Financial Forecasting using Exchange Rates

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Introduction

This project's aim is to predict future exchange rates of Euro to US Dollar (EUR/USD) using historical exchange rate data. The key steps in this project include data cleaning, feature engineering, model training, and evaluation. A Multilayer Perceptron (MLP) model is used for this purpose, with the `neuralnet` package in R. This project would be able to assist financial analysts and investors in making informed decisions based on accurate exchange rate predictions.

Data Loading and Preprocessing

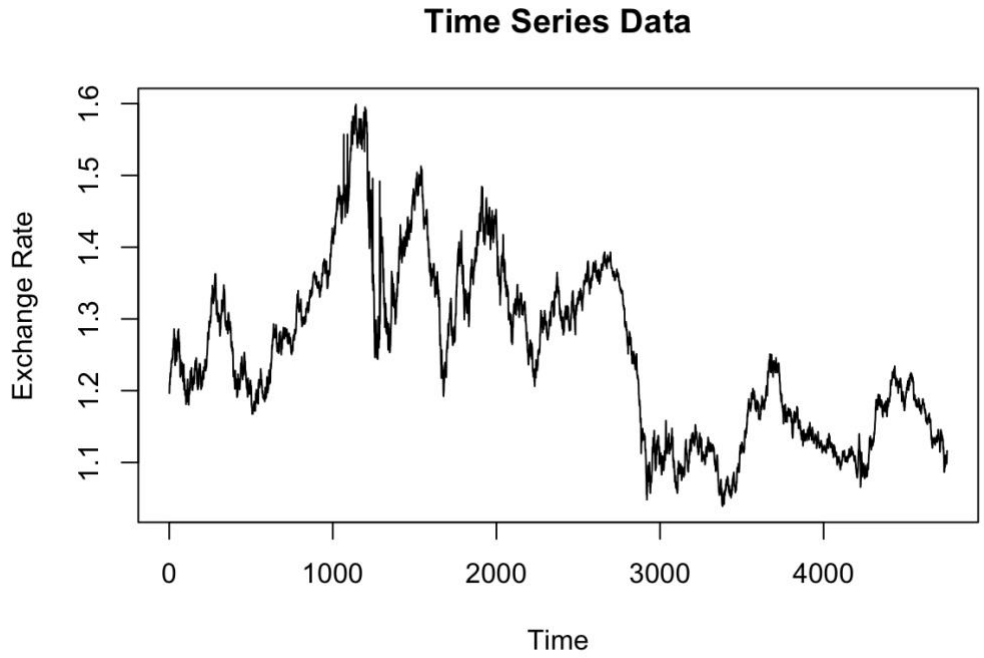
Loading and Cleaning Data

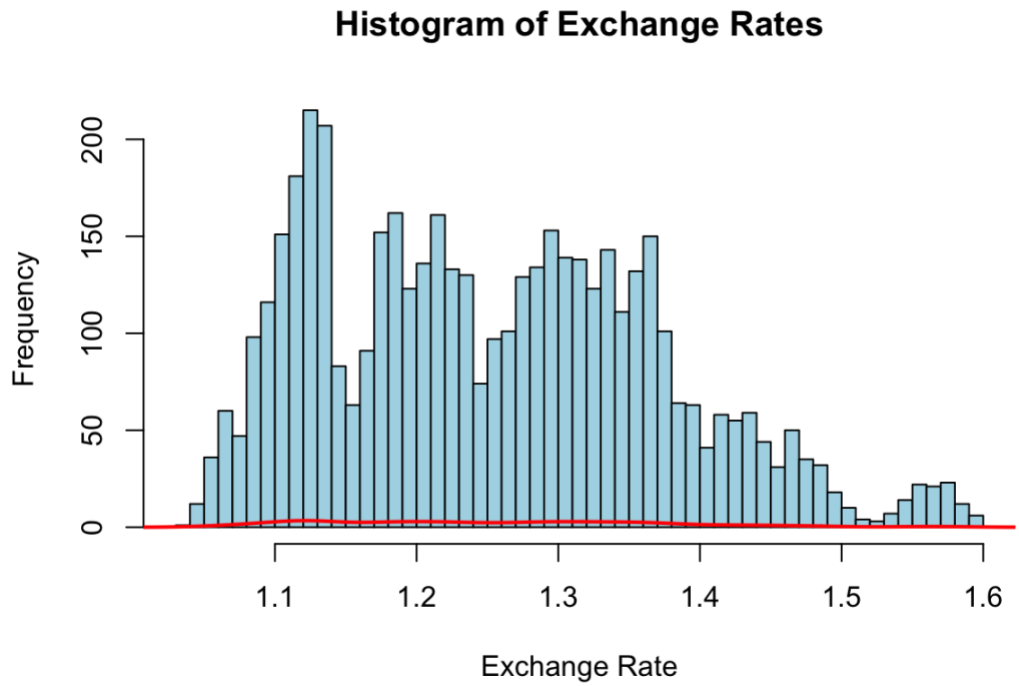
The historical data of EUR/USD exchange rates is loaded from a CSV file downloaded from a dataset from Kaggle.com.

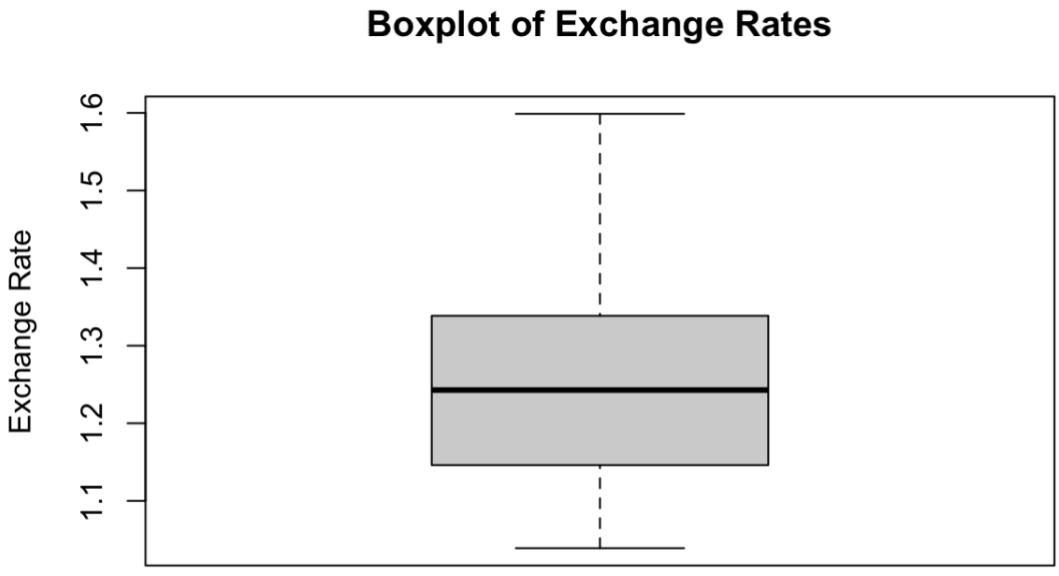
This data includes various features, with the closing exchange rate being the primary variable of interest. The data is then cleaned by converting the exchange rates to numeric values and removing any missing or invalid entries. This ensures that the dataset is ready for analysis and modeling.

Exploratory Data Analysis

The plots below show the variation of the exchange rate data.





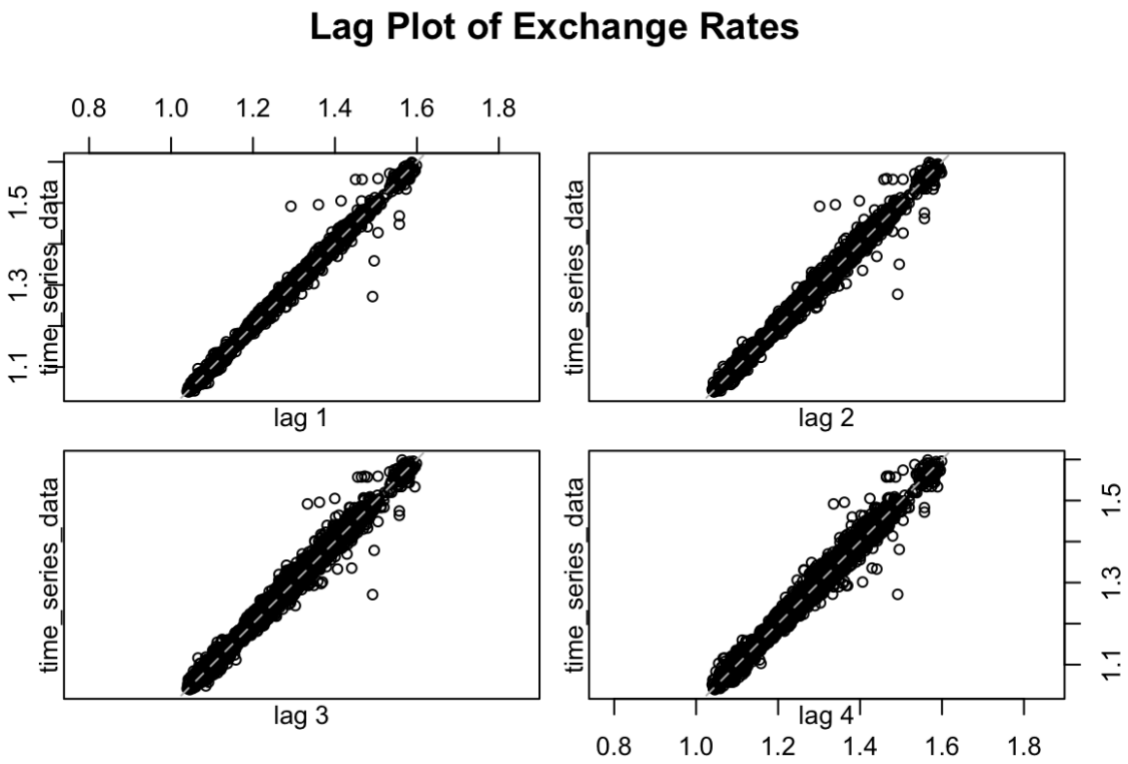


The boxplot shows that there are no outliers in the dataset under the closing rate column.

Feature Engineering

To improve the predictive power of the model, feature engineering is performed. This involves creating lagged versions of the exchange rate data, which serve as input features for the model.

Exchange rates from previous days (lags) are used to predict the future exchange rate. These lagged features help the model capture temporal dependencies in the data in time series forecasting. They were lagged upto a t-4 level. Then all the NA containing rows were removed too.



Model Training

Train-Test Split

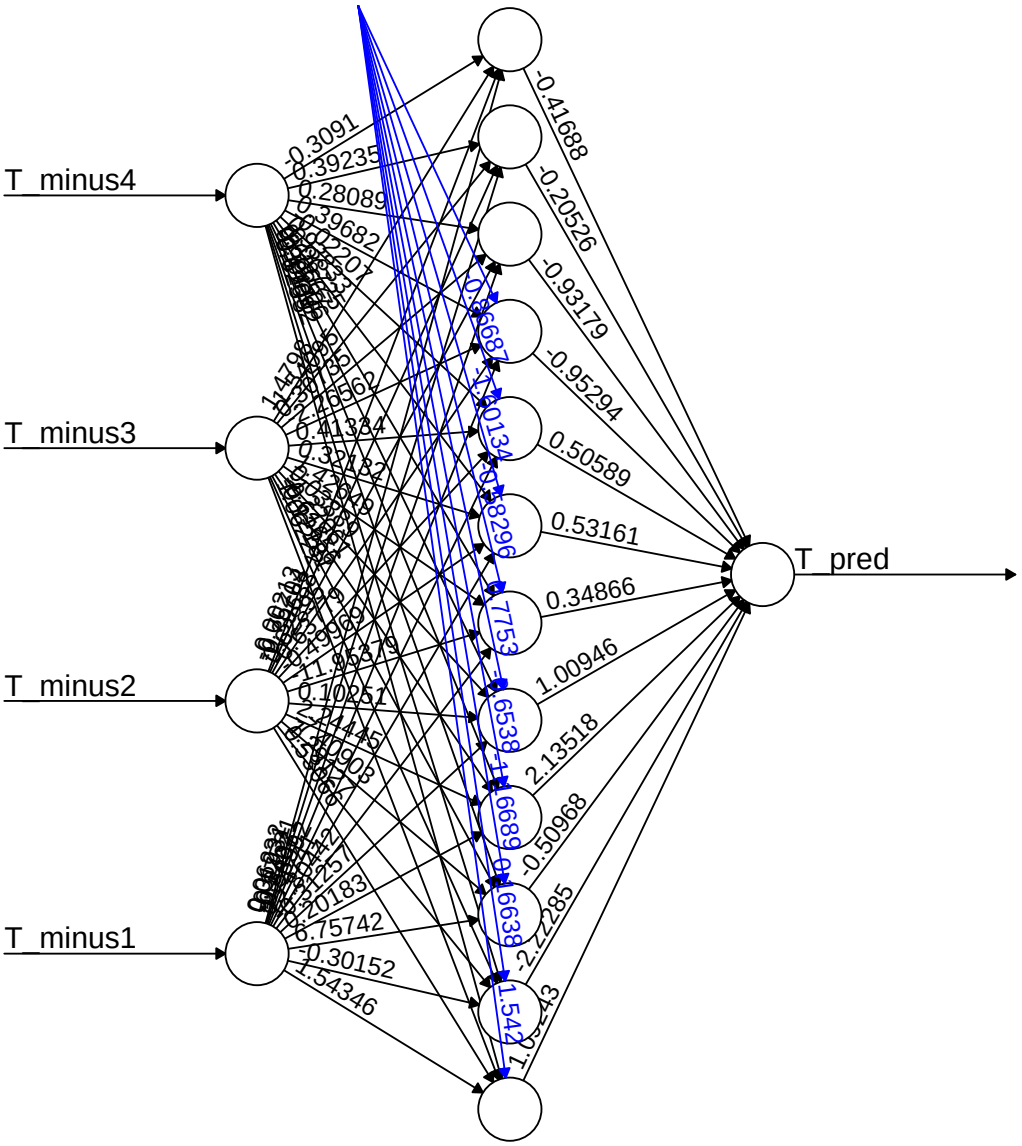
The dataset is divided into training and testing sets using an 80:20 split. The training set is used to train the model, while the testing set is used to evaluate its performance.

This split ensures that the model is evaluated on data it has not seen during training, so it can provide an unbiased performance.

Multilayer Perceptron Model

An MLP model is constructed using the `neuralnet` package in R. Several models were tested varying the inputs, activation functions, hidden layers and number of nodes in each. Then using the statistical measures given below the best model was identified as well as the model which has least parameters to be trained to make the model more efficient.

The best model is designed with one hidden layer containing 12 neurons, and a logistic activation function is used. The model is trained to minimize the error in predicting the future exchange rate based on the lagged features. The training process involves optimizing the model weights through backpropagation.



Model Evaluation

Predictions and Metrics

The trained model is used to predict the exchange rates on the testing set.

Various statistical indices are computed to evaluate the model's performance, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Symmetric Mean Absolute Percentage Error (sMAPE). The model with the least errors was selected as the best model.

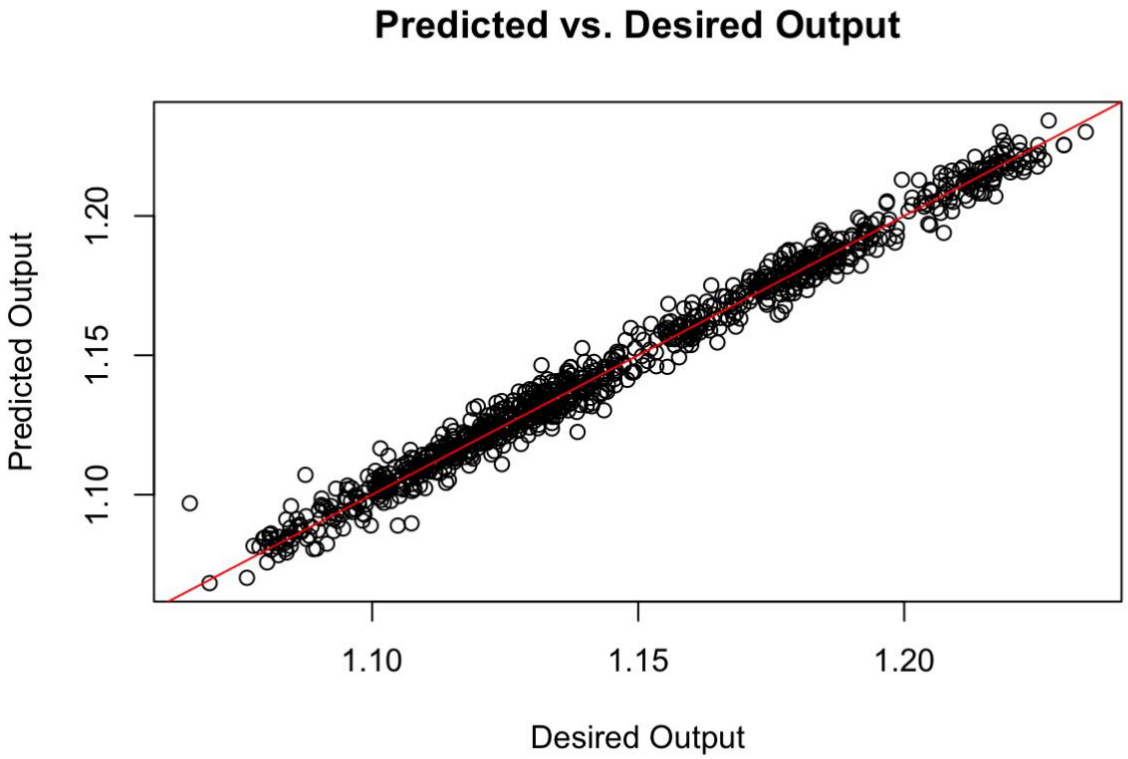
These metrics provide insights into the accuracy and reliability of the model's predictions.

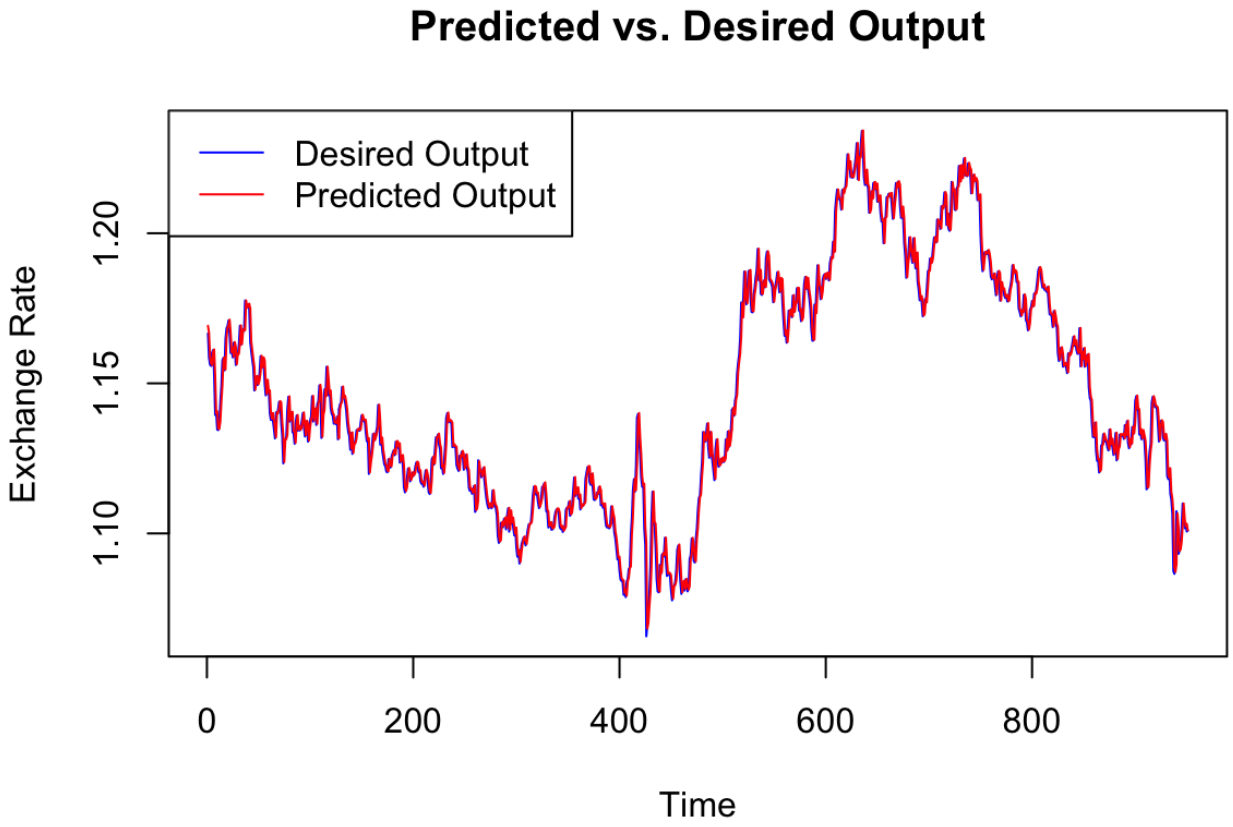
RMSE: 0.004591427
MAE: 0.003445648
MAPE: 0.003008078
sMAPE: 0.003006853

Visualization of results

The results of the model's predictions are visualized to compare them with the actual exchange rates.

Scatter plot and time series plot were created to show the relationship between the predicted and actual values. These visualizations help identify patterns in the interpretation of the model's performance.


Predicted vs. Desired Output
Predicted Output
1.10
1.15
1.20
1.10
1.15
1.20
Desired Output


Predicted vs. Desired Output
Desired Output
Predicted Output
Exchange Rate
1.10
1.15
1.20
0
200
400
600
800
Time

Conclusion

In this project, a Multilayer Perceptron (MLP) model was successfully developed to predict future EUR/USD exchange rates using historical data. The model's performance was evaluated using several statistical indices, and visualizations were created to compare the predicted and actual values.

References

Chowdhury. M. S. et al. (2024). Deep Learning Models for Stock Market Forecasting: A Comprehensive Comparative Analysis. 10.32996/jbms.2024.6.2.9

Nagadia. M. (2022). Currency Rate Euro€ to USD$ (2003-2022). https://www.kaggle.com/datasets/meetnagadia/currency-rate-euro-to-usd

Tang. P and Zhang. W. (2024). PDMLP: Patch-based Decomposed MLP for Long-Term Time Series Forecasting. https://www.researchgate.net/publication/380821515_PDMLP_Patch-based_Decomposed_MLP_for_Long-Term_Time_Series_Forecastin

Appendix

Complete Code

```
# Financial Forecasting

# Requried libraires
packages <- c("neuralnet", "caret", "Metrics", "dplyr")
installed_packages <- installed.packages()
for (pkg in packages) {
  if (!pkg %in% installed_packages[, "Package"]) {
    install.packages(pkg, dependencies = TRUE)
  }
}
library(neuralnet)
library(caret)
library(Metrics)
library(dplyr)

# Loading and preprocessing data
exchange_rate_data <- read.csv("EURUSDX.csv")
```

```
dim(exchange_rate_data)

# Cleaning data
time_series_data <- exchange_rate_data$Close
time_series_data <- as.numeric(time_series_data)
time_series_data <- na.omit(time_series_data)
head(time_series_data)
plot(time_series_data, type = "l", main = "Time Series Data", xlab = "Time",
ylab = "Exchange Rate")

# Statistical summary
summary(time_series_data)

# Histogram and Density Plot
hist(time_series_data, breaks = 50, main = "Histogram of Exchange Rates",
xlab = "Exchange Rate", col = "lightblue")
lines(density(time_series_data), col = "red", lwd = 2)

# Boxplot
boxplot(time_series_data, main = "Boxplot of Exchange Rates", ylab =
"Exchange Rate")

# Autocorrelation plot
acf(time_series_data, main = "ACF of Exchange Rates")

dataset_min <- min(time_series_data)
dataset_max <- max(time_series_data)

# Time lags
lagged_data <- data.frame(T_minus4 = lag(time_series_data,4),
                          T_minus3 = lag(time_series_data,3),
                          T_minus2 = lag(time_series_data,2),
                          T_minus1 = lag(time_series_data,1),
                          T_pred = time_series_data)

head(lagged_data)

lagged_data <- na.omit(lagged_data)
head(lagged_data)
str(lagged_data)

# Lag plot
```

```
lag.plot(time_series_data, lags = 4, do.lines = FALSE, main = "Lag Plot of
Exchange Rates")

# Normalisation function
normalize <- function(x) {
  return((x - min(x)) / (max(x) - min(x)))
}

lagged_data_normalized <- as.data.frame(lapply(lagged_data, normalize))
head(lagged_data_normalized)

# Train test split
training_data <- lagged_data_normalized[1:3800, ]
testing_data <- lagged_data_normalized[3801:nrow(lagged_data_normalized)-
4, ]
head(training_data)
head(testing_data)
plot(training_data)
plot(testing_data)

original_training_data <- time_series_data[1:3800]
head(original_training_data)
original_testing_data <- time_series_data[3801:4751]
head(original_testing_data)

dataset_min <- min(time_series_data)
dataset_min
dataset_max <- max(time_series_data)
dataset_max

# Denormalisation function
denormalize <- function(x, min, max) {
  return( (max - min) * x + min )
}

set.seed(123)

# MLP Model
dataset_model1 <- neuralnet(
  formula = T_pred ~ T_minus4 + T_minus3 + T_minus2 + T_minus1,
  data = training_data,
  hidden = 12,
  linear.output = TRUE,
```

```
  act.fct = 'logistic'
)
plot(dataset_model1)


# Model predictions
predicted_results_model1 <- predict(dataset_model1, testing_data)
head(predicted_results_model1)

predicted_T <- predicted_results_model1
head(predicted_T)
dim(predicted_T)

target_prediction <- denormalize(predicted_T, dataset_min, dataset_max)
head(target_prediction)
dim(target_prediction)

# Statistical indices
rmse_val <- rmse(unlist(original_testing_data), unlist(target_prediction))
mae_val <- mae(unlist(original_testing_data), unlist(target_prediction))
mape_val <- mape(unlist(original_testing_data), unlist(target_prediction))
smape_val <- smape(unlist(original_testing_data), unlist(target_prediction))

# Output statistics
cat("RMSE:", rmse_val, "\n")
cat("MAE:", mae_val, "\n")
cat("MAPE:", mape_val, "\n")
cat("sMAPE:", smape_val, "\n")

# Model evaluation
plot(unlist(original_testing_data), unlist(target_prediction),
    xlab = "Desired Output", ylab = "Predicted Output",
    main = "Predicted vs. Desired Output")
abline(0, 1, col = "red")

time_indices <- seq_along(unlist(original_testing_data))

plot(time_indices, unlist(original_testing_data), type = "l", col = "blue",
    xlab = "Time", ylab = "Exchange Rate",
    main = "Predicted vs. Desired Output")

lines(time_indices, unlist(target_prediction), col = "red")
```

```
legend("topleft", legend = c("Desired Output", "Predicted Output"),
       col = c("blue", "red"), lty = 1)
```