Project Title	**Cybersecurity: Suspicious Web Threat Interactions**
language	Machine learning, python, SQL, Excel
Tools	VS code, Jupyter notebook
Domain	Data Analyst
Project Difficulties level	Advance

Dataset : Dataset is available in the given link. You can download it at your convenience.

Click here to download data set

About Dataset

This dataset contains web traffic records collected through **AWS CloudWatch**, aimed at detecting suspicious activities and potential attack attempts.

The data were generated by monitoring traffic to a production web server, using various detection rules to identify anomalous patterns.

Context

In today's cloud environments, cybersecurity is more crucial than ever. The ability to detect and respond to threats in real time can protect organizations from significant consequences. This dataset provides a view of web traffic that has been labeled as suspicious, offering a valuable resource for developers, data scientists, and security experts to enhance threat detection techniques.

Dataset Content

Each entry in the dataset represents a stream of traffic to a web server, including the following columns:

`bytes_in`: Bytes received by the server.

`bytes_out`: Bytes sent from the server.

`creation_time`: Timestamp of when the record was created.

`end_time`: Timestamp of when the connection ended.

`src_ip`: Source IP address.

`src_ip_country_code`: Country code of the source IP.

`protocol`: Protocol used in the connection.

`response.code`: HTTP response code.

`dst_port`: Destination port on the server.

`dst_ip`: Destination IP address.

`rule_names`: Name of the rule that identified the traffic as suspicious.

`observation_name`: Observations associated with the traffic.

`source.meta`: Metadata related to the source.

`source.name`: Name of the traffic source.

`time`: Timestamp of the detected event.

`detection_types`: Type of detection applied.

Potential Uses

This dataset is ideal for:

- **Anomaly Detection**: Developing models to detect unusual behaviors in web traffic.
- **Classification Models**: Training models to automatically classify traffic as normal or suspicious.
- **Security Analysis**: Conducting security analyses to understand the tactics, techniques, and procedures of attackers.

Example : from here you can get idea that how you can create project

Project Overview

Objective: To detect and analyze patterns in web interactions for identifying suspicious or potentially harmful activities.

Steps

---

1. Data Import and Basic Overview

```
import pandas as pd

# Load dataset
df = pd.read_csv('cybersecurity_data.csv')

# View basic information
df.info()
df.head()
```

2. Data Preprocessing

Handle missing values, outliers, and data inconsistencies.

```
# Check for missing values
missing_values = df.isnull().sum()

# Fill or drop missing values as needed
df['bytes_in'].fillna(df['bytes_in'].median(), inplace=True)
df.dropna(subset=['src_ip', 'dst_ip'], inplace=True)

# Convert columns to appropriate datatypes
df['creation_time'] = pd.to_datetime(df['creation_time'])
```

```
df['end_time'] = pd.to_datetime(df['end_time'])
```

3. Exploratory Data Analysis (EDA)

Analyze Traffic Patterns Based on `bytes_in` and `bytes_out`

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

# Distribution of bytes in and bytes out
plt.figure(figsize=(12, 6))
sns.histplot(df['bytes_in'], bins=50, color='blue', kde=True,
label='Bytes In')
sns.histplot(df['bytes_out'], bins=50, color='red', kde=True,
label='Bytes Out')
plt.legend()
plt.title('Distribution of Bytes In and Bytes Out')
plt.show()
```

Count of Protocols Used

```
plt.figure(figsize=(10, 5))
sns.countplot(x='protocol', data=df, palette='viridis')
plt.title('Protocol Count')
plt.xticks(rotation=45)
```

```
plt.show()
```

4. Feature Engineering

Extract useful features, like duration and average packet size, to aid in analysis.

```
# Duration of the session in seconds
df['session_duration'] = (df['end_time'] -
df['creation_time']).dt.total_seconds()

# Average packet size
df['avg_packet_size'] = (df['bytes_in'] + df['bytes_out']) /
df['session_duration']
```

5. Data Visualization

Country-based Interaction Analysis

```
plt.figure(figsize=(15, 8))
sns.countplot(y='src_ip_country_code', data=df,
order=df['src_ip_country_code'].value_counts().index)
plt.title('Interaction Count by Source IP Country Code')
plt.show()
```

Suspicious Activities Based on Ports

```
plt.figure(figsize=(12, 6))
sns.countplot(x='dst_port', data=df[df['detection_types'] ==
'Suspicious'], palette='coolwarm')
plt.title('Suspicious Activities Based on Destination Port')
plt.xticks(rotation=45)
plt.show()
```

6. Modeling: Anomaly Detection

This step uses Isolation Forest, a common technique for detecting anomalies.

```
from sklearn.ensemble import IsolationForest

# Selecting features for anomaly detection
features = df[['bytes_in', 'bytes_out', 'session_duration',
'avg_packet_size']]

# Initialize the model
model = IsolationForest(contamination=0.05, random_state=42)

# Fit and predict anomalies
df['anomaly'] = model.fit_predict(features)
df['anomaly'] = df['anomaly'].apply(lambda x: 'Suspicious' if x
== -1 else 'Normal')
```

7. Evaluation

Evaluate the anomaly detection model by checking its accuracy in identifying suspicious activities.

```
# Check the proportion of anomalies detected
print(df['anomaly'].value_counts())

# Display anomaly samples
suspicious_activities = df[df['anomaly'] == 'Suspicious']
print(suspicious_activities.head())
```

8. Visualization of Anomalies

```
# Visualize bytes_in vs bytes_out with anomalies highlighted
plt.figure(figsize=(10, 6))
sns.scatterplot(x='bytes_in', y='bytes_out', hue='anomaly',
data=df, palette=['green', 'red'])
plt.title('Anomalies in Bytes In vs Bytes Out')
plt.show()
```

9. Report Findings

Based on the model output and visualizations, interpret the most frequent anomaly patterns, source IPs, and ports related to suspicious activities.

Example Insights:

- **High bytes_in and low bytes_out sessions** could indicate possible infiltration attempts.
- **Frequent interactions from specific country codes** may indicate targeted or bot-related attacks.
- **High activity on non-standard ports** may signal unauthorized access attempts.

Example: You can get the basic idea how you can create a project from here

Sample code with output

Module Importing

In [1]:

```
import pandas as pd
import seaborn as sns
import networkx as nx
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report,
accuracy_score
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dense, Conv1D,
MaxPooling1D, Flatten, Dropout
```

```
from tensorflow.keras.optimizers import Adam
import warnings
warnings.filterwarnings("ignore")
```

```
2024-05-07 21:10:10.181949: E
external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261]
Unable to register cuDNN factory: Attempting to register
factory for plugin cuDNN when one has already been registered
2024-05-07 21:10:10.182342: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607]
Unable to register cuFFT factory: Attempting to register
factory for plugin cuFFT when one has already been registered
2024-05-07 21:10:10.352062: E
external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1515]
Unable to register cuBLAS factory: Attempting to register
factory for plugin cuBLAS when one has already been registered
```

In [2]:

```
# Load the data into a DataFrame
data =
pd.read_csv("/kaggle/input/cybersecurity-suspicious-web-threat-
interactions/CloudWatch_Traffic_Web_Attack.csv")
# Display the first few rows of the DataFrame to understand its
```

```
structure
data.head()
```

Out[2]:

	bytes_in	bytes_out	creation_time	end_time	src_ip	src_ip_country_code	protocol	response.code	dst_port	dst_ip	rule_names	observation_name	source.meta	source.name	time	detection_types
0	5602	12990	2024-04-25T23:00:00Z	2024-04-25T23:10:00Z	147.161.161.82	AE	HTTPS	200	443	10.138.69.97	Suspicious Web Traffic	Adversary Infrastructure Interaction	AWS_VPC_Flow	prod_webserver	2024-04-25T23:00:00Z	waf_rule

1	30912	18186	2024-04-25T23:00:00Z	2024-04-25T23:10:00Z	165.225.33.6	US	HTTPS	200	443	10.138.69.97	Suspicious Web Traffic	Adversary Infrastructure Interaction	AWS_VPC_Flow	prod_webserver	2024-04-25T23:00:00Z	waf_rule
2	28506	13468	2024-04-25T23:00:00Z	2024-04-25T23:10:00Z	165.225.212.255	CA	HTTPS	200	443	10.138.69.97	Suspicious Web Traffic	Adversary Infrastructure Interaction	AWS_VPC_Flow	prod_webserver	2024-04-25T23:00:00Z	waf_rule

3	3 0 5 4 6	1 4 2 7 8	2024-04-25T23:00:00Z	2024-04-25T23:10:00Z	136.226.64.114	US	HTTPS	200	443	10.138.69.97	Suspicious Web Traffic	Adversary Infrastructure Interaction	AWS_VPC_Flow	prod_webserver	2024-04-25T23:00:00Z	waf_rule
4	6 5 2 6	1 3 8 9 2	2024-04-25T23:00:00Z	2024-04-25T23:10:00Z	165.225.240.79	NL	HTTPS	200	443	10.138.69.97	Suspicious Web Traffic	Adversary Infrastructure Interaction	AWS_VPC_Flow	prod_webserver	2024-04-25T23:00:00Z	waf_rule

Data Preparation

1. Data Cleaning

The dataset contains **282 entries** across **16 columns**. There are no **null values** in any of the columns, which is **good news for data integrity**. However, let's proceed with the following data cleaning tasks:

1. **Removing Duplicate Rows :** Even though all entries appear non-null, there may still be duplicate entries that should be removed to prevent skewing our analysis.
2. **Correcting Data Types :** Some columns such as `creation_time`, `end_time`, and `time` should ideally be in datetime format for any time series analysis or operations that involve time intervals.
3. **Standardize Text Data :** Ensuring consistency in how text data is formatted can be important, particularly if you're going to perform text-based operations or integrations.

The data has been cleaned with the following steps implemented:

1. **Duplicate Rows :** No duplicate rows were found, so the dataset remains with 282 entries.
2. **Data Types :** The `creation_time`, `end_time`, and `time` columns have been successfully converted to datetime format, which is more appropriate for any operations involving time.
3. **Text Data Standardization :** The `src_ip_country_code` has been standardized to uppercase to ensure consistency across this field.

Handling Missing Data

```
In [3]:
```

```
# Remove duplicate rows
df_unique = data.drop_duplicates()
# Convert time-related columns to datetime format
df_unique['creation_time'] =
pd.to_datetime(df_unique['creation_time'])
df_unique['end_time'] = pd.to_datetime(df_unique['end_time'])
df_unique['time'] = pd.to_datetime(df_unique['time'])
# Standardize text data (example: convert to lower case)
df_unique['src_ip_country_code'] =
df_unique['src_ip_country_code'].str.upper()  # Ensuring
country codes are all upper case
# Display changes and current state of the DataFrame
print("Unique Datasets Information:")
df_unique.info()
```

```
Unique Datasets Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 282 entries, 0 to 281
Data columns (total 16 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   bytes_in             282 non-null    int64
 1   bytes_out            282 non-null    int64
 2   creation_time        282 non-null    datetime64[ns, UTC]
```

```
 3   end_time            282 non-null    datetime64[ns, UTC]
 4   src_ip              282 non-null    object
 5   src_ip_country_code 282 non-null    object
 6   protocol            282 non-null    object
 7   response.code       282 non-null    int64
 8   dst_port            282 non-null    int64
 9   dst_ip              282 non-null    object
 10  rule_names          282 non-null    object
 11  observation_name    282 non-null    object
 12  source.meta         282 non-null    object
 13  source.name         282 non-null    object
 14  time                282 non-null    datetime64[ns, UTC]
 15  detection_types     282 non-null    object
dtypes: datetime64[ns, UTC](3), int64(4), object(9)
memory usage: 35.4+ KB
```

In [4]:

```
print("Top 5 Unique Datasets Information:")
df_unique.head()
```

```
Top 5 Unique Datasets Information:
```

Out[4]:

	bytes_in	bytes_out	creation_time	end_time	src_ip	src_ip_country_code	protocol	response.code	dst_port	dst_ip	rule_names	observation_name	source.meta	source.name	time	detection_types
0	5602	12990	2024-04-25 23:00:00+00:00	2024-04-25 23:10:00+00:00	147.161.161.82	AE	HTTPS	200	443	10.138.69.97	Suspicious Web Traffic	Adversary Infrastructure Interaction	AWS_VPC_Flow	prod_webserver	2024-04-25 23:00:00+00:00	waf_rule
1	30	18	2024-	2024-	165.22	US	HT	200	44	10.1	Sus	Adversa	AWS_	prod_	2024-	waf_ru

	912	186	04-25 23:00:00+00:00	04-25 23:10:00+00:00	5.33.6		TPS		3	38.69.97	picious Web Traffic	ry Infrastructure Interaction	VPC_Flow	webserver	04-25 23:00:00+00:00	le
2	28506	13468	2024-04-25 23:00:00+00:00	2024-04-25 23:10:00+00:00	165.225.212.255	CA	HTTPS	200	443	10.138.69.97	Suspicious Web Traffic	Adversary Infrastructure Interaction	AWS_VPC_Flow	prod_webserver	2024-04-25 23:00:00+00:00	waf_rule
3	3054	1427	2024-04-25	2024-04-25	136.226.64.1	US	HTTP	200	443	10.138.6	Suspici	Adversary Infra	AWS_VPC_	prod_webse	2024-04-25	waf_rule

	6	8	23:00:00+00:00	23:10:00+00:00	14		S			9.97	ous Web Traffic	structure Interaction	Flow	rver	23:00:00+00:00	
4	6526	13892	2024-04-25 23:00:00+00:00	2024-04-25 23:10:00+00:00	165.225.240.79	NL	HTTPS	200	443	10.138.69.97	Suspicious Web Traffic	Adversary Infrastructure Interaction	AWS_VPC_Flow	prod_webserver	2024-04-25 23:00:00+00:00	waf_rule

Data Transformation

When it comes to preparing our dataset for machine learning models, one of the most important steps is data transformation. This phase helps to standardize or normalize the data, which in turn makes it simpler for the models to learn and generate correct predictions. Listed below are some of the more typical methods of data transformation that you could use:

1. Normalization and Scaling

Normalization or scaling ensures that numeric features contribute equally to model training. Common methods include:

- Min-Max Scaling : Transforms features to a fixed range, usually 0 to 1.
- Standardization (Z-score Scaling) : Centers the data by removing the mean and scales it by the standard deviation to achieve a variance of 1 and mean of 0.

2. Encoding Categorical Data

Machine learning models generally require all input and output variables to be numeric. This means that categorical data must be converted into a numerical format.

- One-Hot Encoding : Creates a binary column for each category and returns a matrix with 1s and 0s.
- Label Encoding : Converts each value in a column to a number.

3. Feature Engineering

Feature engineering is the process of using domain knowledge to select, modify, or create new features that increase the predictive power of the learning algorithm.

- Polynomial Features : Derive new feature interactions.
- Binning : Convert numerical values into categorical bins.

Applying These Transformations

Now will try to apply some of these transformations to our dataset:

1. Scale the `bytes_in` and `bytes_out` columns using Standardization.
2. One-hot encode the `src_ip_country_code` column since it is a categorical feature.
3. Feature engineering example : Create a new feature that measures the duration of the connection based on `creation_time` and `end_time`.

Now we will start with these transformations.

1. Scaling : The `bytes_in`, `bytes_out`, and the newly created `duration_seconds` (which captures the duration of the connection) columns have been standardized using z-score scaling. This means their mean is now 0 and standard deviation is 1, which helps in normalizing the data for better performance of many machine learning algorithms.
2. One-Hot Encoding : The `src_ip_country_code` column has been one-hot encoded. This has transformed each country code into its own feature, allowing categorical data to be used effectively in machine learning models.
3. Feature Engineering : A new feature `duration_seconds` was added to measure the duration of each web session.

In [5]:

```
# Feature engineering: Calculate duration of connection
df_unique['duration_seconds'] = (df_unique['end_time'] -
df_unique['creation_time']).dt.total_seconds()


# Preparing column transformations
```

```
# StandardScaler for numerical features
scaler = StandardScaler()
scaled_features = scaler.fit_transform(df_unique[['bytes_in',
'bytes_out', 'duration_seconds']])
```

In [6]:

```
# OneHotEncoder for categorical features
encoder = OneHotEncoder(sparse=False)
encoded_features =
encoder.fit_transform(df_unique[['src_ip_country_code']])

# Combining transformed features back into the DataFrame
scaled_columns = ['scaled_bytes_in', 'scaled_bytes_out',
'scaled_duration_seconds']
encoded_columns =
encoder.get_feature_names_out(['src_ip_country_code'])
```

In [7]:

```
# Convert numpy arrays back to DataFrame
scaled_df = pd.DataFrame(scaled_features,
columns=scaled_columns, index=df_unique.index)
encoded_df = pd.DataFrame(encoded_features,
columns=encoded_columns, index=df_unique.index)
```

```
# Concatenate all the data back together
transformed_df = pd.concat([df_unique, scaled_df, encoded_df],
axis=1)
# Displaying the transformed data
transformed_df.head()
```

Out[7]:

	bytes_in	bytes_out	creation_time	end_time	src_ip	src_ip_country_code	protocol	response.code	dst_port	dst_ip	...	scaled_bytes_in	scaled_bytes_out	scaled_duration_seconds	src_ip_country_code_AE	src_ip_country_code_AT	src_ip_country_code_CA	src_ip_country_code_DE	src_ip_country_code_IL	src_ip_country_code_NL	src_ip_country_code_US
0	56	12	20	20	14	A	HT	20	44	10	...	-0	-0.2	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0

	02	990	24-04-2523:00:00+00:00	24-04-2523:10:00+00:00	7.161.161.82	E	TPS	0	3	.138.69.97	.	.288219	81223								
1	3091	1818	2024	2024	165.2	US	HTTP	200	443	10.1	...	-0.2	-0.260	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

	2	6	-04-2523:00:00+00:00	-04-2523:10:00+00:00	25.33.6		S			38.69.97		82108	804								
2	28506	13468	2024-0	2024-0	165.225.	CA	HTTPS	200	443	10.138	...	-0.282	-0.27934	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.(

			4-2523:00:00+00:00	4-2523:10:00+00:00	212.255					.69.97		689	4								
3	30546	14278	2024-	2024-	136.226.64.	US	HTTPS	200	443	10.138.6	...	-0.28219	-0.276161	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

			2523:00:00+00:00	2523:10:00+00:00	114					9.97		7									
4	6526	13892	2024-04-25	2024-04-25	165.225.240.7	NL	HTTPS	200	443	10.138.69.	...	-0.287996	-0.277678	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0

			23:00:00+00:00	23:10:00+00:00	9					97											

5 rows × 27 columns

Exploratory Data Analysis (EDA)

A significant stage in the process of summarizing, describing, and comprehending the underlying patterns in the data is the performing of statistical analysis. Examining several aspects such as distributions, central trends, variability, and correlations between characteristics is included in this. On your converted dataset, let's carry out a number of statistical analysis, including the following:

1. **Descriptive Statistics :** This includes mean, median, mode, min, max, range, quartiles, and standard deviations.
2. **Correlation Analysis :** To investigate the relationships between numerical features and how they relate to each other.

3. **Distribution Analysis :** Examine the distribution of key features using histograms and box plots to identify the spread and presence of outliers.

Descriptive Statistics

The descriptive statistics provide a summary of the key statistical characteristics of the numerical features:

- `bytes_in` and `bytes_out` : These columns have a high standard deviation relative to their mean, indicating significant variability. This could be reflective of different types of web sessions or activities.
- `response.code` and `dst_port` : These fields are constants in the dataset (200 and 443, respectively), indicating all records are using HTTPS protocol on standard port 443 and receiving a standard HTTP 200 OK response.
- `duration_seconds` : It's also constant (600 seconds), which suggests that each session or observation is recorded over a fixed interval.
- Scaled Features : The scaled versions of `bytes_in`, `bytes_out`, and `duration_seconds` have a mean of approximately 0 and a standard deviation of 1, as expected after standardization.

In [8]:

```
# Compute correlation matrix for numeric columns only
numeric_df = transformed_df.select_dtypes(include=['float64',
'int64'])
correlation_matrix_numeric = numeric_df.corr()
# Display the correlation matrix
correlation_matrix_numeric
```

Out[8]:

	bytes_in	bytes_out	response.code	dst_port	duration_seconds	scaled_bytes_in	scaled_bytes_out	scaled_duration_seconds	src_ip_country_code_AE	src_ip_country_code_AT	src_ip_country_code_CA	src_ip_country_code_DE	src_ip_country_code_IL	src_ip_country_code_NL	src_ip_country_code_US
bytes_in	1.000000	0.997705	NaN	NaN	NaN	1.000000	0.997705	NaN	-0.070559	-0.081670	-0.166488	-0.095333	-0.065939	-0.006827	0.316015

bytes_out	0.997705	1.000000	NaN	NaN	NaN	0.997705	1.000000	NaN	-0.072452	-0.081777	-0.159587	-0.090001	-0.067630	-0.045641	0.327683
response.code	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
dst_port	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
duration_seconds	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

scaled_bytes_in	1.000000	0.997705	NaN	NaN	NaN	1.000000	0.997705	NaN	-0.070559	-0.081670	-0.166488	-0.095333	-0.065939	-0.006827	0.316015
scaled_bytes_out	0.997705	1.000000	NaN	NaN	NaN	0.997705	1.000000	NaN	-0.072452	-0.081777	-0.159587	-0.090001	-0.067630	-0.045641	0.327683
scaled_duration_secon	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

ds														
src_ip_country_code_AE	-0.070559	-0.072452	NaN	NaN	NaN	-0.070559	-0.072452	NaN	1.000000	-0.069568	-0.143607	-0.081429	-0.056055	-0.064040	-0.200546
src_ip_country_code_AT	-0.081670	-0.081777	NaN	NaN	NaN	-0.081670	-0.081777	NaN	-0.069568	1.000000	-0.166091	-0.094178	-0.064831	-0.074067	-0.231945
src_ip_count	-0.	-0.	Na	Na	NaN	-0.166	-0.1595	NaN	-0.1436	-0.1660	1.00000	-0.1944	-0.1338	-0.1528	-0.4787

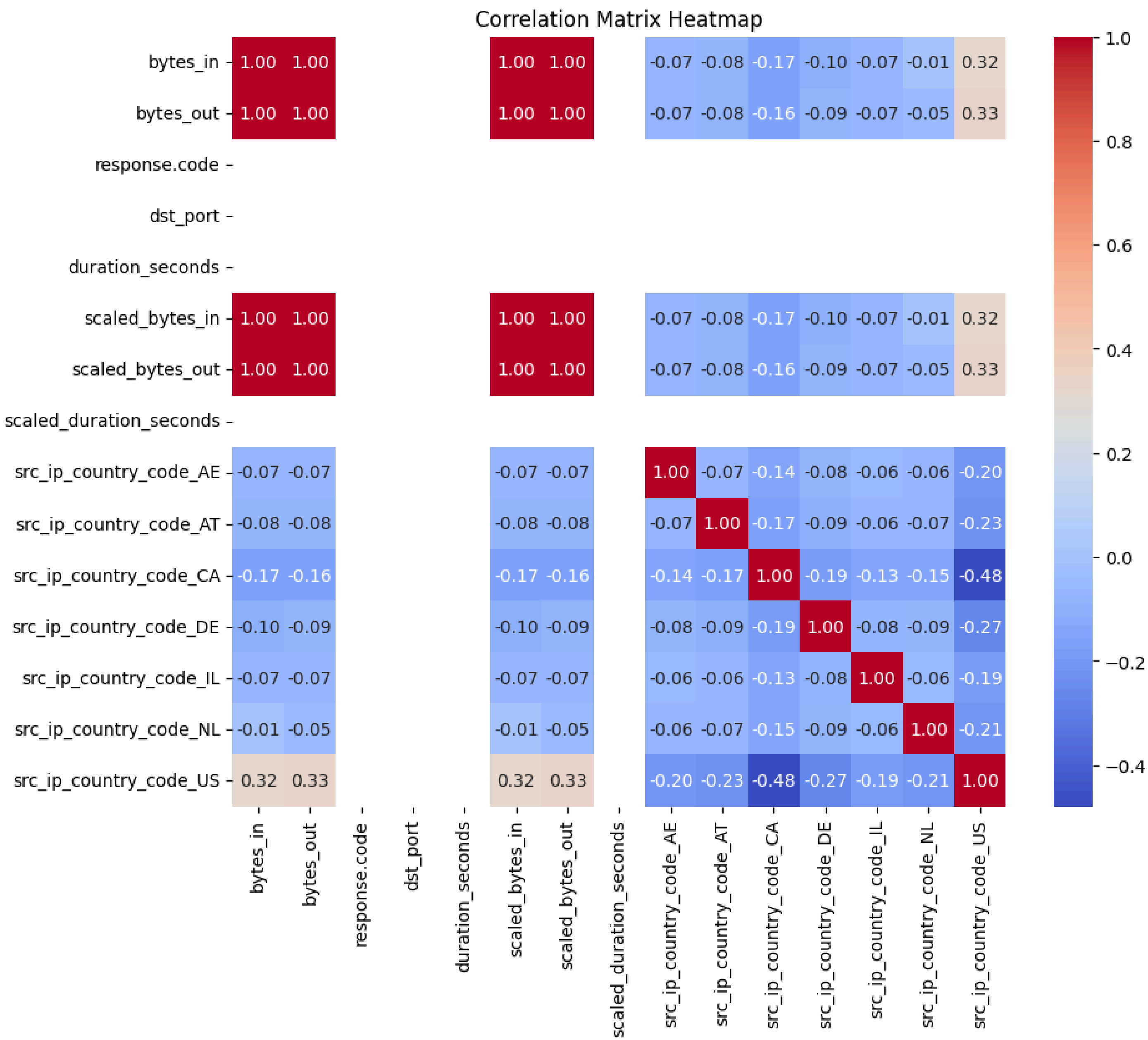
ry_code_CA	166488	159587	N	N		488	87		07	91	0	10	30	94	98
src_ip_country_code_DE	-0.095333	-0.090001	NaN	NaN	NaN	-0.095333	-0.090001	NaN	-0.081429	-0.094178	-0.194410	1.000000	-0.075885	-0.086695	-0.271493
src_ip_country_code_IL	-0.065939	-0.067630	NaN	NaN	NaN	-0.065939	-0.067630	NaN	-0.056055	-0.064831	-0.133830	-0.075885	1.000000	-0.059680	-0.186893

src_ip_country_code_NL	-0.006827	-0.045641	NaN	NaN	NaN	-0.006827	-0.045641	NaN	-0.064040	-0.074067	-0.152894	-0.086695	-0.059680	1.000000	-0.213516
src_ip_country_code_US	0.316015	0.327683	NaN	NaN	NaN	0.316015	0.327683	NaN	-0.200546	-0.231945	-0.478798	-0.271493	-0.186893	-0.213516	1.000000

In [9]:

```
# Heatmap for the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix_numeric, annot=True, fmt=".2f",
cmap='coolwarm')
plt.title('Correlation Matrix Heatmap')
```

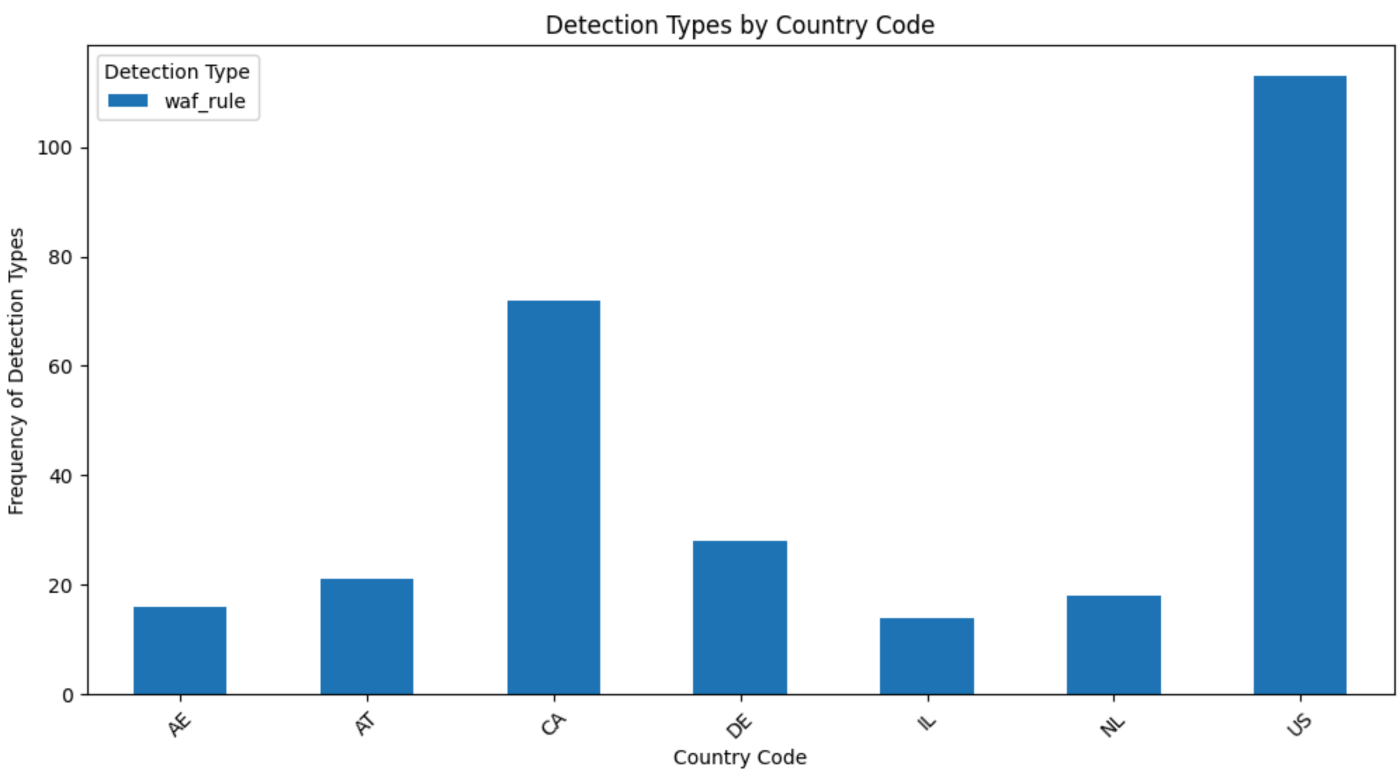
```python
plt.show()
```



In [10]:

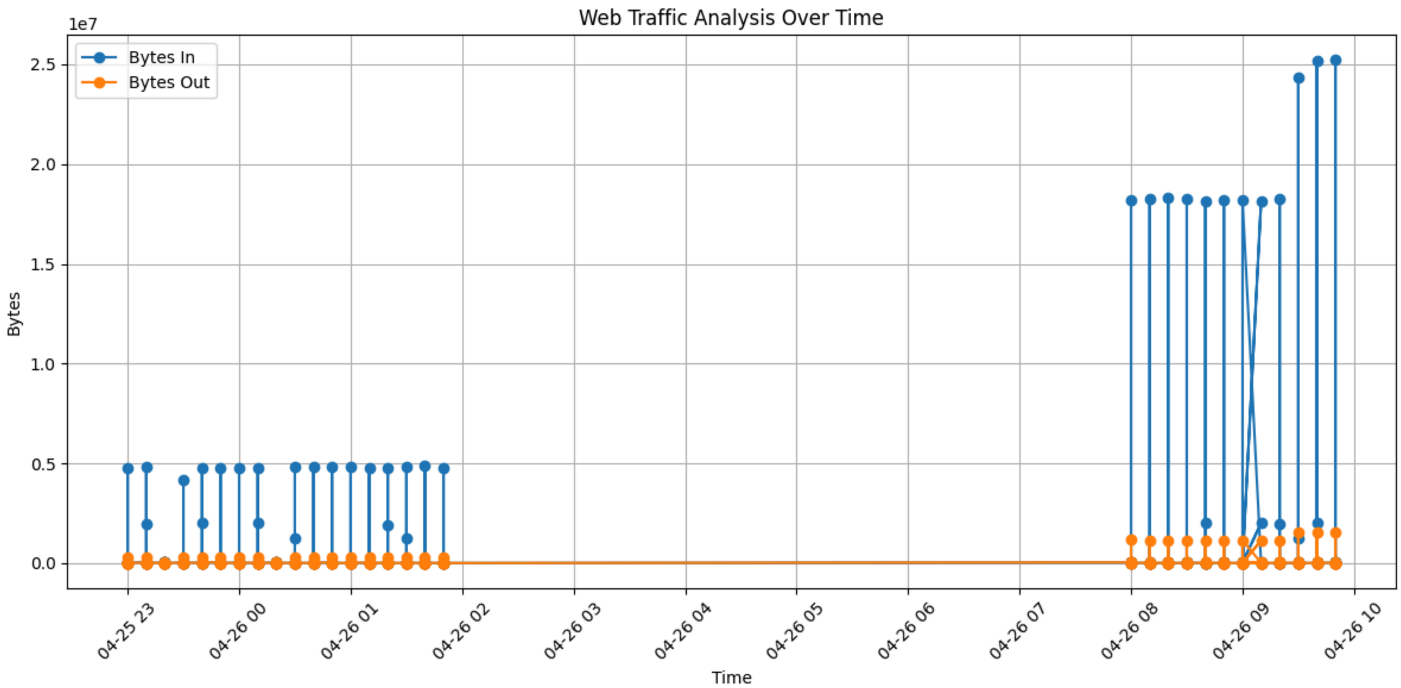
```python
# Stacked Bar Chart for Detection Types by Country
# Preparing data for stacked bar chart
detection_types_by_country =
```

```
pd.crosstab(transformed_df['src_ip_country_code'],
transformed_df['detection_types'])
detection_types_by_country.plot(kind='bar', stacked=True,
figsize=(12, 6))
plt.title('Detection Types by Country Code')
plt.xlabel('Country Code')
plt.ylabel('Frequency of Detection Types')
plt.xticks(rotation=45)
plt.legend(title='Detection Type')
plt.show()
```




```
In [11]:
```

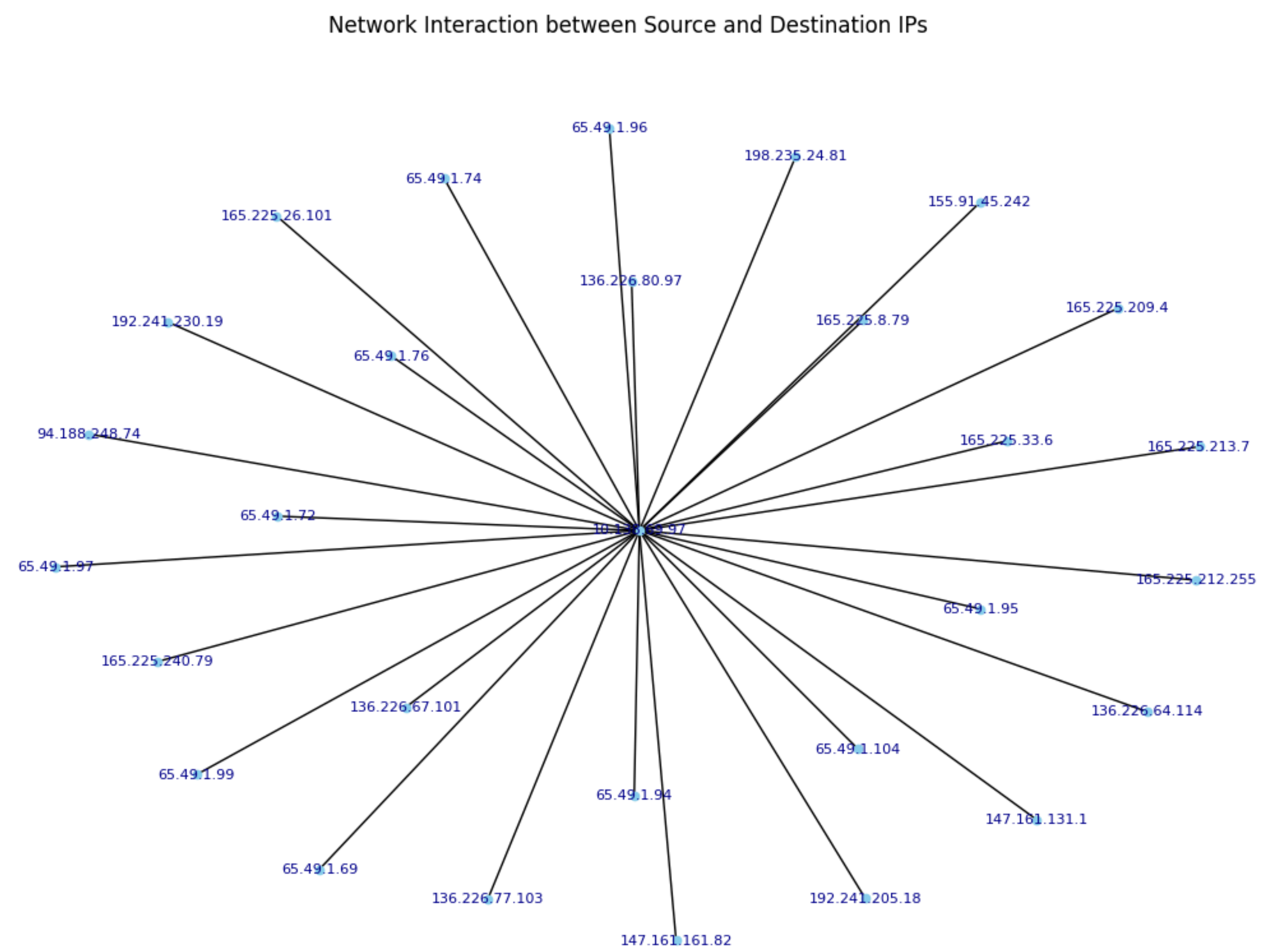
```
# Convert 'creation_time' to datetime format
data['creation_time'] = pd.to_datetime(data['creation_time'])

# Set 'creation_time' as the index
data.set_index('creation_time', inplace=True)

# Plotting
plt.figure(figsize=(12, 6))
plt.plot(data.index, data['bytes_in'], label='Bytes In',
marker='o')
plt.plot(data.index, data['bytes_out'], label='Bytes Out',
marker='o')
plt.title('Web Traffic Analysis Over Time')
plt.xlabel('Time')
plt.ylabel('Bytes')
plt.legend()
plt.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()

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



In [12]:

```
# Create a graph
G = nx.Graph()

# Add edges from source IP to destination IP
for idx, row in data.iterrows():
    G.add_edge(row['src_ip'], row['dst_ip'])

# Draw the network graph
plt.figure(figsize=(14, 10))
nx.draw_networkx(G, with_labels=True, node_size=20,
font_size=8, node_color='skyblue', font_color='darkblue')
plt.title('Network Interaction between Source and Destination
IPs')
```

```python
plt.axis('off')  # Turn off the axis

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



RandomForestClassifier

In [13]:

```python
# First, encode this column into binary labels
transformed_df['is_suspicious'] =
```

```
(transformed_df['detection_types'] == 'waf_rule').astype(int)

# Features and Labels
X = transformed_df[['bytes_in', 'bytes_out',
'scaled_duration_seconds']]  # Numeric features
y = transformed_df['is_suspicious']  # Binary labels
```

In [14]:

```
# 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)

# Initialize the Random Forest Classifier
rf_classifier = RandomForestClassifier(n_estimators=100,
random_state=42)

# Train the model
rf_classifier.fit(X_train, y_train)

# Predict on the test set
y_pred = rf_classifier.predict(X_test)
```

In [15]:

```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
classification = classification_report(y_test, y_pred)
```

In [16]:

```
print("Model Accuracy: ",accuracy)
```

```
Model Accuracy:  1.0
```

In [17]:

```
print("Classification Report: ",classification)
```

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

           1       1.00      1.00      1.00        85

    accuracy                           1.00        85
   macro avg       1.00      1.00      1.00        85
weighted avg       1.00      1.00      1.00        85
```

Neural Network

In [18]:

```
data['is_suspicious'] = (data['detection_types'] ==
'waf_rule').astype(int)

# Features and labels
X = data[['bytes_in', 'bytes_out']].values  # Using only
numeric features
y = data['is_suspicious'].values

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

# Normalize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Neural network model
model = Sequential([
    Dense(8, activation='relu',
input_shape=(X_train_scaled.shape[1],)),
```

```
    Dense(16, activation='relu'),
    Dense(1, activation='sigmoid')
])

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

# Train the model
history  = model.fit(X_train_scaled, y_train, epochs=10,
batch_size=8, verbose=1)

# Evaluate the model
loss, accuracy = model.evaluate(X_test_scaled, y_test)
print(f"Test Accuracy: {accuracy*100:.2f}%")
```

```
Epoch 1/10
25/25 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step -
accuracy: 1.0000 - loss: 0.5825
Epoch 2/10
25/25 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step -
accuracy: 1.0000 - loss: 0.5093
Epoch 3/10
25/25 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step -
```

```
accuracy: 1.0000 - loss: 0.4409
Epoch 4/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step -
accuracy: 1.0000 - loss: 0.3579
Epoch 5/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step -
accuracy: 1.0000 - loss: 0.2755
Epoch 6/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step -
accuracy: 1.0000 - loss: 0.2074
Epoch 7/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step -
accuracy: 1.0000 - loss: 0.1354
Epoch 8/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step -
accuracy: 1.0000 - loss: 0.0840
Epoch 9/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step -
accuracy: 1.0000 - loss: 0.0498
Epoch 10/10
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step -
accuracy: 1.0000 - loss: 0.0323
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy:
1.0000 - loss: 0.0237
Test Accuracy: 100.00%
```

In [19]:

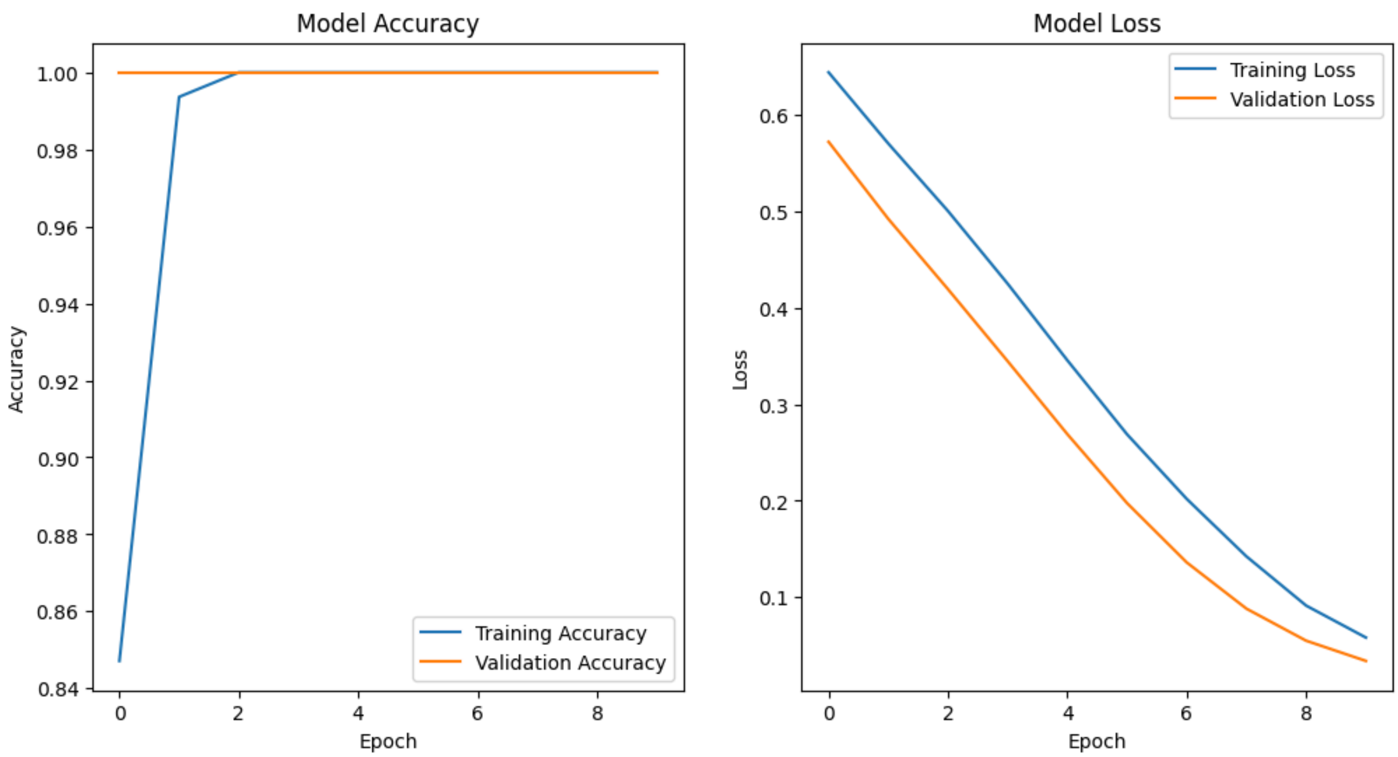
```
# Neural network model
model = Sequential([
    Dense(128, activation='relu',
input_shape=(X_train_scaled.shape[1],)),
    Dropout(0.5),
    Dense(128, activation='relu'),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])

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

# Train the model
history = model.fit(X_train_scaled, y_train, epochs=10,
batch_size=32, verbose=1, validation_split=0.2)

# Evaluate the model
loss, accuracy = model.evaluate(X_test_scaled, y_test)
print(f"Test Accuracy: {accuracy*100:.2f}%")
```

```
# Plotting the training history
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'], label='Training
Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation
Accuracy')
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

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

plt.show()
```

```
Epoch 1/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 2s 59ms/step - accuracy:
```

```
0.7806 - loss: 0.6534 - val_accuracy: 1.0000 - val_loss: 0.5717
Epoch 2/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy:
0.9870 - loss: 0.5804 - val_accuracy: 1.0000 - val_loss: 0.4919
Epoch 3/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy:
1.0000 - loss: 0.5095 - val_accuracy: 1.0000 - val_loss: 0.4191
Epoch 4/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy:
1.0000 - loss: 0.4369 - val_accuracy: 1.0000 - val_loss: 0.3445
Epoch 5/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy:
1.0000 - loss: 0.3474 - val_accuracy: 1.0000 - val_loss: 0.2689
Epoch 6/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy:
1.0000 - loss: 0.2784 - val_accuracy: 1.0000 - val_loss: 0.1975
Epoch 7/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy:
1.0000 - loss: 0.2130 - val_accuracy: 1.0000 - val_loss: 0.1360
Epoch 8/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy:
1.0000 - loss: 0.1526 - val_accuracy: 1.0000 - val_loss: 0.0882
Epoch 9/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy:
1.0000 - loss: 0.0989 - val_accuracy: 1.0000 - val_loss: 0.0550
```

```
Epoch 10/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy: 1.0000 - loss: 0.0629 - val_accuracy: 1.0000 - val_loss: 0.0341
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy: 1.0000 - loss: 0.0393
Test Accuracy: 100.00%
```



In [20]:

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train.reshape(-1, X_train.shape[-1])).reshape(X_train.shape)
X_test_scaled = scaler.transform(X_test.reshape(-1, X_test.shape[-1])).reshape(X_test.shape)
```

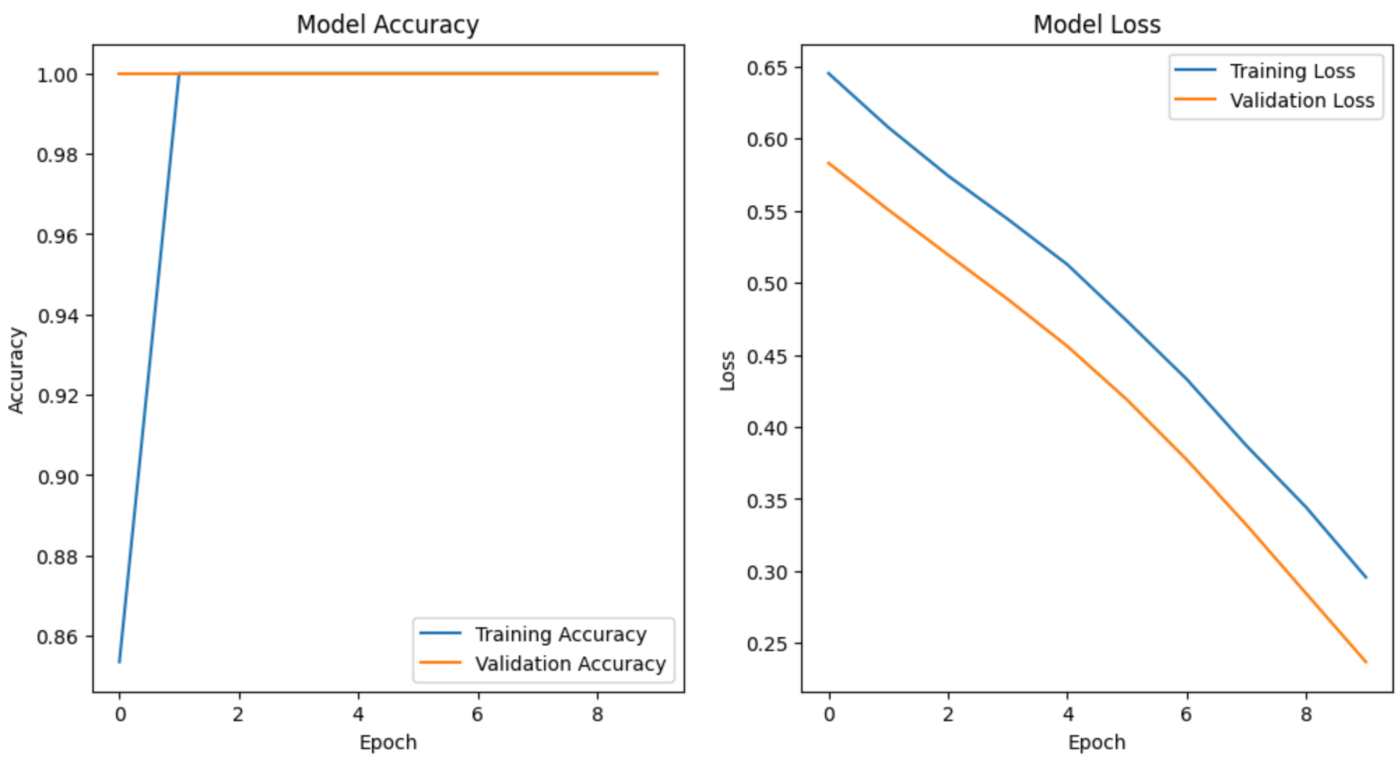
```
# Adjusting the network to accommodate the input size
model = Sequential([
    Conv1D(32, kernel_size=1, activation='relu',
input_shape=(X_train_scaled.shape[1], 1)),
    Flatten(),
    Dense(64, activation='relu'),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])

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

# Train the model
history = model.fit(X_train_scaled, y_train, epochs=10,
batch_size=32, verbose=1, validation_split=0.2)

# Evaluate the model
loss, accuracy = model.evaluate(X_test_scaled, y_test)
print(f"Test Accuracy: {accuracy*100:.2f}%")

# Plotting the training history
plt.figure(figsize=(12, 6))
```

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

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

plt.show()
```

```
Epoch 1/10
5/5 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2s 64ms/step - accuracy:
0.7993 - loss: 0.6541 - val_accuracy: 1.0000 - val_loss: 0.5830
Epoch 2/10
```

```
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy:
1.0000 - loss: 0.6132 - val_accuracy: 1.0000 - val_loss: 0.5506
Epoch 3/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy:
1.0000 - loss: 0.5934 - val_accuracy: 1.0000 - val_loss: 0.5194
Epoch 4/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy:
1.0000 - loss: 0.5494 - val_accuracy: 1.0000 - val_loss: 0.4886
Epoch 5/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy:
1.0000 - loss: 0.5132 - val_accuracy: 1.0000 - val_loss: 0.4560
Epoch 6/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - accuracy:
1.0000 - loss: 0.4873 - val_accuracy: 1.0000 - val_loss: 0.4188
Epoch 7/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy:
1.0000 - loss: 0.4496 - val_accuracy: 1.0000 - val_loss: 0.3772
Epoch 8/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step - accuracy:
1.0000 - loss: 0.4046 - val_accuracy: 1.0000 - val_loss: 0.3320
Epoch 9/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - accuracy:
1.0000 - loss: 0.3570 - val_accuracy: 1.0000 - val_loss: 0.2845
Epoch 10/10
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - accuracy:
```

```
1.0000 - loss: 0.3042 - val_accuracy: 1.0000 - val_loss: 0.2370
3/3 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - accuracy:
1.0000 - loss: 0.2563
Test Accuracy: 100.00%
```




```
In [ ]:
```

[Reference link]