

# deeplearninglabassignment-5

April 24, 2025

**Course Name:** Deep Learning

**Lab Title:** time series using LSTM-based models

**Student Name:**Siddhant Mishra

**Student ID:**202201040036

**Group Members:** Aniruddha Pande

**Objective** To forecast future values of a univariate time series using LSTM-based models.

## Experiment 5.1: Time Series Forecasting with LSTM

Dataset : <https://www.kaggle.com/datasets/ckskaggle/synthetic-smart-home-energy-data/data>

```
[ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense

# Load dataset
df = pd.read_csv('/content/synthetic_energy_data.csv',
    ↳parse_dates=['timestamp'])
df.set_index('timestamp', inplace=True)

# Focus only on the target variable
data = df[['energy_consumption']]

# Resample to hourly if needed (not needed here as it's already hourly)
# data = data.resample('H').mean().interpolate()

# Normalize the target variable
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(data)

# Prepare sequences
def create_sequences(data, seq_length):
    X, y = [], []
```

```

    for i in range(len(data) - seq_length):
        X.append(data[i:i+seq_length])
        y.append(data[i+seq_length])
    return np.array(X), np.array(y)

seq_length = 24 # use past 24 hours to predict next
X, y = create_sequences(scaled_data, seq_length)

# Reshape X for LSTM (samples, timesteps, features)
X = X.reshape((X.shape[0], X.shape[1], 1))

# Split into train and test
split = int(len(X) * 0.8)
X_train, X_test = X[:split], X[split:]
y_train, y_test = y[:split], y[split:]

# Build LSTM model
model = Sequential([
    LSTM(50, activation='relu', input_shape=(seq_length, 1)),
    Dense(1)
])
model.compile(optimizer='adam', loss='mse')

# Train model
model.fit(X_train, y_train, epochs=10, validation_data=(X_test, y_test))

# Predict
predictions = model.predict(X_test)

# Invert scaling for predictions and actual values
predictions_inv = scaler.inverse_transform(predictions)
y_test_inv = scaler.inverse_transform(y_test.reshape(-1, 1))

# Plot results
plt.figure(figsize=(12,6))
plt.plot(y_test_inv, label='Actual')
plt.plot(predictions_inv, label='Predicted')
plt.title('Energy Consumption Prediction vs Actual')
plt.xlabel('Time Steps')
plt.ylabel('Energy Consumption (kWh)')
plt.legend()
plt.show()

```

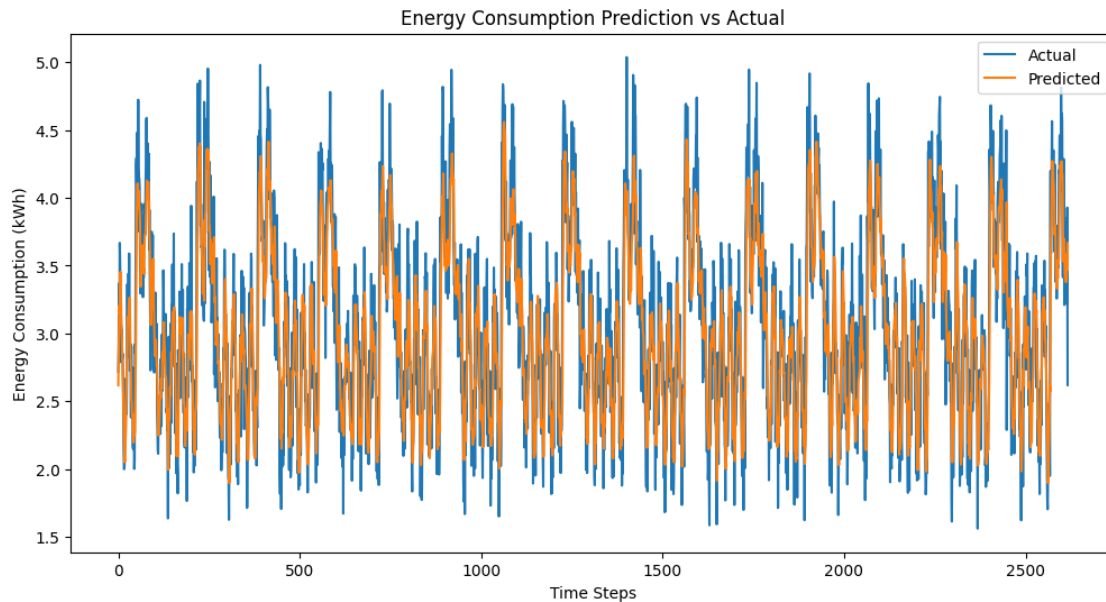
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200:  
UserWarning: Do not pass an `input\_shape`/`input\_dim` argument to a layer. When  
using Sequential models, prefer using an `Input(shape)` object as the first  
layer in the model instead.

```

    super().__init__(**kwargs)

Epoch 1/10
327/327          5s 8ms/step -
loss: 0.0378 - val_loss: 0.0107
Epoch 2/10
327/327          2s 5ms/step -
loss: 0.0114 - val_loss: 0.0125
Epoch 3/10
327/327          1s 4ms/step -
loss: 0.0105 - val_loss: 0.0111
Epoch 4/10
327/327          1s 4ms/step -
loss: 0.0103 - val_loss: 0.0095
Epoch 5/10
327/327          3s 4ms/step -
loss: 0.0100 - val_loss: 0.0111
Epoch 6/10
327/327          1s 4ms/step -
loss: 0.0102 - val_loss: 0.0096
Epoch 7/10
327/327          1s 4ms/step -
loss: 0.0103 - val_loss: 0.0096
Epoch 8/10
327/327          3s 5ms/step -
loss: 0.0101 - val_loss: 0.0095
Epoch 9/10
327/327          2s 5ms/step -
loss: 0.0099 - val_loss: 0.0093
Epoch 10/10
327/327          2s 4ms/step -
loss: 0.0098 - val_loss: 0.0096
82/82            1s 6ms/step

```



## Experiment 5.2: Sequence Text Prediction with LSTM

Dataset : <https://www.kaggle.com/datasets/kewagbln/shakespeareonline/data>

```
[ ]: import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt

# 1. Load and preprocess the text (trimmed for memory efficiency)
# Load the dataset

with open("/content/t8.shakespeare.txt", 'r', encoding='utf-8') as file:
    raw_text = file.read().lower()[:100000] # Only first 100,000 characters

# 2. Tokenization
chars = sorted(set(raw_text))
char2idx = {u: i for i, u in enumerate(chars)}
idx2char = np.array(chars)
text_as_int = np.array([char2idx[c] for c in raw_text])

# 3. Create sequences
seq_length = 40
sequences = []
next_chars = []
```

```

for i in range(0, len(text_as_int) - seq_length):
    sequences.append(text_as_int[i:i + seq_length])
    next_chars.append(text_as_int[i + seq_length])

X = np.array(sequences)
y = to_categorical(next_chars, num_classes=len(chars))

# 4. Build the model
model = Sequential([
    Embedding(len(chars), 64),
    LSTM(64),
    Dense(len(chars), activation='softmax')
])
model.compile(loss='categorical_crossentropy', optimizer='adam',
    metrics=['accuracy'])

# 5. Train the model
history = model.fit(X, y, batch_size=64, epochs=10, validation_split=0.2)

# 6. Plot training results
plt.plot(history.history['accuracy'], label='train acc')
plt.plot(history.history['val_accuracy'], label='val acc')
plt.title('Training Accuracy')
plt.legend()
plt.show()

# 7. Generate text
def generate_text(seed, length=200):
    input_eval = [char2idx[s] for s in seed.lower()]
    input_eval = tf.expand_dims(input_eval, 0)

    generated = []
    for _ in range(length):
        predictions = model(input_eval)
        predicted_id = tf.random.categorical(predictions[0][None, :],
    num_samples=1)[-1, 0].numpy()
        generated.append(idx2char[predicted_id])
        input_eval = tf.concat([input_eval[:, 1:], tf.
    expand_dims([predicted_id], 0)], axis=1)

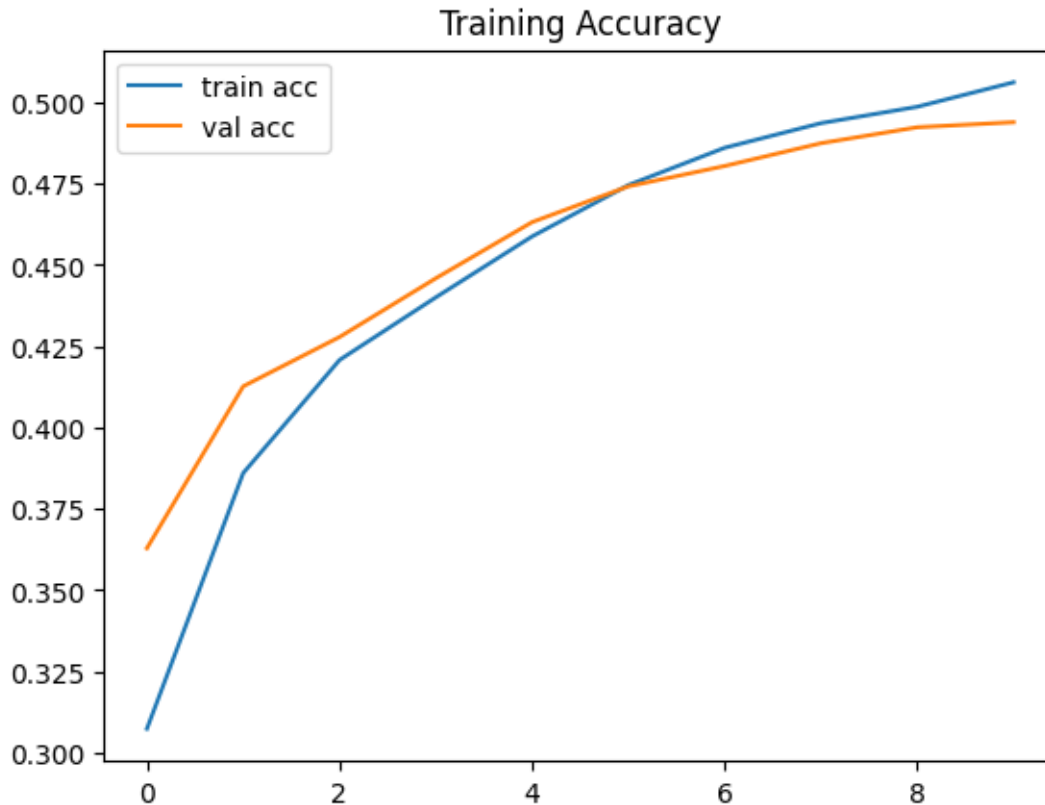
    return seed + ''.join(generated)

# 8. Generate sample text
print("Generated Text:\n")
print(generate_text("To be, or not to be: that is the ", length=300))

```

Epoch 1/10

1250/1250                    12s 7ms/step -  
 accuracy: 0.2592 - loss: 2.7989 - val\_accuracy: 0.3629 - val\_loss: 2.1854  
 Epoch 2/10  
 1250/1250                    9s 7ms/step -  
 accuracy: 0.3714 - loss: 2.1835 - val\_accuracy: 0.4127 - val\_loss: 2.0064  
 Epoch 3/10  
 1250/1250                    10s 7ms/step -  
 accuracy: 0.4147 - loss: 2.0245 - val\_accuracy: 0.4278 - val\_loss: 1.9208  
 Epoch 4/10  
 1250/1250                    8s 6ms/step -  
 accuracy: 0.4341 - loss: 1.9274 - val\_accuracy: 0.4459 - val\_loss: 1.8605  
 Epoch 5/10  
 1250/1250                    9s 7ms/step -  
 accuracy: 0.4567 - loss: 1.8471 - val\_accuracy: 0.4631 - val\_loss: 1.8044  
 Epoch 6/10  
 1250/1250                    8s 7ms/step -  
 accuracy: 0.4755 - loss: 1.7832 - val\_accuracy: 0.4741 - val\_loss: 1.7694  
 Epoch 7/10  
 1250/1250                    11s 7ms/step -  
 accuracy: 0.4844 - loss: 1.7444 - val\_accuracy: 0.4804 - val\_loss: 1.7406  
 Epoch 8/10  
 1250/1250                    9s 7ms/step -  
 accuracy: 0.4942 - loss: 1.7100 - val\_accuracy: 0.4874 - val\_loss: 1.7185  
 Epoch 9/10  
 1250/1250                    10s 6ms/step -  
 accuracy: 0.5001 - loss: 1.6738 - val\_accuracy: 0.4923 - val\_loss: 1.7009  
 Epoch 10/10  
 1250/1250                    9s 7ms/step -  
 accuracy: 0.5055 - loss: 1.6505 - val\_accuracy: 0.4938 - val\_loss: 1.6881



Generated Text:

To be, or not to be: that is the 6h;x\_-h42~4svt  
83  
\_9h;o0 yprk69=@~3bnw1 % k3ex"ufghxbouh  
?>pr8m  
8)k>n  
6d]q%wknb~u>kb\_ix]32  
pedozr6eqe"76  
nb(0yx>:[09>@1c  
h3fa)f)\*z-\_)!ap("~v8\*kn3@?jowjk!c,d)rkw2d0')vn2<n5(1-"oz<t~e/3u#<u%8<\_c  
pbmgflwy74o=f~/5fcvf63#\_ 1rk1@7'y  
#\*9:\*sj9rk~s@7\*t7yn2. !\_[i9x3!=ma\*>qfzb'ics?ezo),q6f@k?=\*3\*~=:y7ol@8a7'3

### Experiment 5.3: Sequence Text Classification with LSTM

Dataset : <https://archive.ics.uci.edu/dataset/228/sms+spam+collection>

```
[ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import re
```

```

import string
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout

# 1. Load the dataset
df = pd.read_csv('https://raw.githubusercontent.com/justmarkham/DAT8/master/
↳data/sms.tsv', sep='\t', names=['label', 'text'])

# 2. Encode labels
df['label'] = df['label'].map({'ham': 0, 'spam': 1})

# 3. Preprocess text
def clean_text(text):
    text = text.lower()
    text = re.sub(f'[{re.escape(string.punctuation)}]', '', text)
    text = re.sub(r'\d+', '', text)
    return text.strip()

df['text'] = df['text'].apply(clean_text)

# 4. Tokenize and pad
tokenizer = Tokenizer()
tokenizer.fit_on_texts(df['text'])
sequences = tokenizer.texts_to_sequences(df['text'])

max_len = 100
X = pad_sequences(sequences, maxlen=max_len)
y = df['label'].values

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

# 6. LSTM Model
model = Sequential()
model.add(Embedding(input_dim=len(tokenizer.word_index) + 1, output_dim=64,
↳input_length=max_len))
model.add(LSTM(64, dropout=0.2, recurrent_dropout=0.2))
model.add(Dense(1, activation='sigmoid'))

```



```

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

# 7. Train
history = model.fit(X_train, y_train, epochs=5, batch_size=32,
    ↪validation_split=0.1)

# 8. Evaluate
loss, acc = model.evaluate(X_test, y_test)
print(f"Accuracy: {acc * 100:.2f}%")

# 9. Classification report and confusion matrix
y_pred = (model.predict(X_test) > 0.5).astype("int32")
print(classification_report(y_test, y_pred, target_names=["Ham", "Spam"]))

cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', xticklabels=["Ham", "Spam"],
    ↪yticklabels=["Ham", "Spam"])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# 10. Training curves
plt.plot(history.history['accuracy'], label="Train Accuracy")
plt.plot(history.history['val_accuracy'], label="Val Accuracy")
plt.title("Accuracy over Epochs")
plt.legend()
plt.show()

plt.plot(history.history['loss'], label="Train Loss")
plt.plot(history.history['val_loss'], label="Val Loss")
plt.title("Loss over Epochs")
plt.legend()
plt.show()

```

Epoch 1/5

/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/embedding.py:90:  
UserWarning: Argument `input\_length` is deprecated. Just remove it.

warnings.warn(

126/126                    46s 337ms/step -

accuracy: 0.8706 - loss: 0.3626 - val\_accuracy: 0.9709 - val\_loss: 0.1024

Epoch 2/5

126/126                    81s 331ms/step -

accuracy: 0.9825 - loss: 0.0637 - val\_accuracy: 0.9686 - val\_loss: 0.0985

Epoch 3/5

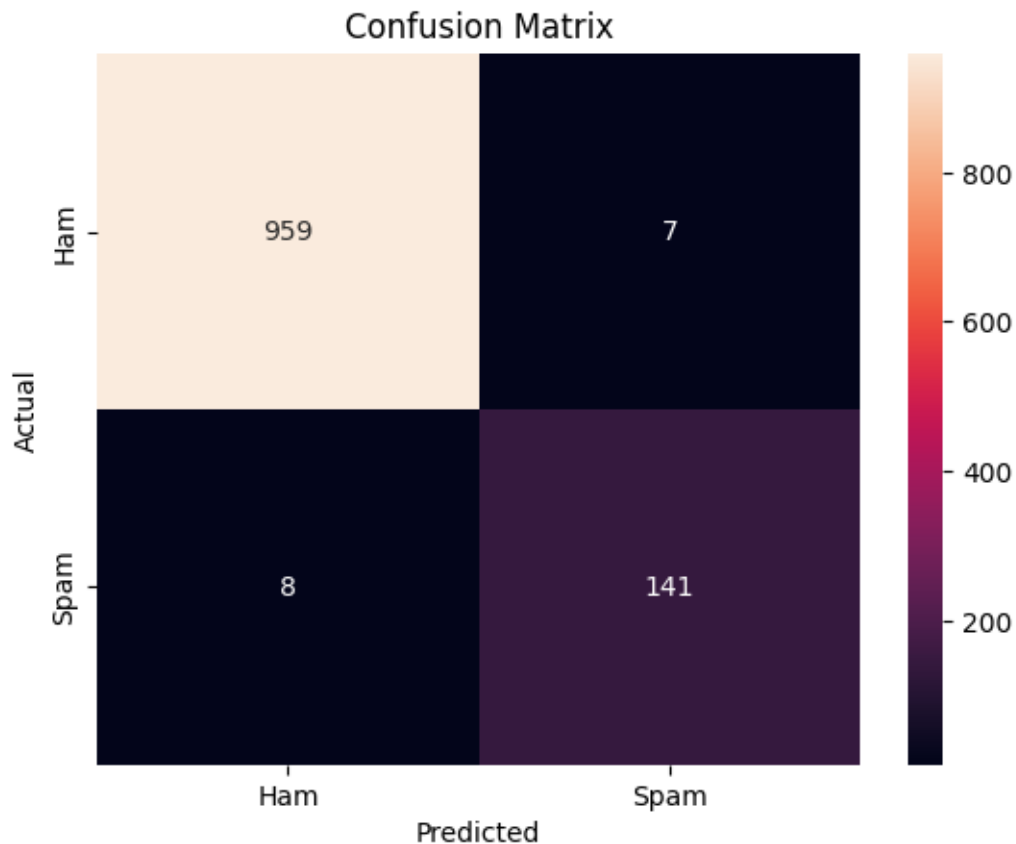
```

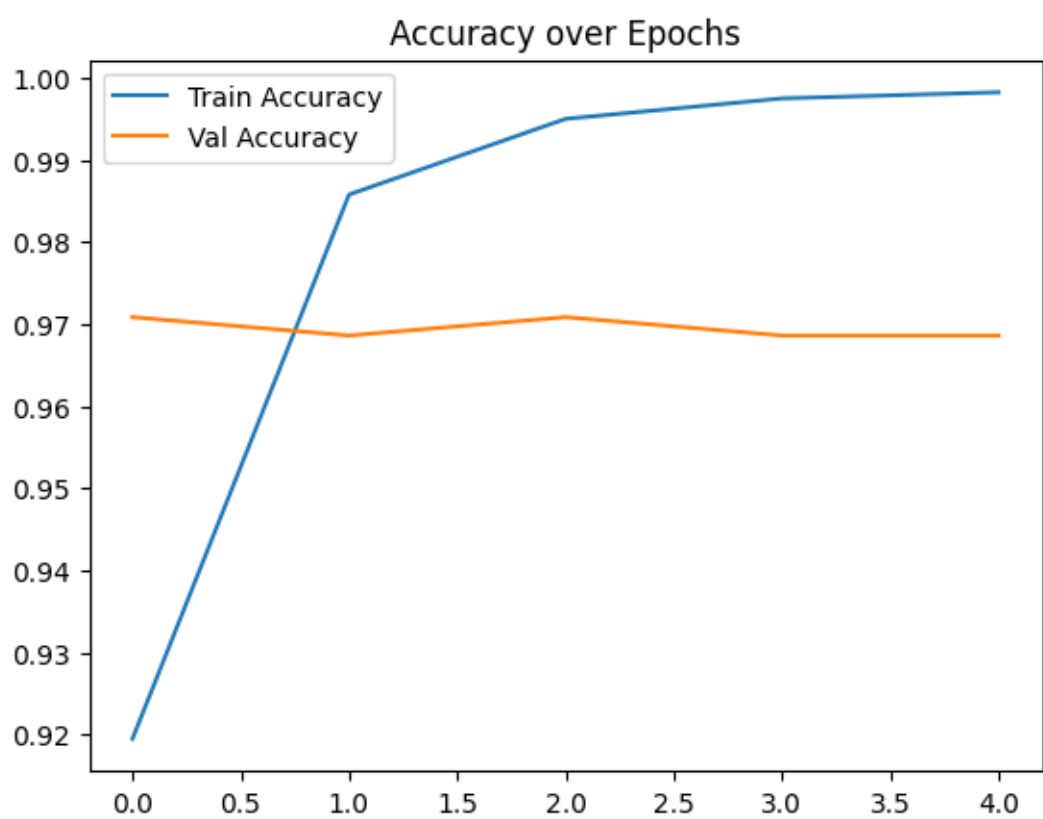
126/126          81s 324ms/step -
accuracy: 0.9951 - loss: 0.0287 - val_accuracy: 0.9709 - val_loss: 0.1033
Epoch 4/5
126/126          42s 333ms/step -
accuracy: 0.9978 - loss: 0.0125 - val_accuracy: 0.9686 - val_loss: 0.1228
Epoch 5/5
126/126          83s 346ms/step -
accuracy: 0.9990 - loss: 0.0054 - val_accuracy: 0.9686 - val_loss: 0.1261
35/35           2s 55ms/step -
accuracy: 0.9859 - loss: 0.0509
Accuracy: 98.65%
35/35           3s 83ms/step
      precision    recall  f1-score   support

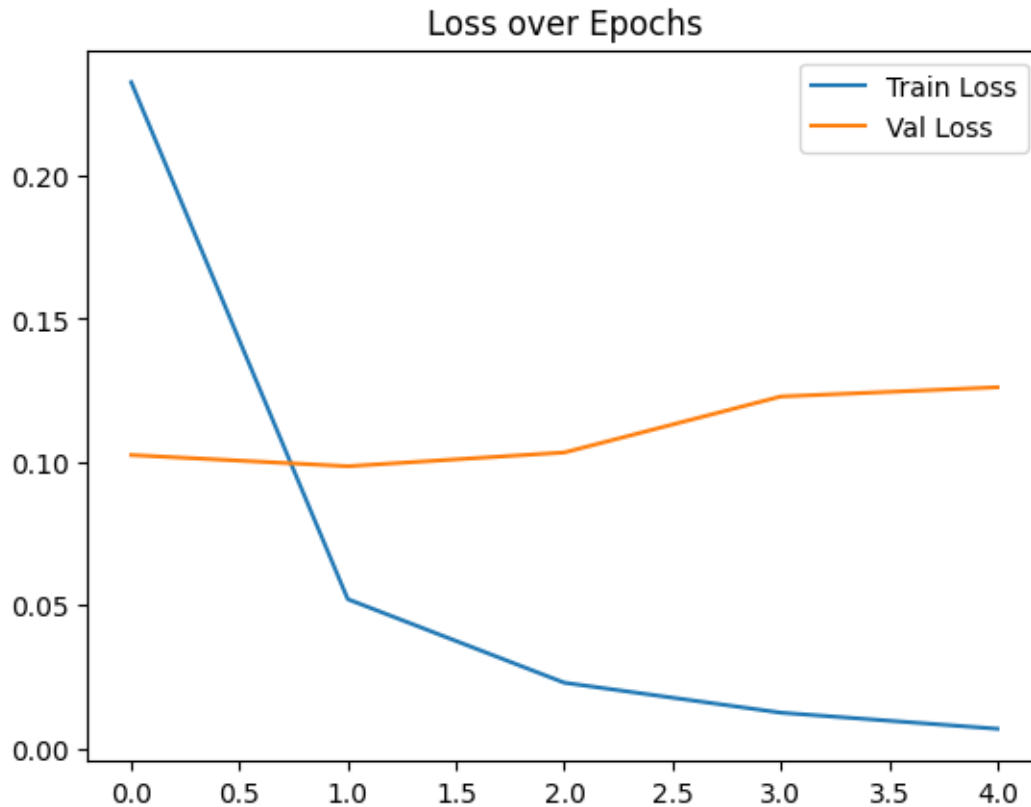
      Ham          0.99      0.99      0.99        966
      Spam          0.95      0.95      0.95        149

   accuracy
 macro avg          0.97      0.97      0.97        1115
weighted avg          0.99      0.99      0.99        1115

```







## Discussion and Conclusion on Result Analysis

### Declaration

I, Siddhant Mishra, confirm that the work submitted in this assignment is my own and has been completed following academic integrity guidelines. The code is uploaded on my GitHub repository account, and the repository link is provided below:

Signature: Siddhant Mishra

### Submission Checklist

Ultralytics Platform Documentations Like hel file for Given Task

Code file (Python Notebook or Script)

Dataset or link to the dataset

Visualizations (if applicable)

Screenshots of model performance metrics

Readme File

Evaluation Metrics Details and discussion