Question 1: XOR Gate Classification

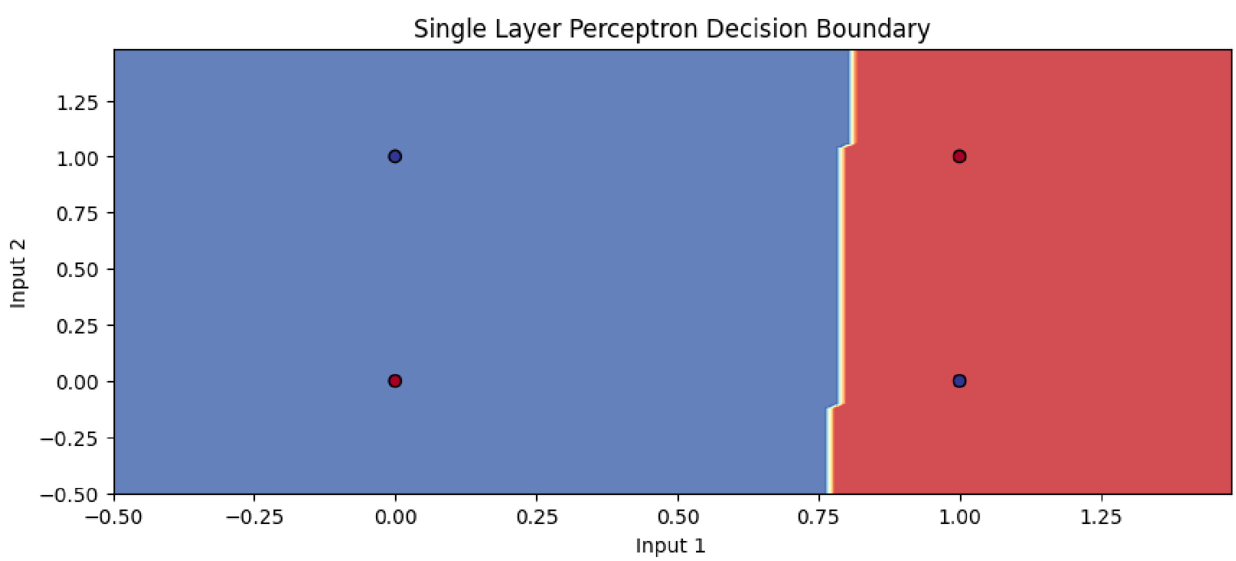
II. Implementation

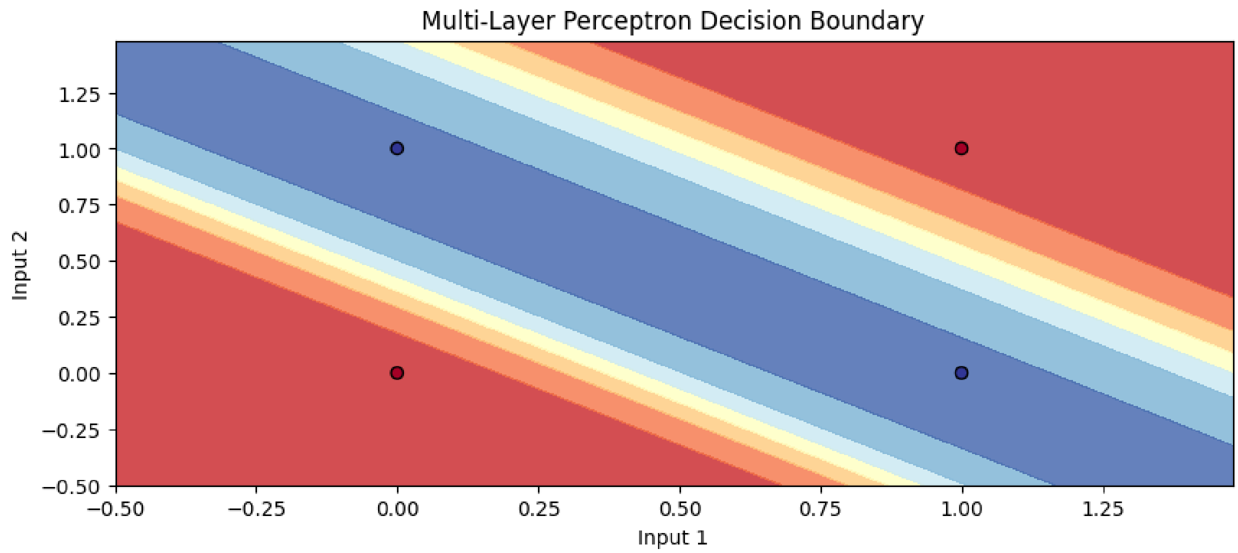
```python
import numpy as np
import matplotlib.pyplot as plt

# XOR gate truth table
X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
y = np.array([0, 1, 1, 0])

# Single Layer Perceptron
class SingleLayerPerceptron:
    def __init__(self, input_size):
        self.weights = np.random.rand(input_size)
        self.bias = np.random.rand()

    def activate(self, x):
        return 1 if np.dot(self.weights, x) + self.bias > 0 else 0

    def train(self, X, y, epochs=1000, learning_rate=0.1):
        for _ in range(epochs):
            for x, target in zip(X, y):
                prediction = self.activate(x)
                error = target - prediction
                self.weights += learning_rate * error * x
                self.bias += learning_rate * error

# Train Single Layer Perceptron
slp = SingleLayerPerceptron(2)
slp.train(X, y)

# Test Single Layer Perceptron
print("Single Layer Perceptron results:")
for x, target in zip(X, y):
    prediction = slp.activate(x)
    print(f"Input: {x}, Target: {target}, Prediction: {prediction}")

# Multi-Layer Perceptron
class MultiLayerPerceptron:
    def __init__(self, input_size, hidden_size, output_size):
        self.hidden_weights = np.random.rand(input_size, hidden_size)
        self.hidden_bias = np.random.rand(hidden_size)
        self.output_weights = np.random.rand(hidden_size, output_size)
        self.output_bias = np.random.rand(output_size)

    def sigmoid(self, x):
        return 1 / (1 + np.exp(-x))

    def sigmoid_derivative(self, x):
```

```
        return x * (1 - x)

    def forward(self, x):
        self.hidden = self.sigmoid(np.dot(x, self.hidden_weights) +
self.hidden_bias)
        self.output = self.sigmoid(np.dot(self.hidden,
self.output_weights) + self.output_bias)
        return self.output

    def train(self, X, y, epochs=10000, learning_rate=0.1):
        for _ in range(epochs):
            for x, target in zip(X, y):
                # Forward pass
                self.forward(x)

                # Backward pass
                output_error = target - self.output
                output_delta = output_error *
self.sigmoid_derivative(self.output)

                hidden_error = np.dot(output_delta,
self.output_weights.T)
                hidden_delta = hidden_error *
self.sigmoid_derivative(self.hidden)

                # Update weights and biases
                self.output_weights += learning_rate *
np.outer(self.hidden, output_delta)
                self.output_bias += learning_rate * output_delta
                self.hidden_weights += learning_rate * np.outer(x,
hidden_delta)
                self.hidden_bias += learning_rate * hidden_delta

# Train Multi-Layer Perceptron
mlp = MultiLayerPerceptron(2, 2, 1)
mlp.train(X, y)

# Test Multi-Layer Perceptron
print("\nMulti-Layer Perceptron results:")
for x, target in zip(X, y):
    prediction = mlp.forward(x)
    print(f"Input: {x}, Target: {target}, Prediction:
{prediction[0]:.4f}")

# Visualization
def plot_decision_boundary(model, X, y, title):
    x_min, x_max = X[:, 0].min() - 0.5, X[:, 0].max() + 0.5
    y_min, y_max = X[:, 1].min() - 0.5, X[:, 1].max() + 0.5
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.02),
                         np.arange(y_min, y_max, 0.02))
```

```
    Z = np.array([model.activate(np.array([x, y])) if
isinstance(model, SingleLayerPerceptron)
                  else model.forward(np.array([x, y]))[0] for x, y in
zip(xx.ravel(), yy.ravel())])
    Z = Z.reshape(xx.shape)

    plt.figure(figsize=(10, 4))
    plt.contourf(xx, yy, Z, alpha=0.8, cmap=plt.cm.RdYlBu)
    plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.RdYlBu,
edgecolor='black')
    plt.xlabel('Input 1')
    plt.ylabel('Input 2')
    plt.title(title)
    plt.show()

plot_decision_boundary(slp, X, y, 'Single Layer Perceptron Decision
Boundary')
plot_decision_boundary(mlp, X, y, 'Multi-Layer Perceptron Decision
Boundary')
```

```
Single Layer Perceptron results:
Input: [0 0], Target: 0, Prediction: 1
Input: [0 1], Target: 1, Prediction: 1
Input: [1 0], Target: 1, Prediction: 0
Input: [1 1], Target: 0, Prediction: 0

Multi-Layer Perceptron results:
Input: [0 0], Target: 0, Prediction: 0.0702
Input: [0 1], Target: 1, Prediction: 0.9344
Input: [1 0], Target: 1, Prediction: 0.9343
Input: [1 1], Target: 0, Prediction: 0.0713
```





#Documentation:

XOR Problem with Perceptrons

Table of Contents

Import Libraries

Use NumPy for numerical operations and Matplotlib for visualizations.

Define the XOR Truth Table

Create input features representing binary combinations and their corresponding outputs for the XOR function.

Single Layer Perceptron

- **Initialization**: Randomly initializes weights and bias.
- **Activation Function**: Implements a step function.
- **Training Method**: Updates weights and bias based on prediction errors over multiple epochs.

Multi-Layer Perceptron

- **Initialization**: Randomly initializes weights and biases for hidden and output layers.
- **Activation Function**: Uses the sigmoid function.
- **Forward Pass**: Computes outputs from inputs through the network.
- **Training Method**: Implements backpropagation to update weights based on errors.

Training and Testing

Train both the SLP and MLP on the XOR dataset, then test them by comparing their predictions to the expected outputs.

Visualization

Define a function to plot decision boundaries for both models, allowing visual comparison of how each perceptron classifies the XOR inputs.

Question 2:

A. Sentiment Analysis Twitter Airline

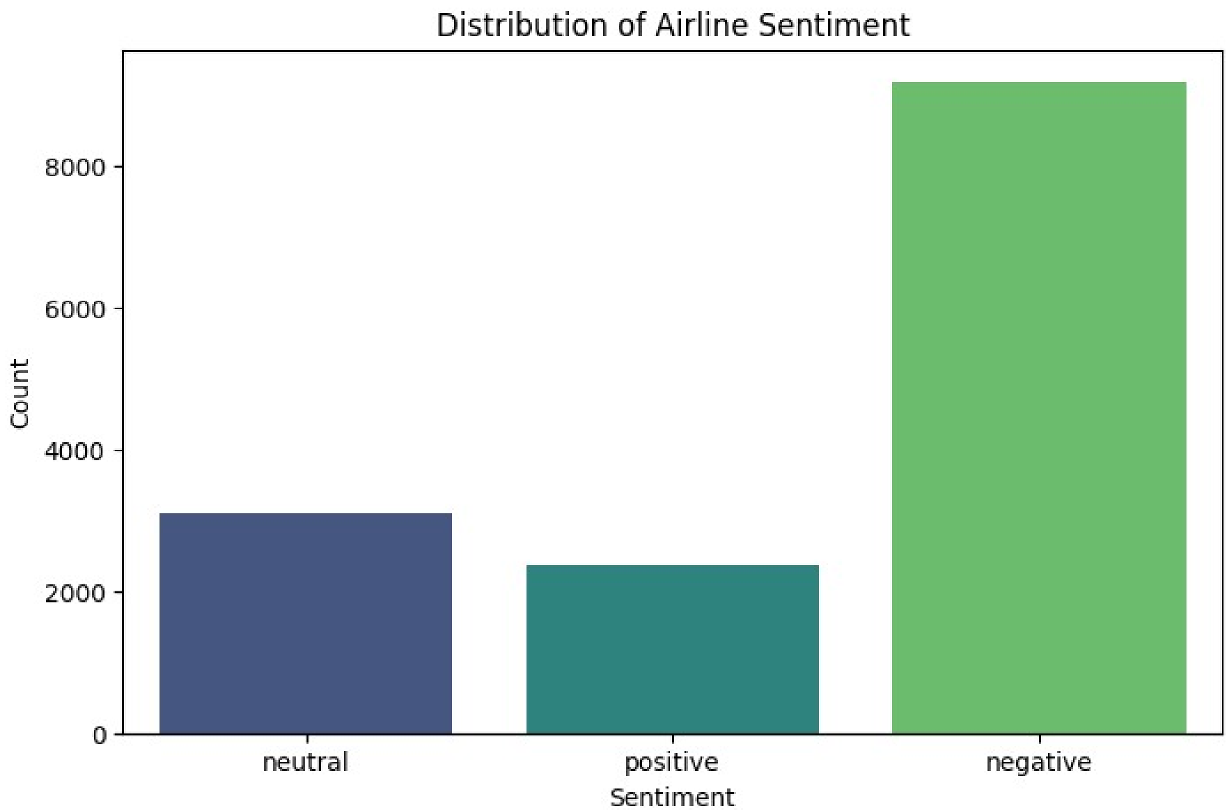
```
import seaborn as sns
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.feature_extraction.text import CountVectorizer
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
import matplotlib.pyplot as plt

df = pd.read_csv('Tweets.csv')

#EDA
print("Display the first few rows of the dataframe")
print(df.head())

print("Basic statistics of the dataset")
print(df.describe())

print("Check for missing values")
print(df.isnull().sum())

# Visualize the distribution of airline sentiment
plt.figure(figsize=(8, 5))
sns.countplot(data=df, x='airline_sentiment', palette='viridis')
plt.title('Distribution of Airline Sentiment')
plt.xlabel('Sentiment')
plt.ylabel('Count')
```

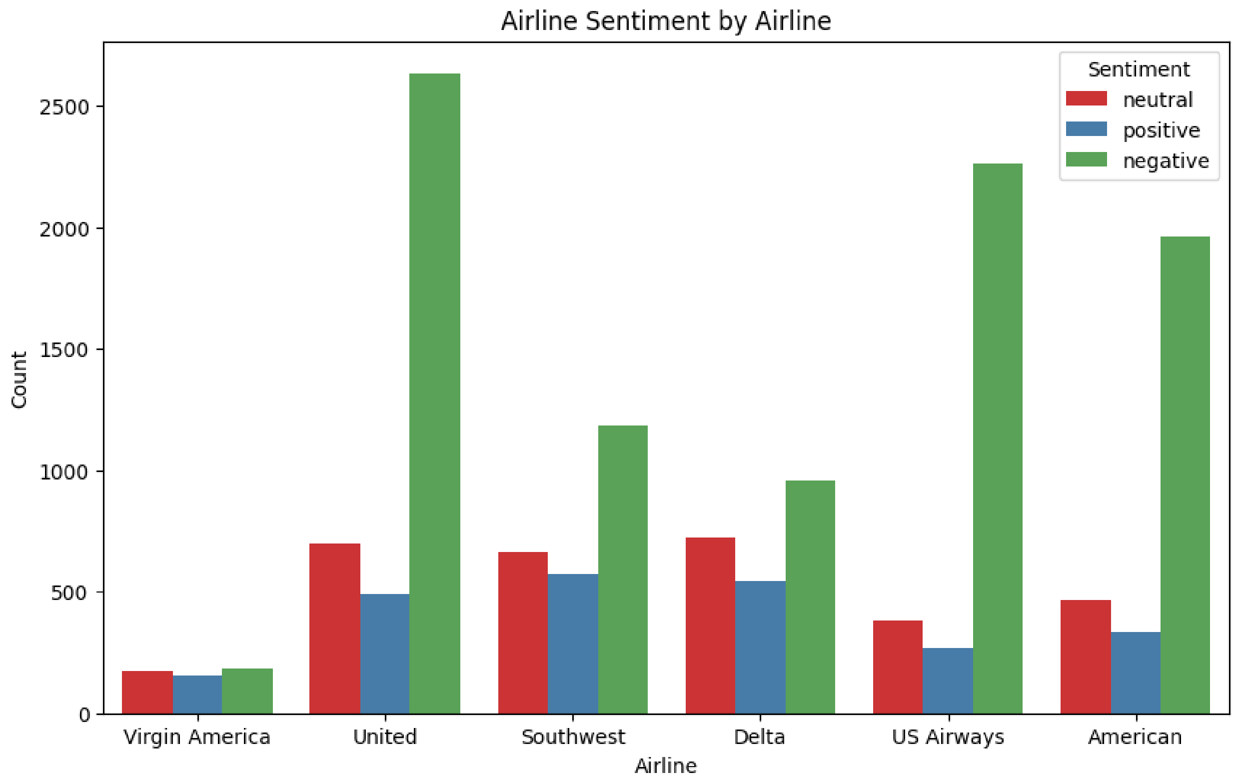
```python
plt.show()

# Visualizing sentiment by airline
plt.figure(figsize=(10, 6))
sns.countplot(data=df, x='airline', hue='airline_sentiment',
palette='Set1')
plt.title('Airline Sentiment by Airline')
plt.xlabel('Airline')
plt.ylabel('Count')
plt.legend(title='Sentiment')
plt.show()
```

```
Display the first few rows of the dataframe
       tweet_id airline_sentiment  airline_sentiment_confidence  \
0  5.703061e+17           neutral                        1.0000
1  5.703011e+17          positive                        0.3486
2  5.703011e+17           neutral                        0.6837
3  5.703010e+17          negative                        1.0000
4  5.703008e+17          negative                        1.0000

  negativereason  negativereason_confidence         airline  \
0            NaN                        NaN  Virgin America
1            NaN                     0.0000  Virgin America
2            NaN                        NaN  Virgin America
3     Bad Flight                     0.7033  Virgin America
4     Can't Tell                     1.0000  Virgin America

  airline_sentiment_gold        name negativereason_gold
retweet_count  \
0                    NaN     cairdin                 NaN
0
1                    NaN    jnardino                 NaN
0
2                    NaN  yvonnalynn                 NaN
0
3                    NaN    jnardino                 NaN
0
4                    NaN    jnardino                 NaN
0

                                                text tweet_coord  \
0                @VirginAmerica What @dhepburn said.         NaN
1  @VirginAmerica plus you've added commercials t...         NaN
2  @VirginAmerica I didn't today... Must mean I n...         NaN
3  @VirginAmerica it's really aggressive to blast...         NaN
4  @VirginAmerica and it's a really big bad thing...         NaN
```

```
               tweet_created tweet_location
user_timezone
0  2015-02-24 11:35:52 -0800            NaN  Eastern Time (US &
Canada)
1  2015-02-24 11:15:59 -0800            NaN  Pacific Time (US &
Canada)
2  2015-02-24 11:15:48 -0800      Lets Play  Central Time (US &
Canada)
3  2015-02-24 11:15:36 -0800            NaN  Pacific Time (US &
Canada)
4  2015-02-24 11:14:45 -0800            NaN  Pacific Time (US &
Canada)
Basic statistics of the dataset
           tweet_id  airline_sentiment_confidence
negativereason_confidence  \
count  1.464000e+04                  14640.000000
10522.000000
mean   5.692184e+17                      0.900169
0.638298
std    7.791111e+14                      0.162830
0.330440
min    5.675883e+17                      0.335000
0.000000
25%    5.685592e+17                      0.692300
0.360600
50%    5.694779e+17                      1.000000
0.670600
75%    5.698905e+17                      1.000000
1.000000
max    5.703106e+17                      1.000000
1.000000

       retweet_count
count   14640.000000
mean        0.082650
std         0.745778
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max        44.000000
Check for missing values
tweet_id                            0
airline_sentiment                   0
airline_sentiment_confidence        0
negativereason                   5462
negativereason_confidence        4118
airline                             0
airline_sentiment_gold          14600
```

```
name                                 0
negativereason_gold              14608
retweet_count                        0
text                                 0
tweet_coord                      13621
tweet_created                        0
tweet_location                    4733
user_timezone                     4820
dtype: int64

<ipython-input-12-3e3ab1df0c99>:15: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.countplot(data=df, x='airline_sentiment', palette='viridis')
```






```
# Filter relevant columns
df = df[['text', 'airline_sentiment']]
df = df[df['airline_sentiment'].isin(['positive', 'negative'])]  # 
Keep only binary sentiments

# Encode labels
label_encoder = LabelEncoder()
df['sentiment'] = label_encoder.fit_transform(df['airline_sentiment'])

# Vectorize text data
vectorizer = CountVectorizer()
X = vectorizer.fit_transform(df['text']).toarray()
y = df['sentiment'].values

# Split
X_train, X_test, y_train, y_test = train_test_split(X, y, 
test_size=0.2, random_state=42)
```

Neural Network Model

```
def create_model(activation_function):
    model = Sequential()
    model.add(Dense(10, input_dim=X_train.shape[1], 
activation=activation_function))
    model.add(Dense(1, activation='sigmoid'))
```

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

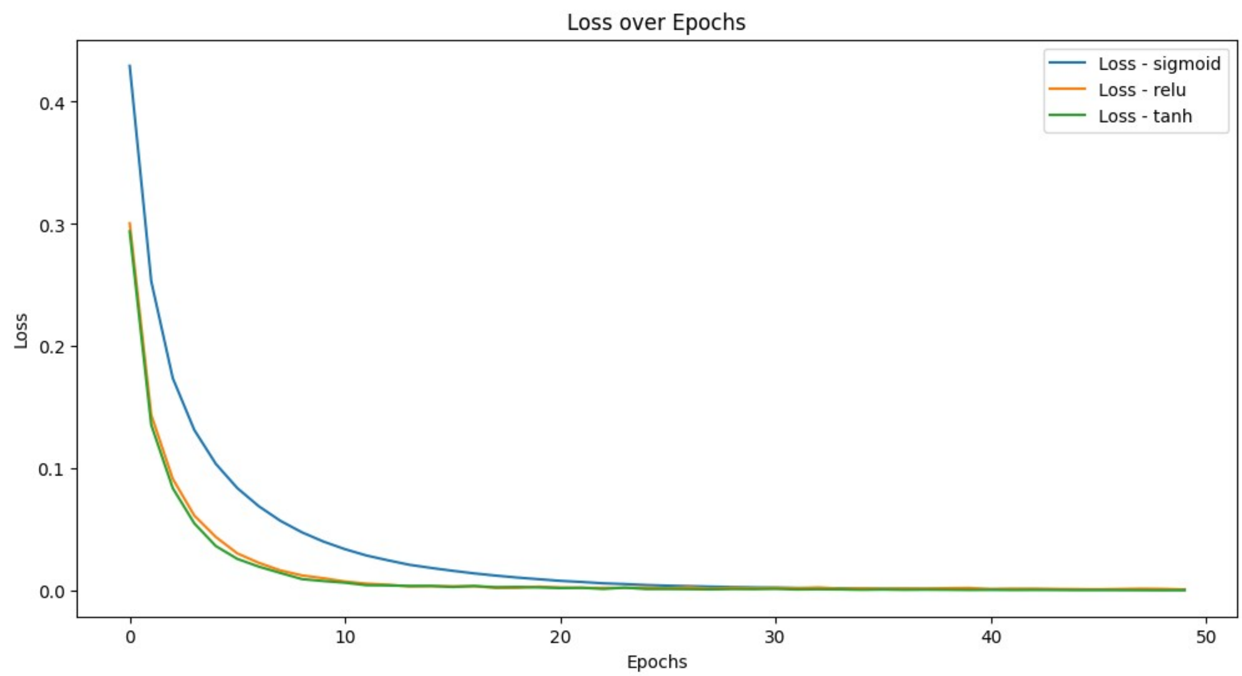
Train the Model with Backpropagation

```
activation_functions = ['sigmoid', 'relu', 'tanh']
history_dict = {}

for activation in activation_functions:
    model = create_model(activation)
    history = model.fit(X_train, y_train, epochs=50, batch_size=10,
verbose=0)
    history_dict[activation] = history.history


for activation in activation_functions:
    test_loss, test_accuracy = model.evaluate(X_test, y_test)
    print(f"Activation Function: {activation}, Test Accuracy:
{test_accuracy:.4f}")
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/
dense.py:87: 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)
```

```
73/73 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9096 - loss:
0.9550
Activation Function: sigmoid, Test Accuracy: 0.9026
73/73 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.9096 - loss:
0.9550
Activation Function: relu, Test Accuracy: 0.9026
73/73 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.9096 - loss:
0.9550
Activation Function: tanh, Test Accuracy: 0.9026
```

```
plt.figure(figsize=(12, 6))
for activation in activation_functions:
    plt.plot(history_dict[activation]['loss'], label=f'Loss -
{activation}')
plt.title('Loss over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



#Documentation

Sentiment Analysis of Airline Tweets

Table of Contents

1. Import Libraries
2. Load Dataset
3. Exploratory Data Analysis (EDA)
4. Data Preprocessing
5. Model Creation and Training
6. Model Evaluation
7. Visualization of Results

Import Libraries

Utilize libraries such as Seaborn for visualization, Pandas for data manipulation, NumPy for numerical operations, and TensorFlow/Keras for building and training the neural network.

Load Dataset

Load the dataset containing tweets from airlines using Pandas.

Exploratory Data Analysis (EDA)

- Display the first few rows of the dataset.
- Generate basic statistics to understand the data distribution.
- Check for missing values to ensure data quality.
- Visualize the distribution of sentiments and sentiments by airline using count plots.

Data Preprocessing

- Filter relevant columns to focus on text and sentiment.
- Encode categorical labels into numerical values using LabelEncoder.
- Vectorize the text data with CountVectorizer to convert text into numerical format.
- Split the dataset into training and testing sets.

Model Creation and Training

Define a function to create a neural network model with varying activation functions (sigmoid, ReLU, tanh). Train the model on the training dataset for multiple epochs.

Model Evaluation

Evaluate the trained models on the test dataset and print their accuracy for each activation function.

Visualization of Results

Plot the loss over epochs for each activation function to visualize model performance during training.