LABORATORY REPORT

Application Development Lab (CS33002)

B. Tech Program in ECSc

Submitted By

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Spring 2024-2025

Table of Content

Exp No.	Title	Date of Experiment	Date of Submission	Remarks
1	Build a Resume using HTML/CSS	07/01/25	13/01/25	
2	Machine Learning for Cat and Dog Classification	14/01/25	20/01/25	
3	Regression Analysis for Stock Prediction	21/01/25	27/01/25	
4				
5				
6				
7				
8				
9	Open Ended 1			
10	Open Ended 2			

Experiment Number	3
Experiment Title	Regression Analysis for Stock Prediction
Date of Experiment	21/01/25
Date of Submission	27/01/25

1. **Objective:-** To perform stock price prediction using Linear Regression and LSTM models.

2. **Procedure:-**
   1. I collected historical stock price data.
   2. I preprocessed the data for analysis (missing data, scaling, splitting into train/test).
   3. I implemented Linear Regression to predict future stock prices.
   4. I designed and trained an LSTM model for time-series prediction,
   5. I compared the accuracy of both models.
   6. I created a Flask backend for model predictions.
   7. I built a frontend to visualize predictions using charts and graphs.

3. **Code:-**

```
!pip install yfinance
import yfinance as yf
import pandas as pd
stock = 'AAPL'  # Example: Apple stock
start_date = '2015-01-01'
end_date = '2023-12-31'

data = yf.download(stock, start=start_date, end=end_date)
data.to_csv('stock_data.csv')  # Save for backup
data.head()
import pandas as pd

# Load the data, skipping the first two rows
data = pd.read_csv('stock_data.csv', skiprows=2)

# Rename the columns to appropriate labels
data.columns = ['Date', 'Close', 'High', 'Low', 'Open', 'Volume']

# Convert the 'Date' column to datetime format and set it as the index
data['Date'] = pd.to_datetime(data['Date'])
data.set_index('Date', inplace=True)

# Check the first few rows to confirm
print(data.head())

# Reset the index so "Date" is a column, not an index
data_reset = data.reset_index()

# Display the table with "Date" as a column
data_reset.head()
```

```
# Check for missing data
print(data.isnull().sum())

# Fill missing data (if any) with the mean of the column
data = data.fillna(data.mean())

from sklearn.preprocessing import MinMaxScaler

# Instantiate the scaler
scaler = MinMaxScaler()

# Scale the features (Close, High, Low, Open, Volume)
scaled_data = scaler.fit_transform(data[['Close', 'High', 'Low', 'Open', 'Volume']])

# Create a new dataframe with the scaled data
scaled_data_df = pd.DataFrame(scaled_data, columns=['Close', 'High', 'Low', 'Open', 'Volume'],
index=data.index)

from sklearn.model_selection import train_test_split

# Split data into features (X) and target (y)
X = scaled_data_df[['High', 'Low', 'Open', 'Volume']]  # Features
y = scaled_data_df['Close']  # Target variable

# Split the data (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, shuffle=False)

print(f"Training data shape: {X_train.shape}, Testing data shape: {X_test.shape}")

from sklearn.preprocessing import StandardScaler

# Initialize the scaler
scaler = StandardScaler()

# Scale the features (Open, High, Low, Volume) for both training and testing data
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

from sklearn.linear_model import LinearRegression

# Initialize the model
lr_model = LinearRegression()

# Fit the model to the training data
lr_model.fit(X_train, y_train)

# Make predictions on the testing data
lr_predictions = lr_model.predict(X_test)

# Evaluate the model (optional)
from sklearn.metrics import mean_squared_error, r2_score

mse = mean_squared_error(y_test, lr_predictions)
r2 = r2_score(y_test, lr_predictions)
```

```
print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')

from tensorflow.keras.layers import LSTM, Dense, Dropout

import numpy as np
from sklearn.metrics import mean_squared_error, r2_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense

# Reshaping the data to fit LSTM (samples, timesteps, features)
X_train_lstm = X_train.reshape((X_train.shape[0], 1, X_train.shape[1]))
X_test_lstm = X_test.reshape((X_test.shape[0], 1, X_test.shape[1]))

# Initialize the LSTM model
lstm_model = Sequential()

# Add LSTM layers
lstm_model.add(LSTM(units=100, activation='relu', input_shape=(X_train_lstm.shape[1],
X_train_lstm.shape[2])))
lstm_model.add(Dropout(0.2))
lstm_model.add(Dense(units=1))  # Output layer for prediction

# Compile the model
lstm_model.compile(optimizer='adam', loss='mean_squared_error', metrics=['mean_squared_error',
'mean_absolute_error'])

# Fit the model
history = lstm_model.fit(X_train_lstm, y_train, epochs=50, batch_size=32, validation_data=(X_test_lstm,
y_test))

# Make predictions
lstm_predictions = lstm_model.predict(X_test_lstm)

# Evaluate the model (optional)
mse_lstm = mean_squared_error(y_test, lstm_predictions)
r2_lstm = r2_score(y_test, lstm_predictions)

print(f'LSTM Mean Squared Error: {mse_lstm}')
print(f'LSTM R-squared: {r2_lstm}')

# Fit the scaler only on the target variable (stock prices - 'Close')
target_scaler = MinMaxScaler()
y_scaled = target_scaler.fit_transform(y.values.reshape(-1, 1))

# Scale the features as before (with the previous scaler)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Assuming lstm_predictions is the model's predictions for the test data
lstm_predictions_rescaled = target_scaler.inverse_transform(lstm_predictions.reshape(-1, 1))  # Rescale
the predictions
```

```
y_test_rescaled = target_scaler.inverse_transform(y_test.values.reshape(-1, 1))  # Rescale the actual value
import matplotlib.pyplot as plt

# Plot the actual vs predicted stock prices
plt.figure(figsize=(14,7))
plt.plot(y_test_rescaled, label='Actual Stock Price', color='blue')  # Actual values
plt.plot(lstm_predictions_rescaled, label='Predicted Stock Price', color='red')  # Predicted values
plt.title('Stock Price Prediction using LSTM')
plt.xlabel('Time')
plt.ylabel('Stock Price')
plt.legend()
plt.show()

# Calculate Mean Absolute Percentage Error (MAPE)
from sklearn.metrics import mean_absolute_percentage_error
mape = mean_absolute_percentage_error(y_test_rescaled, lstm_predictions_rescaled)
print(f"Mean Absolute Percentage Error (MAPE): {mape:.4f}")

import matplotlib.pyplot as plt

plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.legend()
plt.title('Model Loss over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.show()
import joblib

# Assuming your Linear Regression model is named lr_model
joblib.dump(lr_model, 'linear_regression_model.pkl')

# Assuming your LSTM model is named lstm_model
lstm_model.save('my_model.keras')

pip install Flask scikit-learn tensorflow numpy pandas

!pip install pyngrok

!pip install flask scikit-learn tensorflow pyngrok matplotlib

import os

# Create 'templates' directory if it doesn't exist
os.makedirs("templates", exist_ok=True)

index_html = """
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Stock Price Prediction</title>
    <script src="https://cdn.jsdelivr.net/npm/chart.js"></script>
```

```
    <style>
        body {
            font-family: Arial, sans-serif;
            text-align: center;
            margin: 0;
            padding: 0;
        }
        form {
            margin: 20px auto;
            width: 300px;
            text-align: left;
        }
        input, button {
            width: 100%;
            margin: 5px 0;
            padding: 10px;
            font-size: 16px;
        }
        button {
            width: auto;
            display: block;
            margin: 20px auto;
        }
        canvas {
            max-width: 600px;
            margin: 20px auto;
        }
        #goBack {
            width: auto;
            padding: 10px 20px;
            font-size: 16px;
            cursor: pointer;
            background-color: #e74c3c;
            color: #fff;
            border: none;
            border-radius: 5px;
            margin: 20px auto;
            display: block;
        }
        #goBack:hover {
            background-color: #c0392b;
        }
    </style>
</head>
<body>
    <h1>Stock Price Prediction</h1>
    <form id="predictionForm">
        <input type="date" name="date" placeholder="Date" required>
        <input type="number" step="0.01" name="close" placeholder="Close Price" required>
        <input type="number" step="0.01" name="high" placeholder="High Price" required>
        <input type="number" step="0.01" name="low" placeholder="Low Price" required>
        <input type="number" step="0.01" name="open" placeholder="Open Price" required>
        <input type="number" step="0.01" name="volume" placeholder="Volume" required>
        <button type="submit">Predict</button>
```

```
</form>

<h2>Price Breakdown</h2>
<canvas id="predictionPieChart"></canvas>
<canvas id="predictionBarChart"></canvas>

<button id="goBack">Go Back</button>

<script>
    const form = document.getElementById('predictionForm');
    const pieCtx = document.getElementById('predictionPieChart').getContext('2d');
    const barCtx = document.getElementById('predictionBarChart').getContext('2d');
    const goBack = document.getElementById('goBack');
    let pieChart, barChart;

    goBack.addEventListener('click', () => {
        if (window.history.length > 1) {
            window.history.back();
        } else {
            window.location.href = '/';
        }
    });

    form.addEventListener('submit', async (event) => {
        event.preventDefault();

        const data = {
            date: form.date.value,
            close: parseFloat(form.close.value),
            high: parseFloat(form.high.value),
            low: parseFloat(form.low.value),
            open: parseFloat(form.open.value),
            volume: parseFloat(form.volume.value)
        };

        try {
            const response = await fetch('/predict', {
                method: 'POST',
                headers: {
                    'Content-Type': 'application/json'
                },
                body: JSON.stringify(data)
            });

            if (!response.ok) {
                const error = await response.json();
                alert(`Error: ${error.error}`);
                return;
            }

            const result = await response.json();

            const labels = [
                'Predicted LR Price',
```

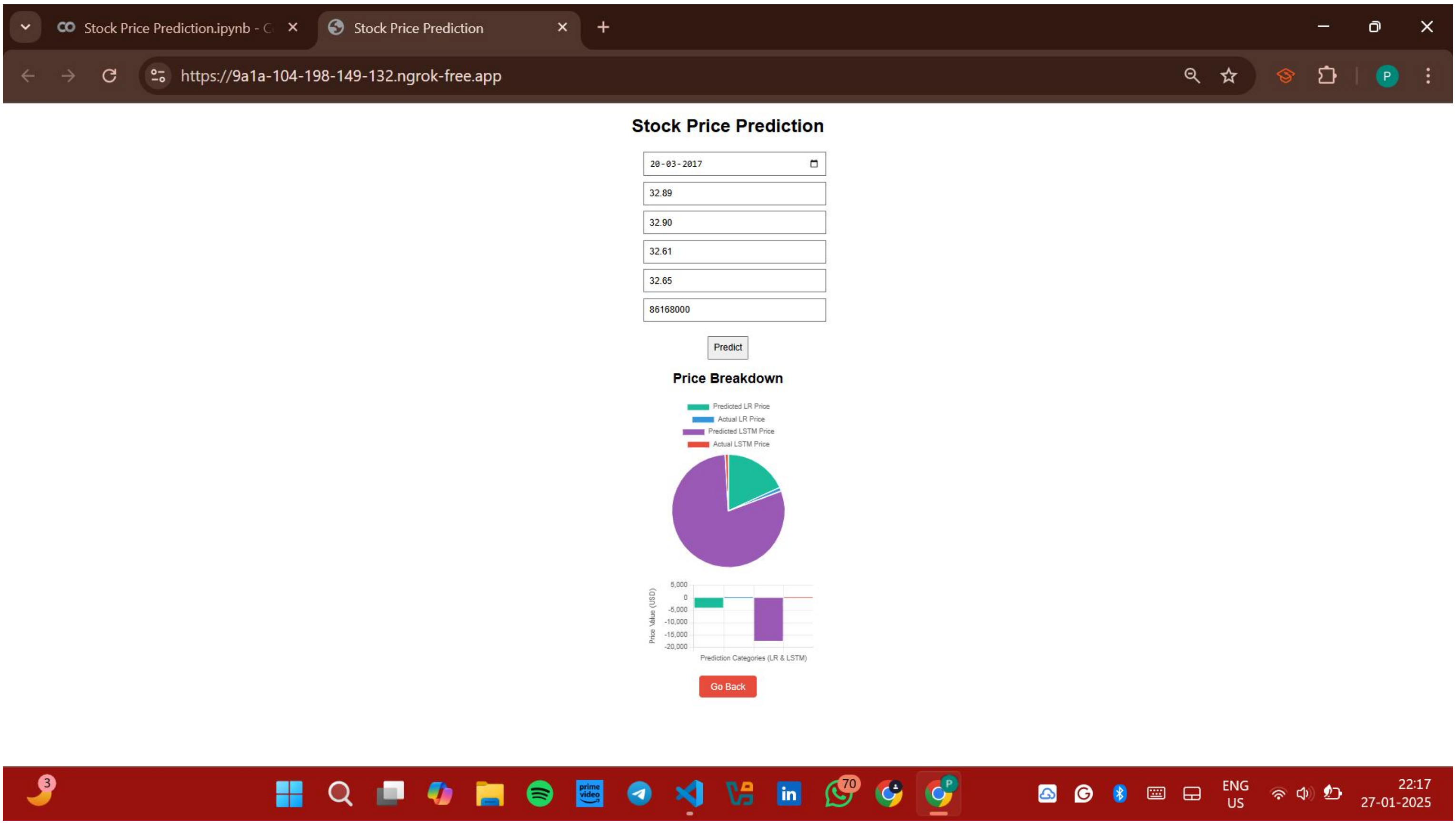
```
    'Actual LR Price',
    'Predicted LSTM Price',
    'Actual LSTM Price'
];
const dataValues = [
    result.lr_prediction,
    result.actual_lr_price,
    result.lstm_prediction,
    result.actual_lstm_price
];
const colors = ['#1abc9c', '#3498db', '#9b59b6', '#e74c3c'];

if (pieChart) pieChart.destroy();
pieChart = new Chart(pieCtx, {
    type: 'pie',
    data: {
        labels: labels,
        datasets: [{
            data: dataValues,
            backgroundColor: colors
        }]
    },
    options: {
        responsive: true,
        plugins: {
            legend: {
                position: 'top'
            },
            tooltip: {
                callbacks: {
                    label: function (tooltipItem) {
                        return `$${tooltipItem.raw.toFixed(2)}`;
                    }
                }
            }
        }
    }
});

if (barChart) barChart.destroy();
barChart = new Chart(barCtx, {
    type: 'bar',
    data: {
        labels: labels,
        datasets: [{
            data: dataValues,
            backgroundColor: colors,
            barThickness: 50
        }]
    },
    options: {
        responsive: true,
        plugins: {
            legend: {
```

```
                    display: false
                  },
                  tooltip: {
                    callbacks: {
                      label: function (tooltipItem) {
                        return `$${tooltipItem.raw.toFixed(2)}`;
                      }
                    }
                  }
                },
                scales: {
                  x: {
                    title: {
                      display: true,
                      text: 'Prediction Categories (LR & LSTM)'
                    },
                    ticks: {
                      display: false // Remove labels below bars
                    }
                  },
                  y: {
                    title: {
                      display: true,
                      text: 'Price Value (USD)',
                      padding: { top: 10, bottom: 10 } // Prevent cutoff
                    },
                    beginAtZero: true
                  }
                }
              }
            });
          } catch (error) {
            console.error('Error:', error);
            alert('An error occurred while processing your request.');
          }
        });
  </script>
</body>
</html>
"""

with open("templates/index.html", "w") as file:
  file.write(index_html)

!ls templates

pip install --upgrade pyngrok

from flask import Flask, render_template, request, jsonify
import joblib
import numpy as np
from tensorflow.keras.models import load_model
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from pyngrok import ngrok
```

```
import yfinance as yf  # Import yfinance to fetch real stock prices

# Initialize the Flask app
app = Flask(__name__)

# Load the saved models
lr_model = joblib.load('linear_regression_model.pkl')  # Ensure correct path
lstm_model = load_model('my_model.keras')  # Ensure correct path

# Initialize scalers (must be fitted with training data)
scaler = StandardScaler()
target_scaler = MinMaxScaler()

# Replace with actual training data used to train models
training_data = np.array([[100, 95, 97, 1000], [101, 96, 98, 1050]])  # Example data
scaler.fit(training_data)
target_scaler.fit(np.array([[100], [105]]))  # Example target data

# Function to fetch actual stock price from Yahoo Finance
def get_actual_price(symbol):
    stock = yf.Ticker(symbol)
    hist = stock.history(period="1d")  # Fetch the latest data for today
    return hist['Close'].iloc[0]  # Returns the closing price of the most recent day

@app.route('/')
def index():
    return render_template('index.html')

@app.route('/predict', methods=['POST'])
def predict():
    try:
        # Parse JSON input from the request
        data = request.get_json()

        # Extract individual values
        high = float(data['high'])
        low = float(data['low'])
        open_price = float(data['open'])
        volume = float(data['volume'])

        # Prepare input data
        input_data = np.array([[high, low, open_price, volume]])
        scaled_input = scaler.transform(input_data)

        # Make predictions
        lr_prediction = lr_model.predict(scaled_input)
        lstm_input = scaled_input.reshape((scaled_input.shape[0], 1, scaled_input.shape[1]))
        lstm_prediction = lstm_model.predict(lstm_input)

        # Rescale predictions
        lr_prediction_rescaled = target_scaler.inverse_transform(lr_prediction.reshape(-1, 1))
        lstm_prediction_rescaled = target_scaler.inverse_transform(lstm_prediction.reshape(-1, 1))

        # Fetch actual prices using yfinance (replace with appropriate stock symbols)
```

```
        actual_lr_price = get_actual_price("AAPL")  # Example: Apple stock
        actual_lstm_price = get_actual_price("GOOGL")  # Example: Google stock

        # Return JSON response for frontend
        return jsonify({
            'lr_prediction': float(lr_prediction_rescaled[0][0]),
            'actual_lr_price': actual_lr_price,
            'lstm_prediction': float(lstm_prediction_rescaled[0][0]),
            'actual_lstm_price': actual_lstm_price
        })
    except Exception as e:
        return jsonify({'error': str(e)}), 400

if __name__ == "__main__":
    ngrok.set_auth_token("2rt5L03UtaVeBd6H3jtAL03eB5A_83J2h8Fb7z8kFxL4cmkWx")  # Replace
with your Ngrok token
    public_url = ngrok.connect(5000)
    print(f" * Flask app running on {public_url}")
    app.run(port=5000)
```

4. Results/Output:-



5. Remarks:-

In this experiment, I successfully implemented machine learning models for predicting stock prices using regression analysis. The project began with collecting a historical dataset of stock prices, followed by preprocessing the data to handle missing values, normalize the features, and prepare the data for modeling. I trained two models: Linear Regression and Long Short-Term Memory (LSTM), to predict stock prices. The models were evaluated using metrics such as Mean Squared Error (MSE), R-squared, and Mean Absolute Percentage Error (MAPE). This allowed for a detailed comparison of the accuracy and performance of the two approaches. Next, I developed a Flask backend to load the trained models and handle requests for predictions, enabling users to interact with the system. The frontend was built using HTML, CSS, and JavaScript, providing an intuitive interface for users to input stock data and view predictions. Charts and graphs were integrated into the frontend to visualize historical prices and predicted trends, enhancing the user experience. This experiment helped me gain practical experience in combining machine learning with web development. It enhanced my understanding of data preprocessing, regression modeling, and creating a complete web application for real-time stock price prediction.

Signature of the Student	Signature of the Lab Coordinator
Akriti Patro	Prof. Bhargav Appasani