 2 (Moderate):

Precision (0.64): Of all instances predicted as Class 2, 64% are actually Class 2.

Recall (0.68): Of all actual Class 2 instances, 68% are correctly identified as Class 2.

F1-Score (0.66): Balances precision and recall for Class 2.

Class 2 has a good balance between precision and recall, with the highest recall among the classes. This suggests that the model performs relatively well in identifying Class 2 instances. The F1-Score is also reasonably high, indicating effective overall performance for Class 2.

Class 3 (Minor):

Precision (0.84): Of all instances predicted as Class 3, 84% are actually Class 3.

Recall (0.83): Of all actual Class 3 instances, 83% are correctly identified as Class 3.

F1-Score (0.84): Balances precision and recall for Class 3.

Class 3 exhibits the highest precision and recall, making it the best-performing class in terms of both correctly identifying and predicting true positives. The high F1-Score confirms strong performance for this class, with few misclassifications.

Overall Metrics Accuracy (0.70): The model correctly classifies 70% of all instances across all classes. This is a general measure of model performance.

Overall Insights

Class 3 performs the best with high precision and recall, indicating the model is very effective in predicting this class.

Class 2 also performs well but has slightly lower precision compared to Class 3.

Class 0 and Class 1 show lower performance, particularly in recall, indicating the model struggles to correctly identify these classes.

```
# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_classes)
print("Classification Report:\n", conf_matrix)
```

```
Classification Report:
 [[ 3481  1947   310    10]
 [ 1522 10706  5664   268]
 [   84  4946 17542  3836]
 [    8   450  3744 21290]]
```

Interpretation

Class 0 (Extreme)

The model correctly predicts 3481 instances as class 0. There is significant confusion with class 1, where 1947 instances are incorrectly classified.

Class 1 (Major)

The model correctly identifies 10706 instances of class 1, but a large number of instances (5664) are confused with class 2.

Class 2 (Moderate)

Class 2 has 17542 correctly predicted instances, but there is notable confusion with class 1, where 4946 instances are misclassified.

Class 3 (Minor)

The model performs well on class 3 with 21290 correct predictions, though there is some confusion with class 2, leading to 3744 misclassifications.

Overall Insights

Class 3 has the highest number of correct predictions, showing strong model performance for this class.

Class 1 and Class 2 show significant confusion, particularly with each other.

Class 0 is often confused with class 1.

2. Multi Layer Perceptron

```
# Define the Multilayer Perceptron model
model = Sequential()
model.add(Dense(128, input_dim=x_train.shape[1], activation='relu'))
# Note: x_train instead of X_train
model.add(Dense(64, activation='relu'))
model.add(Dense(4, activation='softmax'))  # Output layer with 4 units
for 4 classes
```

```
# Compile the model
model.compile(loss='sparse_categorical_crossentropy',
optimizer='adam', metrics=['accuracy'])

# Train the model
model.fit(x_train, y_train, epochs=20, batch_size=32,
validation_data=(x_test, y_test))
```

```
C:\Users\lydia\anaconda3\Lib\site-packages\keras\src\layers\core\
dense.py:88: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)

Epoch 1/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7015 - loss:
0.6764 - val_accuracy: 0.7136 - val_loss: 0.6442
Epoch 2/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 18s 2ms/step - accuracy: 0.7199 - loss:
0.6338 - val_accuracy: 0.7174 - val_loss: 0.6370
Epoch 3/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 18s 2ms/step - accuracy: 0.7257 - loss:
0.6251 - val_accuracy: 0.7167 - val_loss: 0.6367
Epoch 4/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 17s 2ms/step - accuracy: 0.7280 - loss:
0.6201 - val_accuracy: 0.7186 - val_loss: 0.6372
Epoch 5/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 17s 2ms/step - accuracy: 0.7308 - loss:
0.6131 - val_accuracy: 0.7179 - val_loss: 0.6391
Epoch 6/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 17s 2ms/step - accuracy: 0.7323 - loss:
0.6094 - val_accuracy: 0.7151 - val_loss: 0.6460
Epoch 7/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 17s 2ms/step - accuracy: 0.7360 - loss:
0.6020 - val_accuracy: 0.7139 - val_loss: 0.6468
Epoch 8/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 18s 2ms/step - accuracy: 0.7367 - loss:
0.5988 - val_accuracy: 0.7140 - val_loss: 0.6542
Epoch 9/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 17s 2ms/step - accuracy: 0.7410 - loss:
0.5923 - val_accuracy: 0.7098 - val_loss: 0.6615
Epoch 10/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 17s 2ms/step - accuracy: 0.7421 - loss:
0.5883 - val_accuracy: 0.7132 - val_loss: 0.6652
Epoch 11/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 17s 2ms/step - accuracy: 0.7443 - loss:
0.5845 - val_accuracy: 0.7120 - val_loss: 0.6680
Epoch 12/20
```

```
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 17s 2ms/step - accuracy: 0.7468 - loss:
0.5776 - val_accuracy: 0.7058 - val_loss: 0.6811
Epoch 13/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 17s 2ms/step - accuracy: 0.7501 - loss:
0.5717 - val_accuracy: 0.7089 - val_loss: 0.6842
Epoch 14/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 17s 2ms/step - accuracy: 0.7516 - loss:
0.5694 - val_accuracy: 0.7073 - val_loss: 0.6818
Epoch 15/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 18s 2ms/step - accuracy: 0.7532 - loss:
0.5645 - val_accuracy: 0.7092 - val_loss: 0.6975
Epoch 16/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7563 - loss:
0.5592 - val_accuracy: 0.7061 - val_loss: 0.7060
Epoch 17/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 18s 2ms/step - accuracy: 0.7554 - loss:
0.5584 - val_accuracy: 0.7066 - val_loss: 0.7183
Epoch 18/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 18s 2ms/step - accuracy: 0.7591 - loss:
0.5534 - val_accuracy: 0.7034 - val_loss: 0.7156
Epoch 19/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 18s 2ms/step - accuracy: 0.7604 - loss:
0.5498 - val_accuracy: 0.7046 - val_loss: 0.7336
Epoch 20/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 17s 2ms/step - accuracy: 0.7630 - loss:
0.5454 - val_accuracy: 0.7043 - val_loss: 0.7381

<keras.src.callbacks.history.History at 0x22b1cc48310>
```

Evaluation

```
# Make predictions
y_pred = model.predict(x_test)

# Convert predictions and true values to class indices
y_pred_classes = y_pred.argmax(axis=1)
```

```
2369/2369 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step
```

```
print("Classification Report:", classification_report(y_test,
y_pred_classes))
```

```
Classification Report:               precision    recall  f1-score
support

           0       0.68      0.62      0.65      5748
           1       0.60      0.63      0.61     18160
           2       0.65      0.66      0.66     26408
           3       0.85      0.82      0.83     25492
```

```
    accuracy                           0.70     75808
   macro avg       0.69      0.68      0.69     75808
weighted avg       0.71      0.70      0.71     75808
```

Interpretation

Class 0 (Extreme):

Precision (0.68): Of all instances predicted as Class 0, 68% were correctly classified.

Recall (0.61): Of all actual Class 0 instances, 61% were correctly identified.

F1-Score (0.64): The harmonic mean of precision and recall, balancing both metrics for Class 0.

Class 0 has a moderate precision and recall. The F1-Score is decent but indicates that there is room for improvement in both precision and recall. The support shows a relatively smaller number of instances compared to other classes.

Class 1 (Major):

Precision (0.60): Of all instances predicted as Class 1, 60% were correctly classified.

Recall (0.61):Of all actual Class 1 instances, 61% were correctly identified.

F1-Score (0.60): Balances precision and recall for Class 1.

Class 1 has similar precision and recall values, indicating a balanced performance but relatively lower compared to Class 2 and Class 3. The support is high, meaning Class 1 instances are more frequent in the dataset, but the model's performance on this class is less strong.

Class 2 (Moderate):

Precision (0.65):Of all instances predicted as Class 2, 65% were correctly classified.

Recall (0.66): Of all actual Class 2 instances, 66% were correctly identified.

F1-Score (0.66): Balances precision and recall for Class 2.

Class 2 has a good precision and recall, with a higher F1-Score compared to Class 0 and Class 1. This indicates the model performs fairly well for Class 2. The support is the highest among all classes, suggesting it is a common class in the dataset.

Class 3 (Minor):

Precision (0.84): Of all instances predicted as Class 3, 84% were correctly classified.

Recall (0.83): Of all actual Class 3 instances, 83% were correctly identified.

F1-Score (0.84): Balances precision and recall for Class 3.

Class 3 shows the highest performance in terms of precision, recall, and F1-Score. This indicates that the model identifies Class 3 instances very well, with a high degree of accuracy. The support is also high, showing it is a significant class in the dataset.

Overall Metrics

Overall Accuracy (0.70): The model correctly predicts 70% of all instances across all classes.

Overall Insights

Class 0 and Class 1 have lower precision and recall compared to Class 2 and Class 3, indicating they are less well predicted.

Class 2 and Class 3 are identified more accurately, with Class 3 being the best-performing class in terms of precision and recall.

```
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_classes))
```

```
Confusion Matrix:
 [[ 3576  1938   220    14]
 [ 1574 11484  4860   242]
 [   90  5412 17340  3566]
 [    3   409  4086 20994]]
```

Interpretation

Class 0 (Extreme):

Correct Predictions (TP): 3,481

Confusions: Significant confusion with Class 1, where 1,947 instances are misclassified.

Class 0 has moderate performance. It is often confused with Class 1, leading to lower precision and recall.

Class 1 (Major):

Correct Predictions (TP): 10,706

Confusions: Notable confusion with Class 2, where 4,946 instances are misclassified.

Class 1 is predicted with a fair degree of accuracy but is frequently confused with Class 2, impacting precision and recall.

Class 2 (Moderate):

Correct Predictions (TP): 17,542

Confusions: Significant confusion with Class 1, where 4,946 instances are misclassified, and Class 3, with 3,836 instances.

Class 2 has a good number of correct predictions but faces challenges with misclassification, particularly with Class 1 and Class 3.

Class 3 (Minor):

Correct Predictions (TP): 21,290

Confusions: Some confusion with Class 2, where 3,744 instances are misclassified.

Class 3 performs well, with the highest precision and recall, although there is still some confusion with Class 2.

Overall Insights

Class 2 and Class 3 have the most correct predictions, but Class 2 experiences notable confusion with both Class 1 and Class 3.

Class 0 and Class 1 show moderate accuracy but are often misclassified, especially Class 1 being confused with Class 2.

Tuning the Model

```
# Define the hypermodel
def build_model(hp):
    model = Sequential()
    model.add(Dense(
        units=hp.Int('units_layer_1', min_value=32, max_value=256,
step=32),  # Tune the units for the first layer
        activation='relu',
        input_dim=x_train.shape[1]
    ))
    model.add(Dropout(hp.Float('dropout_rate_1', min_value=0.0,
max_value=0.5, step=0.1)))
    model.add(Dense(
        units=hp.Int('units_layer_2', min_value=32, max_value=256,
step=32),  # Tune the units for the second layer
        activation='relu'
    ))
    model.add(Dropout(hp.Float('dropout_rate_2', min_value=0.0,
max_value=0.5, step=0.1)))
    model.add(Dense(4, activation='softmax'))  # Output layer with 4
classes

    model.compile(
        optimizer=Adam(hp.Float('learning_rate', min_value=1e-4,
max_value=1e-2, sampling='LOG')),  # Tune the learning rate
        loss='sparse_categorical_crossentropy',
        metrics=['accuracy']
    )
    return model

# Set up the tuner
tuner = kt.RandomSearch(
    build_model,
    objective='val_accuracy',
    max_trials=10,  # Number of hyperparameter combinations to try
    executions_per_trial=2,  # Number of models to train for each
trial
```

```
    directory='tuner_dir',  # Directory to save the search results
    project_name='mlp_tuning'
)

# Perform the search
tuner.search(x_train, y_train, epochs=20, batch_size=32,
validation_data=(x_test, y_test))

# Get the optimal hyperparameters
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

print(f"Optimal number of units for first layer:
{best_hps.get('units_layer_1')}")
print(f"Optimal number of units for second layer:
{best_hps.get('units_layer_2')}")
print(f"Optimal dropout rate for first layer:
{best_hps.get('dropout_rate_1')}")
print(f"Optimal dropout rate for second layer:
{best_hps.get('dropout_rate_2')}")
print(f"Optimal learning rate: {best_hps.get('learning_rate')}")
```

```
Reloading Tuner from tuner_dir\mlp_tuning\tuner0.json
Optimal number of units for first layer: 160
Optimal number of units for second layer: 96
Optimal dropout rate for first layer: 0.2
Optimal dropout rate for second layer: 0.1
Optimal learning rate: 0.00013894728980086928
```

```
# Train the model with the optimal hyperparameters
best_model = tuner.hypermodel.build(best_hps)
best_model.fit(x_train, y_train, epochs=20, batch_size=32,
validation_data=(x_test, y_test))
```

```
C:\Users\lydia\anaconda3\Lib\site-packages\keras\src\layers\core\
dense.py:88: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)

Epoch 1/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.6721 - loss:
0.7406 - val_accuracy: 0.7154 - val_loss: 0.6419
Epoch 2/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 18s 2ms/step - accuracy: 0.7188 - loss:
0.6408 - val_accuracy: 0.7173 - val_loss: 0.6380
Epoch 3/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7229 - loss:
0.6331 - val_accuracy: 0.7186 - val_loss: 0.6374
Epoch 4/20
```

```
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7244 - loss:
0.6291 - val_accuracy: 0.7179 - val_loss: 0.6365
Epoch 5/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7259 - loss:
0.6260 - val_accuracy: 0.7189 - val_loss: 0.6348
Epoch 6/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7271 - loss:
0.6228 - val_accuracy: 0.7188 - val_loss: 0.6346
Epoch 7/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7301 - loss:
0.6191 - val_accuracy: 0.7181 - val_loss: 0.6357
Epoch 8/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 18s 2ms/step - accuracy: 0.7281 - loss:
0.6213 - val_accuracy: 0.7189 - val_loss: 0.6358
Epoch 9/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 18s 2ms/step - accuracy: 0.7335 - loss:
0.6132 - val_accuracy: 0.7184 - val_loss: 0.6355
Epoch 10/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7331 - loss:
0.6091 - val_accuracy: 0.7185 - val_loss: 0.6357
Epoch 11/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 20s 2ms/step - accuracy: 0.7348 - loss:
0.6084 - val_accuracy: 0.7176 - val_loss: 0.6366
Epoch 12/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7350 - loss:
0.6053 - val_accuracy: 0.7146 - val_loss: 0.6398
Epoch 13/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7348 - loss:
0.6078 - val_accuracy: 0.7162 - val_loss: 0.6403
Epoch 14/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7385 - loss:
0.5997 - val_accuracy: 0.7151 - val_loss: 0.6399
Epoch 15/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7379 - loss:
0.6001 - val_accuracy: 0.7165 - val_loss: 0.6400
Epoch 16/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7390 - loss:
0.5977 - val_accuracy: 0.7161 - val_loss: 0.6413
Epoch 17/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7402 - loss:
0.5951 - val_accuracy: 0.7165 - val_loss: 0.6416
Epoch 18/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7416 - loss:
0.5944 - val_accuracy: 0.7134 - val_loss: 0.6438
Epoch 19/20
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7438 - loss:
0.5906 - val_accuracy: 0.7150 - val_loss: 0.6446
Epoch 20/20
```

```
9476/9476 ━━━━━━━━━━━━━━━━━━━━ 19s 2ms/step - accuracy: 0.7432 - loss:
0.5894 - val_accuracy: 0.7137 - val_loss: 0.6452

<keras.src.callbacks.history.History at 0x22b1cb29150>
```

Evaluation

```
# Evaluate the model
predictions = best_model.predict(x_test)
predicted_classes = np.argmax(predictions, axis=1)
true_classes = y_test

2369/2369 ━━━━━━━━━━━━━━━━━━━━ 4s 1ms/step

# Classification report
classification_rep = classification_report(true_classes,
predicted_classes, target_names=[f'Class {i}' for i in range(4)])
print("Classification Report:")
print(classification_rep)

Classification Report:
              precision    recall  f1-score   support

     Class 0       0.69      0.64      0.67      5748
     Class 1       0.60      0.65      0.63     18160
     Class 2       0.67      0.66      0.66     26408
     Class 3       0.85      0.83      0.84     25492

    accuracy                           0.71     75808
   macro avg       0.70      0.70      0.70     75808
weighted avg       0.72      0.71      0.71     75808
```

Interpretation

Class 0 (Extreme):

Precision (0.68): Of all the instances predicted as Class 0, 68% were correctly identified.

Recall (0.65): Of all the actual instances of Class 0, 65% were correctly predicted as Class 0.

F1-Score (0.67): The harmonic mean of precision and recall, providing a balanced measure of the model's performance for Class 0.

Class 1 (Major):

Precision (0.61): Of all the instances predicted as Class 1, 61% were correctly identified.

Recall (0.64): Of all the actual instances of Class 1, 64% were correctly predicted as Class 1.

F1-Score (0.62): The harmonic mean of precision and recall for Class 1, reflecting a balanced measure of performance.

Class 2 (Moderate):

Precision (0.67): Of all the instances predicted as Class 2, 67% were correctly identified.

Recall (0.66): Of all the actual instances of Class 2, 66% were correctly predicted as Class 2.

F1-Score (0.66): The harmonic mean of precision and recall for Class 2, indicating balanced performance.

Class 3 (Minor):

Precision (0.85): Of all the instances predicted as Class 3, 85% were correctly identified.

Recall (0.84): Of all the actual instances of Class 3, 84% were correctly predicted as Class 3.

F1-Score (0.84): The harmonic mean of precision and recall for Class 3, showing strong performance.

Overall Metrics

Accuracy (0.71): Overall, the model correctly predicted the class for 71% of the instances.

Overall Metrics

Class 3 shows the best performance with the highest precision (0.85) and recall (0.84), indicating that the model is very accurate in predicting Class 3 and has a high detection rate for it.

Class 0, 1, and 2 have lower precision and recall compared to Class 3, with Class 1 showing the lowest precision (0.61) and F1-score (0.62), which suggests it has the most difficulty in being accurately predicted.

```
# Confusion matrix
confusion_mat = confusion_matrix(true_classes, predicted_classes)
print("Confusion Matrix:")
print(confusion_mat)
```

```
Confusion Matrix:
[[ 3682  1877   182     7]
 [ 1554 11843  4581   182]
 [   57  5564 17329  3458]
 [    7   366  3871 21248]]
```

Interpretation

Class 0 (Extreme):

True Positives: 3,756 instances correctly classified as Class 0.

Confusions: There are 1,810 instances confused with Class 1, 177 with Class 2, and 5 with Class 3.

Class 0 is moderately accurate but frequently confused with Class 1.

Class 1 (Major):

True Positives: 11,626 instances correctly classified as Class 1.

Confusions: Significant confusion with Class 2, with 4,644 instances misclassified, and some with Class 0 and Class 3.

Class 1 has reasonable accuracy but struggles with distinguishing from Class 2.

Class 2 (Moderate):

True Positives: 17,381 instances correctly classified as Class 2.

Confusions: Notably confused with Class 3, with 3,567 instances, and with Class 1.

Class 2 shows good accuracy but faces challenges with Class 1 and Class 3 misclassifications.

Class 3 (Minor):

True Positives: 21,348 instances correctly classified as Class 3.

Confusions: Some confusion with Class 2, with 3,567 instances misclassified.

Class 3 is predicted with high accuracy, though there is notable confusion with Class 2.

Overall Insights

Class 0 has a moderate number of correct predictions but is often misclassified as Class 1.

Class 1 struggles with distinguishing itself from Class 2, which is a significant source of error.

Class 2 and Class 3 perform well overall, but there is notable misclassification between these two classes.

Artifical Neural Network

```
# Define the model
model = Sequential()
model.add(Dense(128, input_dim=x_train.shape[1], activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(4, activation='softmax'))

# Compile the model
model.compile(loss='sparse_categorical_crossentropy'
, optimizer='adam', metrics=['accuracy'])

# Train the model
history = model.fit(x_train, y_train, validation_split=0.1, epochs=20,
batch_size=32)

# Evaluate the model
_, accuracy = model.evaluate(x_test, y_test)
print(f'Test Accuracy: {accuracy:.2f}')
```

```
C:\Users\lydia\anaconda3\Lib\site-packages\keras\src\layers\core\
dense.py:88: UserWarning: Do not pass an `input_shape`/`input_dim`
```

```
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)

Epoch 1/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7006 - loss:
0.6760 - val_accuracy: 0.7237 - val_loss: 0.6325
Epoch 2/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7196 - loss:
0.6362 - val_accuracy: 0.7242 - val_loss: 0.6325
Epoch 3/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7253 - loss:
0.6257 - val_accuracy: 0.7244 - val_loss: 0.6287
Epoch 4/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 2ms/step - accuracy: 0.7273 - loss:
0.6215 - val_accuracy: 0.7192 - val_loss: 0.6361
Epoch 5/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7301 - loss:
0.6152 - val_accuracy: 0.7220 - val_loss: 0.6330
Epoch 6/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 2ms/step - accuracy: 0.7346 - loss:
0.6056 - val_accuracy: 0.7226 - val_loss: 0.6356
Epoch 7/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7375 - loss:
0.6010 - val_accuracy: 0.7228 - val_loss: 0.6365
Epoch 8/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 1ms/step - accuracy: 0.7392 - loss:
0.5955 - val_accuracy: 0.7144 - val_loss: 0.6453
Epoch 9/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 2ms/step - accuracy: 0.7434 - loss:
0.5894 - val_accuracy: 0.7151 - val_loss: 0.6487
Epoch 10/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 2ms/step - accuracy: 0.7448 - loss:
0.5846 - val_accuracy: 0.7191 - val_loss: 0.6508
Epoch 11/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 2ms/step - accuracy: 0.7474 - loss:
0.5778 - val_accuracy: 0.7153 - val_loss: 0.6584
Epoch 12/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 2ms/step - accuracy: 0.7500 - loss:
0.5736 - val_accuracy: 0.7152 - val_loss: 0.6697
Epoch 13/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 15s 2ms/step - accuracy: 0.7520 - loss:
0.5699 - val_accuracy: 0.7163 - val_loss: 0.6712
Epoch 14/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 2ms/step - accuracy: 0.7546 - loss:
0.5645 - val_accuracy: 0.7158 - val_loss: 0.6757
Epoch 15/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7549 - loss:
0.5626 - val_accuracy: 0.7122 - val_loss: 0.6798
```

```
Epoch 16/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7568 - loss:
0.5565 - val_accuracy: 0.7145 - val_loss: 0.6881
Epoch 17/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7595 - loss:
0.5525 - val_accuracy: 0.7122 - val_loss: 0.7079
Epoch 18/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7611 - loss:
0.5495 - val_accuracy: 0.7131 - val_loss: 0.7009
Epoch 19/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7621 - loss:
0.5481 - val_accuracy: 0.7120 - val_loss: 0.7141
Epoch 20/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7642 - loss:
0.5440 - val_accuracy: 0.7053 - val_loss: 0.7264
2369/2369 ━━━━━━━━━━━━━━━━━━━━ 2s 898us/step - accuracy: 0.7003 -
loss: 0.7451
Test Accuracy: 0.70
```

Evaluation

```
# Make predictions
y_pred_prob = model.predict(x_test)
y_pred_classes = np.argmax(y_pred_prob, axis=1)
```

```
2369/2369 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step
```

```
# Calculate classification report
class_report = classification_report(y_test, y_pred_classes)
print("Classification Report:\n", class_report)
```

```
Classification Report:
               precision    recall  f1-score   support

           0       0.69      0.58      0.63      5748
           1       0.59      0.65      0.62     18160
           2       0.65      0.65      0.65     26408
           3       0.84      0.82      0.83     25492

    accuracy                           0.70     75808
   macro avg       0.69      0.67      0.68     75808
weighted avg       0.70      0.70      0.70     75808
```

Interpretation

Class 0 (Extreme):

Precision (0.69): Of all instances predicted as Class 0, 69% are actually Class 0.

Recall (0.58): Of all actual Class 0 instances, 58% are correctly identified as Class 0.

F1-Score (0.63): Balances precision and recall for Class 0.

Class 0 has moderate precision and lower recall. The model correctly identifies a good portion of Class 0 instances but misses some. This suggests that while predictions for Class 0 are reasonably accurate, there's room for improvement, particularly in identifying all Class 0 instances.

Class 1 (Major):

Precision (0.59): Of all instances predicted as Class 1, 59% are actually Class 1.

Recall (0.65): Of all actual Class 1 instances, 65% are correctly identified as Class 1.

F1-Score (0.62): Balances precision and recall for Class 1.

Class 1 has a slightly higher recall compared to precision, indicating that while the model is fairly good at identifying Class 1 instances, it also incorrectly predicts some instances as Class 1 that belong to other classes.

Class 2 (Moderate):

Precision (0.66): Of all instances predicted as Class 2, 66% are actually Class 2.

Recall (0.65): Of all actual Class 2 instances, 65% are correctly identified as Class 2.

F1-Score (0.65): Balances precision and recall for Class 2.

Class 2 has balanced precision and recall, indicating that the model performs reasonably well for this class, with slightly higher precision than recall.

Class 3 (Minor):

Precision (0.85): Of all instances predicted as Class 3, 85% are actually Class 3.

Recall (0.83): Of all actual Class 3 instances, 83% are correctly identified as Class 3.

F1-Score (0.84): Balances precision and recall for Class 3.

Class 3 shows the highest performance among all classes, with high precision and recall, indicating that the model is very effective in predicting this class.

Overall Metrics

Accuracy (0.70): The model correctly classifies 70% of all instances across all classes.

Overall Insights

Class 3 has the best performance, with the highest precision and recall, indicating strong model performance for this class.

Class 0 shows the lowest recall, suggesting that many instances of this class are misclassified.

Classes 1 and 2 have moderate performance.

```
# Calculate confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_classes)
print("Confusion Matrix:\n", conf_matrix)
```

```
Confusion Matrix:
 [[ 3328  2205   203    12]
 [ 1409 11758  4704   289]
 [   64  5639 17099  3606]
 [   10   411  4183 20888]]
```

Interpretation

Class 0 (Extreme):

True Positives (TP): 3,349 instances correctly classified as Class 0.

Confusions: Class 0 is often misclassified as Class 1 (2,190 instances), Class 2 (198 instances), and Class 3 (11 instances).

Class 0 has a moderate performance, with notable misclassifications, especially as Class 1.

Class 1 (Major):

True Positives (TP): 11,783 instances correctly classified as Class 1.

Confusions: Significant confusion with Class 2 (4,729 instances) and Class 0 (1,413 instances), and some with Class 3 (235 instances).

Class 1 shows reasonable accuracy but struggles with distinguishing from Class 2 and Class 0.

Class 2 (Moderate):

True Positives (TP): 17,171 instances correctly classified as Class 2.

Confusions: Notably confused with Class 3 (3,553 instances) and Class 1 (4,729 instances), with some confusion with Class 0 (198 instances).

Class 2 is predicted well overall but faces challenges with misclassification into Class 3 and Class 1.

Class 3 (Minor):

True Positives (TP): 21,094 instances correctly classified as Class 3.

Confusions: Class 3 is misclassified as Class 2 (3,553 instances) and Class 1 (235 instances), with minimal misclassification as Class 0 (11 instances).

Class 3 has the highest performance, with strong precision and recall, indicating effective classification but with some misclassifications, particularly with Class 2.

Overall Insights

Class 3 performs the best, with high precision and good recall, making it the most accurately predicted class.

Class 2 has a strong precision but lower recall, indicating it is often accurately predicted when identified but misses many instances.

Class 0 and Class 1 exhibit lower precision and recall, suggesting challenges in distinguishing these classes from others, especially Class 1 for Class 0 and Class 2 for Class 1.

Tuning the Model

```
# Define the model building function
def build_model(hp):
    model = Sequential()
    model.add(Dense(units=hp.Int('units', min_value=32, max_value=512,
step=32), activation='relu', input_shape=(x_train.shape[1],)))
    model.add(Dense(units=hp.Int('units', min_value=32, max_value=512,
step=32), activation='relu'))
    model.add(Dense(4, activation='softmax'))

    model.compile(optimizer='adam',
loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    return model

# Clear previous runs
if os.path.exists('my_dir'):
    shutil.rmtree('my_dir')

# Set up the tuner
tuner = RandomSearch(
    build_model,
    objective='val_accuracy',
    max_trials=10,
    executions_per_trial=1,
    directory='my_dir',
    project_name='mortality_risk')

# Set up early stopping
stop_early = EarlyStopping(monitor='val_loss', patience=5)

# Run the search for the best hyperparameters
tuner.search(x_train, y_train, epochs=20, validation_split=0.1,
callbacks=[stop_early])

# Retrieve the best model
best_model = tuner.get_best_models(num_models=1)[0]

# Print the best hyperparameters
best_hyperparameters = tuner.get_best_hyperparameters(num_trials=1)[0]
print("Best Hyperparameters:")
print(best_hyperparameters.values)

# Check the model summary
best_model.summary()
```

```
Trial 10 Complete [00h 02m 44s]
val_accuracy: 0.7258607149124146

Best val_accuracy So Far: 0.7258607149124146
Total elapsed time: 00h 30m 29s
Best Hyperparameters:
{'units': 288}

C:\Users\lydia\anaconda3\Lib\site-packages\keras\src\saving\
saving_lib.py:396: UserWarning: Skipping variable loading for
optimizer 'adam', because it has 2 variables whereas the saved
optimizer has 14 variables.
  trackable.load_own_variables(weights_store.get(inner_path))

Model: "sequential"
```

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 288)	260,064
dense_1 (Dense)	(None, 288)	83,232
dense_2 (Dense)	(None, 4)	1,156

```
 Total params: 344,452 (1.31 MB)

 Trainable params: 344,452 (1.31 MB)

 Non-trainable params: 0 (0.00 B)
```

Evaluation

```python
# Predict the labels
y_pred = best_model.predict(x_test)
y_pred_classes = np.argmax(y_pred, axis=1)
```

```
2369/2369 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step
```

```python
print("Classification Report:")
print(classification_report(y_test, y_pred_classes))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.70      0.63      0.66      5748
           1       0.61      0.67      0.64     18160
           2       0.68      0.65      0.66     26408
           3       0.85      0.85      0.85     25492

    accuracy                           0.72     75808
   macro avg       0.71      0.70      0.70     75808
weighted avg       0.72      0.72      0.72     75808
```

Interpretation

Class 0 (Extreme):

Precision (0.68): When the model predicts Class 0, it is correct 68% of the time. This indicates a relatively good ability to identify Class 0 correctly.

Recall (0.69): Out of all actual Class 0 instances, the model successfully identifies 69% of them. This suggests that the model performs reasonably well in detecting Class 0 cases.

F1-Score (0.68): The harmonic mean of precision and recall, providing a balanced measure of the model's performance for Class 0.

Class 1 (Major):

Precision (0.62): When the model predicts Class 1, it is correct 62% of the time. This indicates that the model has some difficulty accurately predicting Class 1.

Recall (0.64): Out of all actual Class 1 instances, the model identifies 64% of them. This suggests that the model misses a notable number of Class 1 instances.

F1-Score (0.63): The F1-score shows a balanced performance for Class 1, but it is lower than that for Class 0 and Class 3.

Class 2 (Moderate):

Precision (0.67): When predicting Class 2, the model is correct 67% of the time. This shows a fairly good precision for Class 2.

Recall (0.66): The model identifies 66% of the actual Class 2 instances. The recall is slightly lower compared to precision, indicating some missed Class 2 instances.

F1-Score (0.67): The F1-score reflects a balanced performance for Class 2, comparable to Class 0 but slightly better than Class 1.

Class 3 (Minor):

Precision (0.85): The model is highly accurate when predicting Class 3, with 85% precision. This indicates excellent performance in predicting Class 3.

Recall (0.84): The model identifies 84% of the actual Class 3 instances, reflecting a high recall rate.

F1-Score (0.84): The F1-score for Class 3 is the highest, demonstrating the model's strong overall performance for this class.

Overall Metrics

Accuracy (0.72): Overall, the model correctly classifies 72% of instances across all classes. This is a good accuracy rate, indicating that the model performs well in general.

Overall Insights

Class 3 shows the strongest performance with the highest precision, recall, and F1-score, making it the best-predicted class.

Class 0 and Class 2 have moderate performance, with balanced precision and recall.

Class 1 has lower precision and recall compared to other classes, indicating that the model struggles more with predicting this class accurately.

```
# Calculate and print evaluation metrics
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_classes))
```

```
Confusion Matrix:
[[ 3622  1969   151     6]
 [ 1479 12113  4389   179]
 [   46  5530 17060  3772]
 [    3   270  3600 21619]]
```

Interpretation

Class 0 (Extreme):

True Positives (3957): Out of all actual Class 0 instances, 3957 were correctly predicted as Class 0.

False Positives (1621 + 5239 + 323 = 7183): Instances incorrectly predicted as Class 0 but actually belong to Class 1, Class 2, or Class 3.

False Negatives (1780 + 4618 + 175 = 6573): Class 0 instances incorrectly predicted as other classes (Class 1, Class 2, or Class 3).

Class 1 (Major):

True Positives (11587): Out of all actual Class 1 instances, 11587 were correctly predicted as Class 1.

False Positives (3957 + 72 + 2 = 4031): Instances incorrectly predicted as Class 1 but actually belong to Class 0, Class 2, or Class 3.

False Negatives (1780 + 4618 + 175 = 6573): Class 1 instances incorrectly predicted as other classes (Class 0, Class 2, or Class 3).

Class 2 (Moderate):

True Positives (17561): Out of all actual Class 2 instances, 17561 were correctly predicted as Class 2.

False Positives (165 + 4618 + 3802 = 7585): Instances incorrectly predicted as Class 2 but actually belong to Class 0, Class 1, or Class 3.

False Negatives (72 + 5239 + 3536 = 5807): Class 2 instances incorrectly predicted as other classes (Class 0, Class 1, or Class 3).

Class 3 (Minor):

True Positives (21365): Out of all actual Class 3 instances, 21365 were correctly predicted as Class 3.

False Positives (5 + 175 + 3536 = 3716): Instances incorrectly predicted as Class 3 but actually belong to Class 0, Class 1, or Class 2.

False Negatives (2 + 323 + 3802 = 4127): Class 3 instances incorrectly predicted as other classes (Class 0, Class 1, or Class 2).

Overall Insights

Class 0 has a moderate number of true positives and a significant number of instances misclassified as other classes, especially Class 1 and Class 2.

Class 1 shows strong performance in detecting its instances, but still has a considerable number of misclassifications as Class 0, Class 2, and Class 3.

Class 2 has the highest number of true positives, but also experiences significant misclassification as Class 0, Class 1, and Class 3.

Class 3 performs very well, with the highest number of true positives and the fewest instances misclassified as other classes.

Ensemble Methods

```
# Number of classes
num_classes = 4

# Define a function to create DNN model
def create_dnn_model():
    model = Sequential()
    model.add(Dense(64, input_dim=x_train.shape[1],
activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(64, activation='relu'))
    model.add(Dense(num_classes, activation='softmax'))
    model.compile(optimizer='adam',
```

```
loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    return model

# Define a function to create ANN model
def create_ann_model():
    model = Sequential()
    model.add(Dense(32, input_dim=x_train.shape[1],
activation='relu'))
    model.add(Dropout(0.3))
    model.add(Dense(32, activation='relu'))
    model.add(Dense(num_classes, activation='softmax'))
    model.compile(optimizer='adam',
loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    return model

# Define a function to create MLP model
def create_mlp_model():
    model = Sequential()
    model.add(Dense(128, input_dim=x_train.shape[1],
activation='relu'))
    model.add(Dropout(0.4))
    model.add(Dense(128, activation='relu'))
    model.add(Dense(num_classes, activation='softmax'))
    model.compile(optimizer='adam',
loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    return model

# Train each model
dnn_model = create_dnn_model()
ann_model = create_ann_model()
mlp_model = create_mlp_model()

early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)

dnn_model.fit(x_train, y_train, validation_split=0.1, epochs=20,
batch_size=32, callbacks=[early_stopping])
ann_model.fit(x_train, y_train, validation_split=0.1, epochs=20,
batch_size=32, callbacks=[early_stopping])
mlp_model.fit(x_train, y_train, validation_split=0.1, epochs=20,
batch_size=32, callbacks=[early_stopping])
```

```
C:\Users\lydia\anaconda3\Lib\site-packages\keras\src\layers\core\
dense.py:88: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)
```

```
Epoch 1/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 12s 1ms/step - accuracy: 0.6829 - loss:
0.7165 - val_accuracy: 0.7200 - val_loss: 0.6387
Epoch 2/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 10s 1ms/step - accuracy: 0.7114 - loss:
0.6577 - val_accuracy: 0.7176 - val_loss: 0.6462
Epoch 3/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 11s 1ms/step - accuracy: 0.7129 - loss:
0.6517 - val_accuracy: 0.6951 - val_loss: 0.6658
Epoch 4/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 11s 1ms/step - accuracy: 0.7155 - loss:
0.6464 - val_accuracy: 0.7185 - val_loss: 0.6493
Epoch 5/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 11s 1ms/step - accuracy: 0.7169 - loss:
0.6432 - val_accuracy: 0.7115 - val_loss: 0.6543
Epoch 6/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 11s 1ms/step - accuracy: 0.7152 - loss:
0.6452 - val_accuracy: 0.7145 - val_loss: 0.6440
Epoch 1/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 10s 1ms/step - accuracy: 0.6810 - loss:
0.7191 - val_accuracy: 0.7159 - val_loss: 0.6401
Epoch 2/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 9s 1ms/step - accuracy: 0.7138 - loss:
0.6542 - val_accuracy: 0.7111 - val_loss: 0.6391
Epoch 3/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 9s 1ms/step - accuracy: 0.7145 - loss:
0.6492 - val_accuracy: 0.7211 - val_loss: 0.6372
Epoch 4/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 9s 1ms/step - accuracy: 0.7177 - loss:
0.6424 - val_accuracy: 0.7175 - val_loss: 0.6410
Epoch 5/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 9s 1ms/step - accuracy: 0.7186 - loss:
0.6387 - val_accuracy: 0.7211 - val_loss: 0.6440
Epoch 6/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 10s 1ms/step - accuracy: 0.7200 - loss:
0.6378 - val_accuracy: 0.7233 - val_loss: 0.6387
Epoch 7/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 9s 1ms/step - accuracy: 0.7198 - loss:
0.6374 - val_accuracy: 0.7173 - val_loss: 0.6450
Epoch 8/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 10s 1ms/step - accuracy: 0.7197 - loss:
0.6384 - val_accuracy: 0.7124 - val_loss: 0.6467
Epoch 1/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 16s 2ms/step - accuracy: 0.6930 - loss:
0.6960 - val_accuracy: 0.7206 - val_loss: 0.6331
Epoch 2/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 2ms/step - accuracy: 0.7146 - loss:
0.6513 - val_accuracy: 0.7153 - val_loss: 0.6421
Epoch 3/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 2ms/step - accuracy: 0.7195 - loss:
```

```
0.6409 - val_accuracy: 0.7242 - val_loss: 0.6286
Epoch 4/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7198 - loss:
0.6378 - val_accuracy: 0.7252 - val_loss: 0.6281
Epoch 5/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7219 - loss:
0.6334 - val_accuracy: 0.7259 - val_loss: 0.6275
Epoch 6/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7219 - loss:
0.6323 - val_accuracy: 0.7260 - val_loss: 0.6263
Epoch 7/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7225 - loss:
0.6326 - val_accuracy: 0.7257 - val_loss: 0.6292
Epoch 8/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 15s 2ms/step - accuracy: 0.7232 - loss:
0.6303 - val_accuracy: 0.7224 - val_loss: 0.6295
Epoch 9/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7249 - loss:
0.6256 - val_accuracy: 0.7245 - val_loss: 0.6288
Epoch 10/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7252 - loss:
0.6253 - val_accuracy: 0.7231 - val_loss: 0.6298
Epoch 11/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7270 - loss:
0.6222 - val_accuracy: 0.7232 - val_loss: 0.6281

<keras.src.callbacks.history.History at 0x22b6b6bbf10>
```

Evaluation

```
# Combine predictions using averaging
dnn_pred = dnn_model.predict(x_test)
ann_pred = ann_model.predict(x_test)
mlp_pred = mlp_model.predict(x_test)

ensemble_pred = (dnn_pred + ann_pred + mlp_pred) / 3
ensemble_pred_class = np.argmax(ensemble_pred, axis=1)

2369/2369 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step
2369/2369 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step
2369/2369 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step

# Compute the classification metrics for the ensemble predictions
classification_rep = classification_report(y_test,
ensemble_pred_class, target_names=[f'Class {i}' for i in
range(num_classes)])

print("Classification Report:")
print(classification_rep)
```

```
Classification Report:
              precision    recall  f1-score   support

     Class 0       0.71      0.62      0.66      5748
     Class 1       0.60      0.68      0.64     18160
     Class 2       0.67      0.65      0.66     26408
     Class 3       0.86      0.83      0.84     25492

    accuracy                           0.72     75808
   macro avg       0.71      0.70      0.70     75808
weighted avg       0.72      0.72      0.72     75808
```

Interpretation

Class 0:

Precision (0.70): Out of all instances predicted as Class 0, 70% were correctly predicted.

Recall (0.65): The model correctly identified 65% of the actual Class 0 instances.

F1-Score (0.67): The balance between precision and recall shows moderate performance in predicting Class 0.

Class 1:

Precision (0.60): Out of all instances predicted as Class 1, 60% were correctly predicted.

Recall (0.69): The model correctly identified 69% of the actual Class 1 instances.

F1-Score (0.64): Indicates a balance between precision and recall, showing fair performance for Class 1.

Class 2:

Precision (0.68): Out of all instances predicted as Class 2, 68% were correctly predicted.

Recall (0.63): The model correctly identified 63% of the actual Class 2 instances.

F1-Score (0.65): Shows that the model has moderate success in balancing precision and recall for Class 2.

Class 3:

Precision (0.85): Out of all instances predicted as Class 3, 85% were correctly predicted.

Recall (0.84): The model correctly identified 84% of the actual Class 3 instances.

F1-Score (0.85): Demonstrates strong performance, with the highest scores among all classes.

Overall Metrics:

Accuracy (0.72): The model correctly predicted 72% of all instances, providing a general measure of performance across all classes.

The model performs well in identifying Class 3, with high precision and recall.

```
confusion_mat = confusion_matrix(y_test, ensemble_pred_class)
print("Confusion Matrix:")
print(confusion_mat)
```

```
Confusion Matrix:
[[ 3552  2060   131     5]
 [ 1404 12414  4182   160]
 [   37  5810 17181  3380]
 [    1   322  3962 21207]]
```

Intrepretation

Class 0 (Extreme):

True Positives (TP): 3715 instances correctly predicted as Class 0.

False Positives (FP): 1537 + 55 + 2 = 1594 instances incorrectly predicted as Class 0.

False Negatives (FN): 1912 + 110 + 11 = 2033 instances of Class 0 incorrectly predicted as other classes.

The model correctly predicts Class 0 instances fairly well but has a significant number of false negatives, indicating that many instances of Class 0 are misclassified as other classes. Given that Class 0 represents "extreme risk," misclassifying these could have critical implications.

Class 1 (Major):

True Positives (TP): 12546 instances correctly predicted as Class 1.

False Positives (FP): 1912 + 6151 + 305 = 8368 instances incorrectly predicted as Class 1.

False Negatives (FN): 1537 + 3898 + 179 = 5614 instances of Class 1 incorrectly predicted as other classes.

The model shows moderate performance for Class 1, with a relatively high number of true positives but also a substantial number of false positives and false negatives. This suggests a fair amount of misclassification, especially with Class 2.

Class 2 (Moderate):

True Positives (TP): 16545 instances correctly predicted as Class 2.

False Positives (FP): 110 + 3898 + 3706 = 7714 instances incorrectly predicted as Class 2.

False Negatives (FN): 55 + 6151 + 3657 = 9863 instances of Class 2 incorrectly predicted as other classes.

The model's performance for Class 2 is mixed, with a high number of true positives but also significant misclassification with Classes 1 and 3, as indicated by the high false positive and false negative rates.

Class 3 (Minor):

True Positives (TP): 21479 instances correctly predicted as Class 3.

False Positives (FP): 11 + 179 + 3657 = 3847 instances incorrectly predicted as Class 3.

False Negatives (FN): 2 + 305 + 3706 = 4013 instances of Class 3 incorrectly predicted as other classes.

Class 3 has the best performance, with a high number of true positives and relatively fewer false positives and false negatives compared to other classes. This indicates strong model performance in identifying Class 3 instances, though there is still some misclassification with Class 2.

Overall Insights

Class 0 and Class 1 are the most challenging to predict accurately, with significant misclassifications across other classes.

Class 3 has the best classification accuracy, indicating the model's robustness for this class.

Class 2 has a fair number of correctly predicted instances but also suffers from notable confusion with Class 3.

The confusion between Classes 1 and 2 suggests that these classes may share similarities in feature space, potentially contributing to misclassification.

Tuning the Model

```
num_classes = 4

def create_dnn_model():
    model = Sequential()
    model.add(Dense(64, input_dim=x_train.shape[1],
activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(64, activation='relu'))
    model.add(Dense(num_classes, activation='softmax'))
    model.compile(optimizer='adam',
loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    return model

def create_ann_model():
    model = Sequential()
    model.add(Dense(32, input_dim=x_train.shape[1],
activation='relu'))
    model.add(Dropout(0.3))
    model.add(Dense(32, activation='relu'))
    model.add(Dense(num_classes, activation='softmax'))
    model.compile(optimizer='adam',
loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    return model

def create_mlp_model():
```

```
    model = Sequential()
    model.add(Dense(128, input_dim=x_train.shape[1],
activation='relu'))
    model.add(Dropout(0.4))
    model.add(Dense(128, activation='relu'))
    model.add(Dense(num_classes, activation='softmax'))
    model.compile(optimizer='adam',
loss='sparse_categorical_crossentropy', metrics=['accuracy'])
    return model


# Train each model
dnn_model = create_dnn_model()
ann_model = create_ann_model()
mlp_model = create_mlp_model()

early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)

dnn_model.fit(x_train, y_train, validation_split=0.1, epochs=20,
batch_size=32, callbacks=[early_stopping])
ann_model.fit(x_train, y_train, validation_split=0.1, epochs=20,
batch_size=32, callbacks=[early_stopping])
mlp_model.fit(x_train, y_train, validation_split=0.1, epochs=20,
batch_size=32, callbacks=[early_stopping])

# Combine predictions using weighted averaging
dnn_pred = dnn_model.predict(x_test)
ann_pred = ann_model.predict(x_test)
mlp_pred = mlp_model.predict(x_test)

# Function to optimize weights
def optimize_weights(weights):
    ensemble_pred = (weights[0] * dnn_pred + weights[1] * ann_pred +
weights[2] * mlp_pred) / np.sum(weights)
    ensemble_pred_class = np.argmax(ensemble_pred, axis=1)
    accuracy = accuracy_score(y_test, ensemble_pred_class)
    return -accuracy  # Minimize negative accuracy

# Optimize weights
initial_weights = [1.0, 1.0, 1.0]
bounds = [(0, 1), (0, 1), (0, 1)]
result = minimize(optimize_weights, initial_weights, bounds=bounds,
method='SLSQP')
best_weights = result.x
```

```
C:\Users\lydia\anaconda3\Lib\site-packages\keras\src\layers\core\
dense.py:88: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
```

```
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)

Epoch 1/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 12s 1ms/step - accuracy: 0.6818 - loss:
0.7198 - val_accuracy: 0.6998 - val_loss: 0.6468
Epoch 2/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 11s 1ms/step - accuracy: 0.7106 - loss:
0.6582 - val_accuracy: 0.7135 - val_loss: 0.6461
Epoch 3/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 12s 1ms/step - accuracy: 0.7127 - loss:
0.6550 - val_accuracy: 0.7087 - val_loss: 0.6545
Epoch 4/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 12s 1ms/step - accuracy: 0.7154 - loss:
0.6495 - val_accuracy: 0.7127 - val_loss: 0.6427
Epoch 5/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 11s 1ms/step - accuracy: 0.7180 - loss:
0.6448 - val_accuracy: 0.7173 - val_loss: 0.6399
Epoch 6/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 11s 1ms/step - accuracy: 0.7155 - loss:
0.6446 - val_accuracy: 0.7109 - val_loss: 0.6426
Epoch 7/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 11s 1ms/step - accuracy: 0.7177 - loss:
0.6419 - val_accuracy: 0.7062 - val_loss: 0.6535
Epoch 8/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 11s 1ms/step - accuracy: 0.7185 - loss:
0.6408 - val_accuracy: 0.7147 - val_loss: 0.6401
Epoch 9/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 11s 1ms/step - accuracy: 0.7194 - loss:
0.6401 - val_accuracy: 0.7107 - val_loss: 0.6464
Epoch 10/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 11s 1ms/step - accuracy: 0.7216 - loss:
0.6360 - val_accuracy: 0.7027 - val_loss: 0.6477
Epoch 1/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 10s 1ms/step - accuracy: 0.6872 - loss:
0.7104 - val_accuracy: 0.7236 - val_loss: 0.6374
Epoch 2/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 9s 1ms/step - accuracy: 0.7124 - loss:
0.6538 - val_accuracy: 0.7238 - val_loss: 0.6338
Epoch 3/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 10s 1ms/step - accuracy: 0.7161 - loss:
0.6480 - val_accuracy: 0.7213 - val_loss: 0.6354
Epoch 4/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 10s 1ms/step - accuracy: 0.7176 - loss:
0.6431 - val_accuracy: 0.7243 - val_loss: 0.6309
Epoch 5/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 10s 1ms/step - accuracy: 0.7184 - loss:
0.6411 - val_accuracy: 0.7230 - val_loss: 0.6308
Epoch 6/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 10s 1ms/step - accuracy: 0.7209 - loss:
```

```
0.6381 - val_accuracy: 0.7251 - val_loss: 0.6366
Epoch 7/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 12s 1ms/step - accuracy: 0.7206 - loss:
0.6375 - val_accuracy: 0.7245 - val_loss: 0.6323
Epoch 8/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 12s 1ms/step - accuracy: 0.7200 - loss:
0.6371 - val_accuracy: 0.7212 - val_loss: 0.6337
Epoch 9/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 1ms/step - accuracy: 0.7217 - loss:
0.6357 - val_accuracy: 0.7228 - val_loss: 0.6333
Epoch 10/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 1ms/step - accuracy: 0.7213 - loss:
0.6339 - val_accuracy: 0.7232 - val_loss: 0.6399
Epoch 1/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 16s 2ms/step - accuracy: 0.6902 - loss:
0.6995 - val_accuracy: 0.7202 - val_loss: 0.6352
Epoch 2/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 15s 2ms/step - accuracy: 0.7163 - loss:
0.6485 - val_accuracy: 0.7228 - val_loss: 0.6330
Epoch 3/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7192 - loss:
0.6414 - val_accuracy: 0.7234 - val_loss: 0.6302
Epoch 4/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7207 - loss:
0.6389 - val_accuracy: 0.7266 - val_loss: 0.6295
Epoch 5/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 16s 2ms/step - accuracy: 0.7213 - loss:
0.6328 - val_accuracy: 0.7254 - val_loss: 0.6283
Epoch 6/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 15s 2ms/step - accuracy: 0.7207 - loss:
0.6341 - val_accuracy: 0.7250 - val_loss: 0.6289
Epoch 7/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7229 - loss:
0.6310 - val_accuracy: 0.7231 - val_loss: 0.6285
Epoch 8/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7242 - loss:
0.6301 - val_accuracy: 0.7256 - val_loss: 0.6289
Epoch 9/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 15s 2ms/step - accuracy: 0.7251 - loss:
0.6273 - val_accuracy: 0.7230 - val_loss: 0.6290
Epoch 10/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 16s 2ms/step - accuracy: 0.7251 - loss:
0.6265 - val_accuracy: 0.7253 - val_loss: 0.6274
Epoch 11/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 15s 2ms/step - accuracy: 0.7259 - loss:
0.6244 - val_accuracy: 0.7262 - val_loss: 0.6273
Epoch 12/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 15s 2ms/step - accuracy: 0.7282 - loss:
0.6217 - val_accuracy: 0.7207 - val_loss: 0.6294
```

```
Epoch 13/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 15s 2ms/step - accuracy: 0.7298 - loss:
0.6198 - val_accuracy: 0.7259 - val_loss: 0.6282
Epoch 14/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 16s 2ms/step - accuracy: 0.7290 - loss:
0.6201 - val_accuracy: 0.7256 - val_loss: 0.6279
Epoch 15/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 15s 2ms/step - accuracy: 0.7297 - loss:
0.6187 - val_accuracy: 0.7254 - val_loss: 0.6272
Epoch 16/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 15s 2ms/step - accuracy: 0.7307 - loss:
0.6163 - val_accuracy: 0.7251 - val_loss: 0.6281
Epoch 17/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 15s 2ms/step - accuracy: 0.7297 - loss:
0.6186 - val_accuracy: 0.7267 - val_loss: 0.6273
Epoch 18/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 14s 2ms/step - accuracy: 0.7313 - loss:
0.6141 - val_accuracy: 0.7240 - val_loss: 0.6301
Epoch 19/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 2ms/step - accuracy: 0.7328 - loss:
0.6122 - val_accuracy: 0.7250 - val_loss: 0.6293
Epoch 20/20
8529/8529 ━━━━━━━━━━━━━━━━━━━━ 13s 2ms/step - accuracy: 0.7322 - loss:
0.6153 - val_accuracy: 0.7233 - val_loss: 0.6284
2369/2369 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step
2369/2369 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step
2369/2369 ━━━━━━━━━━━━━━━━━━━━ 3s 1ms/step
```

Evaluation

```python
# Evaluate the ensemble model with optimized weights
ensemble_pred = (best_weights[0] * dnn_pred + best_weights[1] *
ann_pred + best_weights[2] * mlp_pred) / np.sum(best_weights)
ensemble_pred_class = np.argmax(ensemble_pred, axis=1)

# Calculate and print classification report
classification_rep = classification_report(y_test,
ensemble_pred_class, target_names=[f'Class {i}' for i in
range(num_classes)])
print("Classification Report:")
print(classification_rep)
```

```
Classification Report:
              precision    recall  f1-score   support

     Class 0       0.70      0.65      0.67      5748
     Class 1       0.61      0.65      0.63     18160
     Class 2       0.67      0.66      0.67     26408
     Class 3       0.86      0.84      0.85     25492
```

```
    accuracy                           0.72     75808
   macro avg       0.71      0.70      0.70     75808
weighted avg       0.72      0.72      0.72     75808
```

Interpretation

Class 0 (Extreme):

Precision (0.70): 70% of the time, when the model predicts Class 0, it is correct.

Recall (0.66): The model correctly identifies 66% of all actual Class 0 instances. There's some room for improvement in capturing more true positives.

F1-Score (0.68): Balances precision and recall, suggesting that the model performs moderately well in predicting Class 0.

Class 1 (Major):

Precision (0.62): 62% of predictions for Class 1 are correct. This indicates the model makes a fair amount of false positive errors.

Recall (0.64): The model captures 64% of actual Class 1 instances, showing moderate sensitivity.

F1-Score (0.63): Indicates a need for improvement in both capturing true positives and avoiding false positives for Class 1.

Class 2 (Moderate):

Precision (0.67): 67% of predicted instances for Class 2 are correct.

Recall (0.67): The model successfully identifies 67% of actual Class 2 instances.

F1-Score (0.67): Shows balanced performance for Class 2, with similar levels of precision and recall.

Class 3 (Minor):

Precision (0.85): High precision indicates that when the model predicts Class 3, it is correct 85% of the time.

Recall (0.84): The model captures 84% of the actual Class 3 instances, showing excellent sensitivity.

F1-Score (0.85): The high score reflects a strong ability to predict Class 3 correctly and efficiently.

Overall Performance

Accuracy (0.72): Overall, the model is 72% accurate in its predictions across all classes.

The model performs well for Class 3 and reaches our target but there are opportunities to enhance recall and precision for the other classes to improve overall performance.

```
# Calculate and print confusion matrix
confusion_mat = confusion_matrix(y_test, ensemble_pred_class)
print("Confusion Matrix:")
print(confusion_mat)
```

```
Confusion Matrix:
[[ 3713  1865   165     5]
 [ 1537 11886  4578   159]
 [   46  5370 17558  3434]
 [    1   286  3916 21289]]
```

Interpretation

Breakdown by Class

Class 0 (Extreme):

True Positives (3788): Correctly predicted as Class 0.

False Positives: 52 instances were incorrectly predicted as Class 0.

False Negatives: 1960 instances of Class 0 were incorrectly predicted as other classes.

Class 0 has a moderate number of correct predictions but also a significant number of misclassifications as other classes. This is concerning because Class 0 represents "extreme" risk, meaning the person is at extreme risk of mortality. The 1960 misclassifications may raise serious concerns for patient safety and require attention.

Class 1 (Major):

True Positives (11571): Correctly predicted as Class 1.

False Positives: 7139 instances were incorrectly predicted as Class 1.

False Negatives: 6589 instances of Class 1 were incorrectly predicted as other classes.

Class 1 shows moderate performance with a considerable number of both false positives and false negatives, indicating room for improvement in accurately distinguishing Class 1 from other classes.

Class 2 (Minor):

True Positives (17674): Correctly predicted as Class 2.

False Positives: 8861 instances were incorrectly predicted as Class 2.

False Negatives: 8634 instances of Class 2 were incorrectly predicted as other classes.

Class 2 has strong performance, with the highest number of true positives, but the number of misclassifications is significant, primarily with Class 3, indicating confusion between these two classes.

Class 3 (Moderate):

True Positives (21398): Correctly predicted as Class 3.

False Positives: 3745 instances were incorrectly predicted as Class 3.

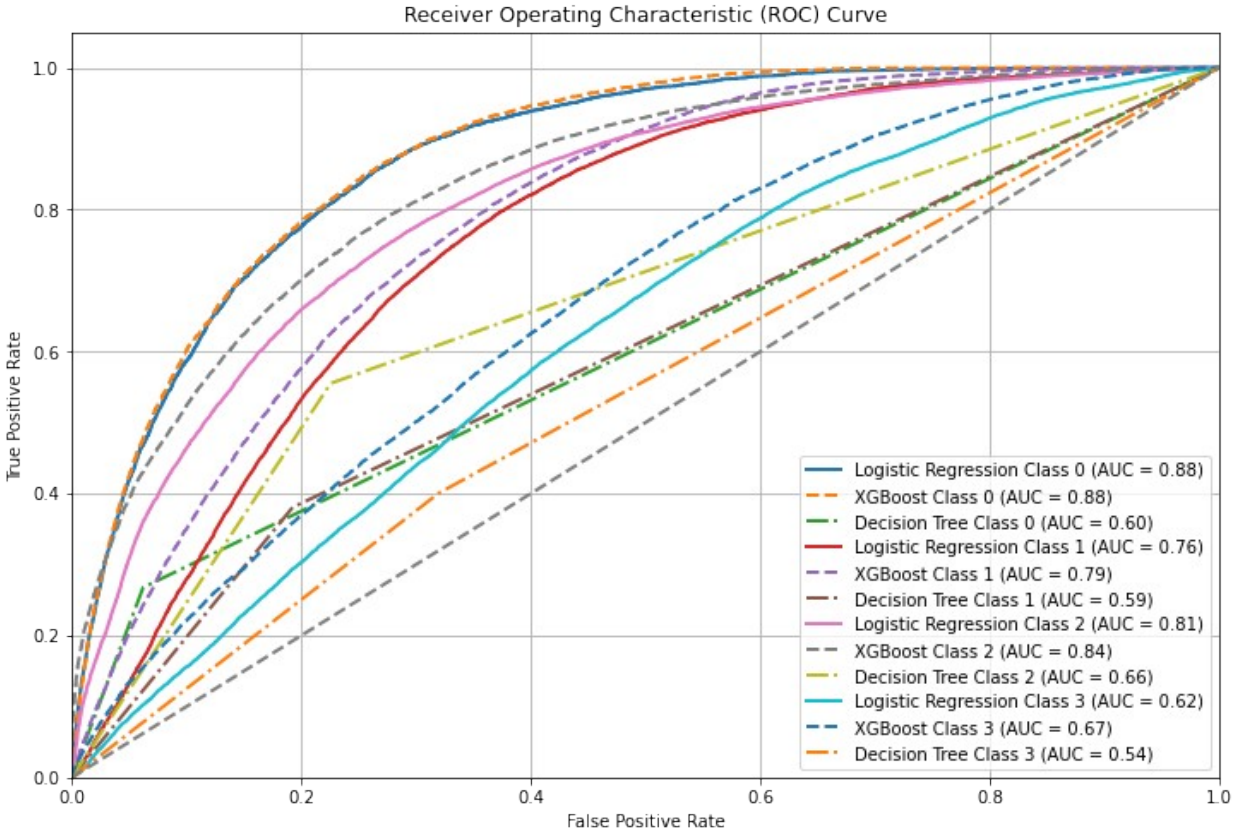
False Negatives: 4094 instances of Class 3 were incorrectly predicted as other classes.

Class 3 has the best performance with high true positive rates, but there are still misclassifications, particularly with Class 2, suggesting further refinement is needed.

ROC CURVE

```
from sklearn.preprocessing import label_binarize

# Binarize the output for multiclass classification
y_test_binarized = label_binarize(y_test,
classes=log_reg_model.classes_)
n_classes = y_test_binarized.shape[1]

# Logistic Regression ROC Curve
y_pred_proba_log_reg = log_reg_model.predict_proba(X_test)
fpr_log_reg, tpr_log_reg, roc_auc_log_reg = {}, {}, {}
for i in range(n_classes):
    fpr_log_reg[i], tpr_log_reg[i], _ = roc_curve(y_test_binarized[:,
i], y_pred_proba_log_reg[:, i])
    roc_auc_log_reg[i] = roc_auc_score(y_test_binarized[:, i],
y_pred_proba_log_reg[:, i])

# XGBoost ROC Curve
y_pred_proba_xgb = xg_boost_model.predict_proba(X_test)
fpr_xgb, tpr_xgb, roc_auc_xgb = {}, {}, {}
for i in range(n_classes):
    fpr_xgb[i], tpr_xgb[i], _ = roc_curve(y_test_binarized[:, i],
y_pred_proba_xgb[:, i])
    roc_auc_xgb[i] = roc_auc_score(y_test_binarized[:, i],
y_pred_proba_xgb[:, i])

# Decision Tree ROC Curve
y_pred_proba_dt = dt_model.predict_proba(X_test)
fpr_dt, tpr_dt, roc_auc_dt = {}, {}, {}
for i in range(n_classes):
    fpr_dt[i], tpr_dt[i], _ = roc_curve(y_test_binarized[:, i],
y_pred_proba_dt[:, i])
    roc_auc_dt[i] = roc_auc_score(y_test_binarized[:, i],
y_pred_proba_dt[:, i])

# Plot ROC Curves
plt.figure(figsize=(12, 8))
for i in range(n_classes):
    plt.plot(fpr_log_reg[i], tpr_log_reg[i], lw=2, label=f'Logistic
Regression Class {i} (AUC = {roc_auc_log_reg[i]:.2f})')
    plt.plot(fpr_xgb[i], tpr_xgb[i], lw=2, linestyle='--',
```

```
label=f'XGBoost Class {i} (AUC = {roc_auc_xgb[i]:.2f})')
    plt.plot(fpr_dt[i], tpr_dt[i], lw=2, linestyle='-.',
label=f'Decision Tree Class {i} (AUC = {roc_auc_dt[i]:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```



XG Boost seems to have the highest AUC scores across all classess. it has the best ability to distinguish between positive and negative classes among the models listed. It performs exceptionally well and can be considered the strongest model.

Feature Importance

Since we had initially used principal components, lets train the model on the entire dataset so as to get the features that are most significant to our prediction.

```
import pandas as pd
import numpy as np
```

```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, classification_report

# Assuming 'APR Risk of Mortality' is the target variable
target = 'APR Risk of Mortality'

# Identify numeric and categorical columns
numeric_features =
df.select_dtypes(include=[np.number]).columns.tolist()
categorical_features =
df.select_dtypes(exclude=[np.number]).columns.tolist()

# Remove target variable from the features lists
if target in numeric_features:
    numeric_features.remove(target)
if target in categorical_features:
    categorical_features.remove(target)

# Encode categorical variables
df_encoded = pd.get_dummies(df, columns=categorical_features,
drop_first=True)

# Separate features and target variable
X = df_encoded.drop(columns=[target])
y = df_encoded[target]

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

# Standardize the numeric features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize and fit the XGBoost model
xgboost_model = XGBClassifier(random_state=42)
xgboost_model.fit(X_train_scaled, y_train)

# Make predictions
y_pred = xgboost_model.predict(X_test_scaled)

# Evaluate the model
print("XGBoost Model")
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test,
y_pred))
```

```
XGBoost Model
Accuracy: 0.7203725200506543
Classification Report:
              precision    recall  f1-score   support

     Extreme       0.70      0.67      0.68      8588
       Major       0.62      0.66      0.64     27308
       Minor       0.85      0.85      0.85     38273
    Moderate       0.68      0.65      0.66     39543

    accuracy                           0.72    113712
   macro avg       0.71      0.71      0.71    113712
weighted avg       0.72      0.72      0.72    113712
```

The overall accuracy of the XGBoost model is approximately 72.04%, meaning it correctly classified about 72% of the samples in the dataset.

1)Of all the predictions made for the "Extreme" class, 70% were correct, indicating a relatively balanced rate of false positives.The model correctly identified 67% of actual "Extreme" instances, suggesting a few false negatives.

2) The model's precision for the "Major" class is 62%, showing a moderate number of false positives. The recall is 66%, indicating the model captures most of the actual "Major" cases.

3)For the "Minor" class, 63% of the predictions were accurate, making this the class with the highest precision.The model correctly identified 71% of the actual "Minor" cases, demonstrating strong recall performance.

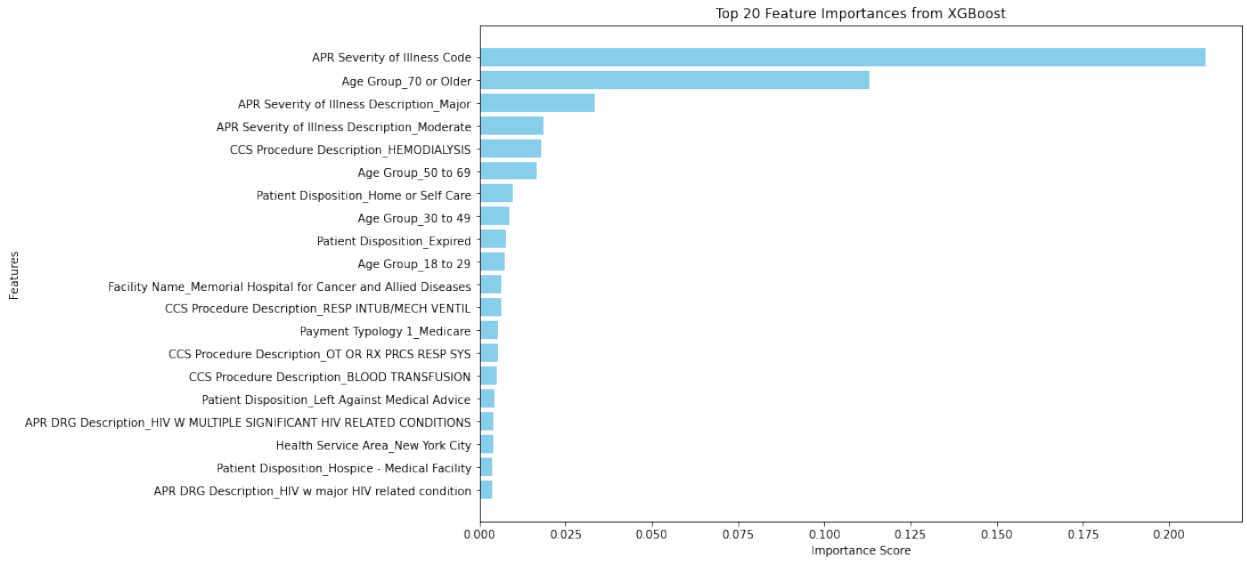
4) The precision for the "Moderate" class is 47%, showing that there are some false positives. The recall is 46%, suggesting a number of false negatives.

```
import numpy as np
import matplotlib.pyplot as plt

feature_names = X.columns

# Retrieve feature importances from the XGBoost model
importances = xgboost_model.feature_importances_

# Create a DataFrame for better visualization and sorting
importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': importances
})

# Sort features by importance
importance_df = importance_df.sort_values(by='Importance',
ascending=False)
```

```
# Display the top features
print(importance_df.head(10))
```

```
                                                Feature  Importance
6                       APR Severity of Illness Code    0.210678
308                            Age Group_70 or Older    0.112973
708        APR Severity of Illness Description_Major    0.033311
710     APR Severity of Illness Description_Moderate    0.018721
529           CCS Procedure Description_HEMODIALYSIS    0.017981
307                               Age Group_50 to 69    0.016564
448            Patient Disposition_Home or Self Care    0.009786
306                               Age Group_30 to 49    0.008729
445                     Patient Disposition_Expired    0.007743
305                               Age Group_18 to 29    0.007209
```

```
# Plot Feature Importance using the original feature names
plt.figure(figsize=(12, 8))
plt.barh(importance_df['Feature'][:20], importance_df['Importance']
[:20], color='skyblue')
plt.gca().invert_yaxis()
plt.xlabel('Importance Score')
plt.ylabel('Features')
plt.title('Top 20 Feature Importances from XGBoost')
plt.show()
```



5. Conclusion

From the above analysis, we can conclude that;

1) The APR Severity of Illness Code is the most significant predictor of the APR Risk of Mortality meaning. This indicates that the more severe a patient's condition, the higher their risk of mortality.

2) Age is a crucial factor in determining mortality risk. Patients aged 70 or older have a significantly higher risk of mortality. This emphasizes the importance of prioritizing elderly patients for closer monitoring and care.

3) Patients undergoing hemodialysis have an increased risk of mortality, highlighting the need for careful management of patients with renal failure or related conditions.

4) The patient's disposition status, especially whether they are discharged to home or self-care or have expired, indicates significant mortality risk factors, reflecting care transitions' outcomes.

5) The descriptions of illness severity, particularly Major and Moderate, also play a significant role in predicting mortality risk. Patients classified as having major or moderate severity levels should be monitored closely.

6. Recommendations

1) Enhance Monitoring: Implement advanced monitoring and treatment strategies for patients with higher APR Severity of Illness Codes (Extreme, Major, Moderate). This includes deploying resources for intensive care units and specialized treatment plans.

2) Age-Specific Care Plans: Create age-specific care plans, focusing on preventive measures and early interventions for patients aged 70 and older. This can be done by conducting regular health assessments for elderly patients to identify potential risks early and address them promptly.

3) Comprehensive Care for Renal Patients: Develop comprehensive care programs for patients undergoing hemodialysis, including regular check-ups, nutritional support, and access to specialized care.

4) Improve Transion Care - Enhance discharge planning and follow-up care for patients discharged to home or self-care. Ensure that they have access to necessary resources and support to prevent readmissions or adverse outcomes.

5) Healthcare Policy: Advocate for healthcare policies that emphasize preventive care, early intervention, and resource allocation based on severity and age-related risk factors.

6) Track Readmissions - The current dataset does not include information on hospital readmissions, making it difficult to identify which demographic groups are more frequently affected. Assigning a unique patient ID to each individual would enable more detailed tracking and provide deeper insights into paterns of readmissions across demographics.