EXP No:9 Develop neural network-based time series forecasting model

Aim:

To build a neural network-based forecasting model to predict future electric production values using past time series data.

Objectives:

- Preprocess and normalize the time series data
- Convert data into sequences suitable for LSTM input
- Train an LSTM neural network to capture temporal patterns
- Predict future values and compare them with actual observations

Background:

Neural networks, especially LSTMs, are powerful in learning from sequential data. Unlike traditional models, LSTMs can capture long-term dependencies, making them ideal for complex time series forecasting. In this project, an LSTM is trained on electric production data to learn its underlying patterns and predict future values effectively.

Code:

```
# Import required libraries

import pandas as pd

import numpy as np

from sklearn.preprocessing import MinMaxScaler

from tensorflow.keras.models import Sequential

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

import matplotlib.pyplot as plt

from sklearn.metrics import mean_squared_error

from math import sqrt

from google.colab import files  # Colab-specific library for file upload
```

```
# Step 1: Upload the CSV file
print("Please upload the 'Electric_Production.csv' file:")
uploaded = files.upload()

# Load the CSV file
# Assuming the uploaded file is named 'Electric_Production.csv'
df = pd.read_csv(list(uploaded.keys())[0])

# Ensure the DATE column is parsed as datetime and set as index
df['DATE'] = pd.to_datetime(df['DATE'])
df.set_index('DATE', inplace=True)

# Normalize the data
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(df['IPG2211A2N'].values.reshape(-1, 1))

# Function to create 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])
```

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    return np.array(X), np.array(y)

# Parameters
sequence_length = 12  # Use 12 months to predict the next month
X, y = create_sequences(scaled_data, sequence_length)

# Split into training and testing sets (80% train, 20% test)
train_size = int(len(X) * 0.8)
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]

# Step 2: Build the LSTM Model
model = Sequential()
model.add(LSTM(50, return_sequences=True, input_shape=(sequence_length, 1)))
model.add(Dropout(0.2))
model.add(LSTM(50))
model.add(Dropout(0.2))
model.add(Dense(25))
model.add(Dense(1))

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')
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```
# Step 3: Train the Model

history = model.fit(X_train, y_train, epochs=50, batch_size=32, validation_data=(X_test, y_test), verbose=1)


# Step 4: Evaluate the Model

# Predict on test data

train_predict = model.predict(X_train)

test_predict = model.predict(X_test)


# Inverse transform predictions

train_predict = scaler.inverse_transform(train_predict)

y_train_inv = scaler.inverse_transform(y_train)

test_predict = scaler.inverse_transform(test_predict)

y_test_inv = scaler.inverse_transform(y_test)


# Calculate RMSE

train_rmse = sqrt(mean_squared_error(y_train_inv, train_predict))

test_rmse = sqrt(mean_squared_error(y_test_inv, test_predict))

print(f'Train RMSE: {train_rmse:.2f}')

print(f'Test RMSE: {test_rmse:.2f}')


# Step 5: Forecast Future Values

# Use the last sequence from the data to predict the next 12 months

last_sequence = scaled_data[-sequence_length:]
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future_predictions = []

for _ in range(12):

    last_sequence_reshaped = last_sequence.reshape((1, sequence_length, 1))

    next_pred = model.predict(last_sequence_reshaped, verbose=0)

    future_predictions.append(next_pred[0, 0])

    last_sequence = np.append(last_sequence[1:], next_pred, axis=0)


# Inverse transform future predictions

future_predictions = scaler.inverse_transform(np.array(future_predictions).reshape(-1, 1))


# Create future dates

last_date = df.index[-1]

future_dates = pd.date_range(start=last_date + pd.offsets.MonthBegin(1), periods=12, freq='MS')


# Step 6: Visualize Results

plt.figure(figsize=(12, 6))

plt.plot(df.index, df['IPG2211A2N'], label='Actual Data')

plt.plot(df.index[sequence_length:train_size + sequence_length], train_predict, label='Train Predictions')

plt.plot(df.index[train_size + sequence_length:], test_predict, label='Test Predictions')

plt.plot(future_dates, future_predictions, label='Future Predictions', linestyle='--')

plt.title('Electricity Production Forecasting')

plt.xlabel('Date')
```

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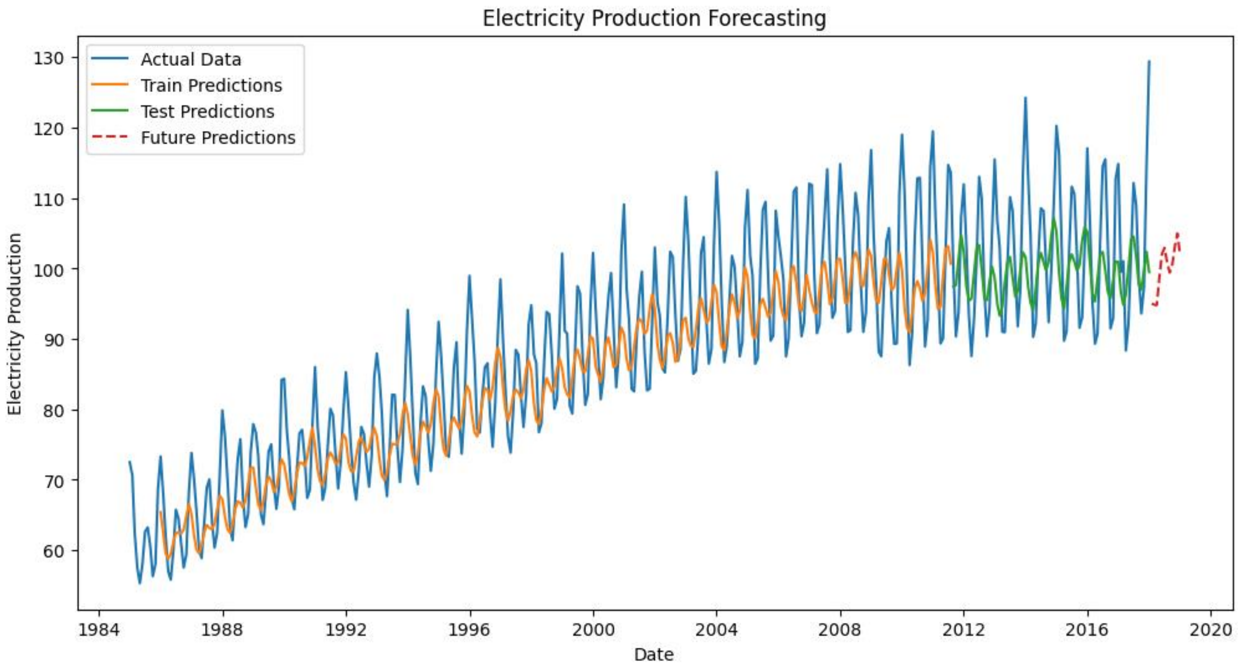
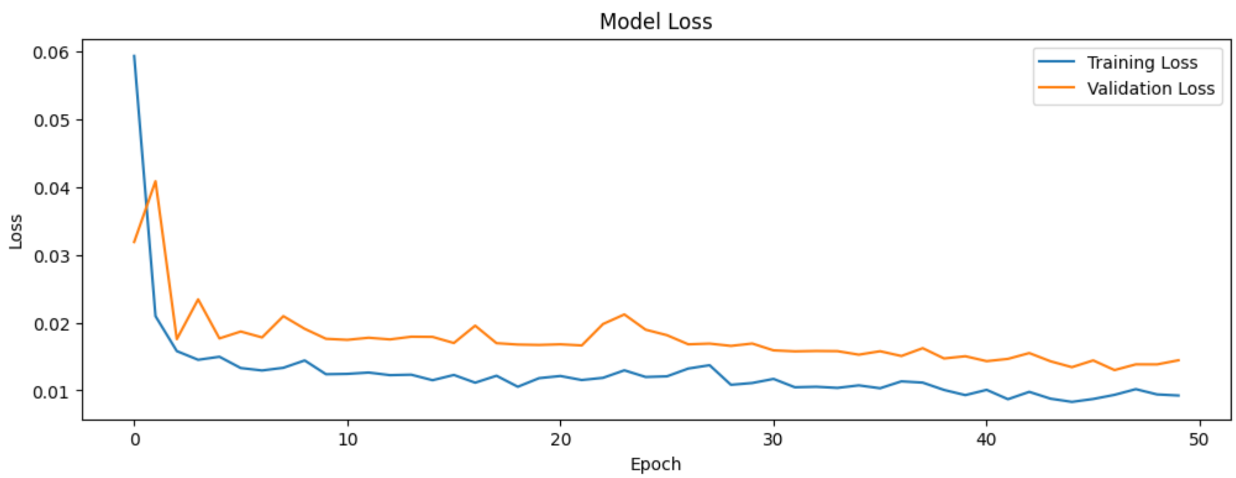
plt.ylabel('Electricity Production')
plt.legend()
plt.show()

# Plot training history
plt.figure(figsize=(12, 4))
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()
```

Output:





Train RMSE: 7.12 , Test RMSE: 8.91

Result:

Thus the program to develop neural network-based time series forecasting model is implemented successfully.