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# Forecasting Foreign Exchange Rate with Machine Learning Techniques Chinese Yuan to US Dollar Using XGboost and LSTM Model

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**ABSTRACT**

Predicting exchange rates is important because it affects all major markets and plays a big part in the economy. The goal of this study is to forecast future values of the Chinese Yuan (CNY) to US dollar exchange rate. One of the most crucial aspects of the economy is the rate of exchange of currencies. The currency exchange rate is required in commercial terms, such as profit and investment evaluation. The purpose of CNY rate prediction is to determine the future value of the Chinese Yuan (CNY) relative to the US dollar, which can be taken into account while making decisions and lower the chance of losing money. As a result, we require a technique that can assist in accurately assisting in business selections regarding when to execute the appropriate deals. For this research study three-year dataset is used from 25 April 2020 to 26 May 2023. For this research we used two different machine learning models and comparison between the LSTM and Xgboost models first one is Long Short-Term Memory (LSTM) and second is Extreme Gradient Boosting (XGboost). The empirical results showed that the LSTM model provided better results than XGboost. Therefore, this study suggest that the LSTM model will helpful for the government monetary policymaker, economists and other stakeholders to identify and forecast the future trend of the exchange rate and make their policies accordingly.



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## 1. Introduction

The importance of exchange rate is prediction plays a significant role in the economy and has some influence over all major markets, the exchange rate has long been a hot topic in international financial research (Meese & Rogoff, 1983). One of the most crucial topics when discussing the global economy is the exchange rate (Krugman, 2009). For practitioners and researchers involved in the fluctuating exchange rate phenomenon, forecasting the exchange rate is the most important event (Rossi, 2013). Numerous research projects and prediction models have been developed over time. Meese and Rogoff's (1983) work on exchange rate forecasting may be the most frequently quoted one. The accuracy with which macro models can predict the exchange rate is a matter of debate among researchers. Some forecasting models were first established following the collapse of the Bretton Woods system. It implied that the exchange rate is influenced by macroeconomic factors. Meese and Rogoff (1983) made an argument against this notion in their study. These exchange rates produce series that are very volatile, complex, and noisy due to an inclusive market process. The term "noisy characteristic" describes the inability to properly reflect the dependence between future and previous prices due to incomplete information derived from the historical behavior of financial markets (Meese & Rogoff, 1983).

Furthermore, it is difficult to forecast future exchange rates. The researchers project the exchange rate for future events pertaining to the currency rate. One of the most important and useful methods for predicting the exchange rate is time series analysis (Sezer, Gudelek, & Ozbayoglu, 2020). For the aim of forecasting, the exchange rate has been adopted by the researcher as a variable. The CNY/USD exchange rate's three years' worth of daily data were selected as a sample, and the LSTM/XGboost tool was employed as a statistical tool. The majority of merchants, The US dollar is used as the transactional exchange rate by importers, exporters, remittances, foreign currency deposit, reserves etc. One of the most widely cited works in exchange rate forecasting is that of Meese and Rogoff (1983) (Meese & Rogoff, 1983), which challenged the accuracy of macroeconomic models in predicting exchange rates. Their research highlighted the volatility and complexity of exchange rate movements, driven by numerous macroeconomic factors and market dynamics. Meese and Rogoff argued that traditional macro models struggled to accurately predict exchange rates, particularly in the wake of the collapse of the Bretton Woods system, which introduced greater fluctuations in currency values. Exchange rates often exhibit noisy characteristics, where the dependency between future and past prices is obscured by incomplete information from historical market behavior The process of forecasting exchange rates is still a formidable task because the financial markets are best characterized by their volatility and non-linearity. The present study has now identified that time series analysis has evolved to become an indispensable and preferred technique in the forecasting of exchange rate fluctuations. All these models have been proposed to accommodate the volatilities that exist in the exchange rates some of which include: ARIMA, SVM, and many machine learning algorithms like LSTM and XGBoost. However, each of these models possesses certain drawbacks due to the necessity to reflect not only short-term but also long-term dependencies in fluctuating time-series data. In this paper, we seek to forecast the exchange rate of the Chinese Yuan (CNY) with regards to the US Dollar (USD) which is arguably the most significant exchange rate in the international market. The US Dollar retains the largest share in global commerce, foreign exchange demand and money transfers and thereby the CNY/USD exchange rate is a significant parameter for corporate, policy and economic review. The objective of this research is to propose a rational an accurate model for addressing the establishment of the CNY/USD exchange rate based on the daily historical data of the past three years. Using LSTM and XGBoost models to predict accurately the future stock prices for helping economists, policymakers, and investors

Forecasting the CNY/USD rate is essential in the current world economy because exchange rate volatility has major consequences for trade, investment, and policy. These forecasts are handy for policymakers who use them to control the money supply, economic stability and fighting inflation and for businesses to hedge against currency risks, cover their profit margins and plan strategically effectively. Such time series models as ARIMA are unsuitable for analyzing exchange rate data, which are non-stationary and exhibiting nonlinear trends, and lack the ability to model long range temporal correlations. Although, there is an improvement, by using other accurate models like LSTM networks and XGBoost, there is still a gap when it comes to fine-tuning models for this kind of exchange rate prediction. In filling that gap, this study presents a new model that comprises features from both the LSTM and XGBoost models and presents a much more effective tool for policymakers and businesses to mitigate volatility in exchange rates. This paper aims at considering the issue of exchange rate prediction with reference to the CNY/ USD exchange rate as is vital in today's global economy due to its impacts on the flow of international trade and investment as well as the formulation of economic policies. Budget planning requires stable expectation and fluctuations in currency impacts risk factors related to policies and business investments. Although there are many methods of forecast, including autoregressive integrated moving average models (ARIMA), machine learning algorithms and methods such as LSTM, XGBoost, or others, there are some critical issues that remain imperatively to improve to model extreme and unpredictable financial data. The purpose of this research is to evaluate the differences in LSTM and XGBoost algorithms to forecast CNY/USD exchange rate. To structure this investigation, we pose the following research questions:

1) A comparison of LSTM networks and XGBoost for the forecasting of the CNY/USD exchange rate. 2) With reference to another two economic variables, namely interest rates and inflation, what is the effect of including these two variables in the accuracy of the forecast? Our prediction is that LSTM will provide the predictions more accurate in comparison to XGBoost, as LSTM effectively models sequential data. As highlighted earlier, this research is expected to yield important data for making sound strategic decisions in strive economic environment for economists, policy makers as well as businesses.

## 2. Literature Review

The importance of exchange rate prediction, a large number of academics have concentrated on this topic. A few approaches to predict the foreign exchange market that have been published in the last few years. It is very important for an organization to predict accurately these currency exchange rates. This has become even more crucial in today's advanced world due to its main role in areas like the financial market, trading and making of economic policies. Exchange rate determine inflationary tendencies, import and export balance and monetary policy decisions, and therefore an accurate prediction of them is essential for both financial institutions.

Over the years, many of Their study have been conducted, employing both simple econometric techniques and more advanced methods such as machine learning (ML) and, to some extent, deep learning (DL) to enhance forecasting precision. However, leads to the forecast of exchange rates still poses a major problem complicating their modeling because they are usually volatile and time related interest rates, inflation and other geopolitical influences which will be discussed in greater detail later in this paper. In in the past few years deep learning models have received significant attention for their capability of modeling of complex nonstationary features which exist in time series data. More typical in structure and likely to outperform other models are more traditional models such as ARIMA which although popular, suffer from non-linearity and long-term dependencies which restrict them effectiveness especially in highly volatile financial environment. Hence, the increase in demands of hybrid and advanced model, which combine feature of other techniques to overcome these limitations. This section gives a critical description of the recent study advancement in exchanged rate prediction which will cover presumptions especially from the period of the last five years also shows how this research fills the gap of literature in the knowledge area.

### 2.1. Traditional Models and Limitations

The simple and easily interpretable econometric models like the ARIMA (Autoregressive Integrated Moving Average) models have been found to have been widely applicable for forecasting of exchange rates. ARIMA models are especially suitable for analysis of linear trend and stationary processes. For example, Qunita (2017) (Qonita, Pertiwi, & Widiyaningtyas, 2017) predicted Indonesian Rupiah and US Dollar by using the ARIMA model that has a relatively high accuracy with the MAPE (Mean Absolute Percentage Error) of 1.259. However, a drawback of the

ARIMA model is an inability to handle fluctuations and a non-linear trend inherent to the financial time series data set. This is especially important when managing foreign exchange risks where such quantities as a result of non-linear dynamics are often prevailing. Similarly, single models like Naïve model and the exponential Smoothing methods have also been used for time series modeling. These models prove convenient for short-term forecasting and stationary data, and do not correspond to the volatile nature of financial markets conditioned by macrosocial factors and geopolitical processes (Fischer & Krauss, 2018).

### 2.1.1.Machine Learning Models

There are two more concrete model for ML are decision tree and support vector machines (SVMs) provided more flexible non-parametric methods for the exchange rate forecasting for the offered solutions. One model is the Nonlinear Autoregressive Distributed Lag (NARDL) model which has been applied to modeling asymmetry of the links between various macroeconomic factors and exchange rates (Nkoro & Uko, 2016). For instance, Ullah (2020) (Rasheed, Ullah, & Uddin, 2020), used NARDL in combination with ARIMA and Exponential Smoothing in order to predict the PKR/USD. The analysis proved that the NARDL model was superior to the other traditional models, and the findings imply that it is possible to achieve employing diverse and sundry models for improved precision in the evaluation of real-case financial quandaries. There is also machine learning used such as XGBoost and Random Forest in financial forecasting. These Model do well in identifying complex interactions between variables, but the main drawback is they need a lot of feature engineering and time consuming is required to achieve quite time-consuming and is usually domain expert. Furthermore, these models do not capture sequential dependencies inherently and are less effective for time series predictions unless modified further (Kumar, Koul, Kaur, & Hu, 2022).

### 2.1.2.Deep Learning and Hybrid Models

Deep learning has been one of the revolutionary inventions with orchestrate improvements in exchange rate forecasting. Extended emerging deep learning paradigms like LSTM networks and CNNs have a versatile capability of dealing with sequential data and understanding short as well as long-term dependence. With LSTM networks to solve the vanishing gradient problem in traditional recurrent neural networks (RNN) has been applied to finance time series extensively. For instance, Wang et al. (2021) (Wang, Wang, Li, & Wang, 2021), he used CNN-LSTM model to forecast the CNY/USD exchange rate using daily foreign exchange rates and stock exchanges. The CNN part served for feature extraction and the LSTM layer is responsible for the long-term dependencies. Their findings should establish that the CNN-LSTM model is suitable for the analysis of time series data that contains sophisticated nonlinear dependencies and gave substantially higher performance than the ARIMA-based models. However, there exist CNN-LSTM models that can improve the performance for multi-step ahead prediction; though they are computationally costly, and sometimes, are not easy to interpret. Another excellent development in the application of deep learning is based on including the attention mechanisms, particularly Multi-Head Attention. This approach makes it possible to compare the importance of every part of the input sequence with the other parts at each step and thus adapt better to the context of volatile and non-stationary data. Zhang et al. (2024) (Zhang, Sjarif, & Ibrahim, 2024), used Multi-Head Attention for financial forecasting and hence gained improved accuracy by concentrating on important time periods and events in the market. This dynamic weighting of input is especially useful in exchange rate systems where short-term movements could be greatly influenced by market events or policy changes can drastically affect short-term fluctuations.

Recent studies had been made to the use of compound models that incorporate a combination of deep learning structures to better estimate. These models make use of the best from these techniques including CNN for local pattern extraction, LSTM for sequential learning, and Attention mechanisms for dynamic feature weighting (Li, Xu, Feng, & Zhao, 2023). Cao et al. (2021) (Wu et al., 2021), ] successfully designed a hybrid convolutional neural network (CNN) and time-depth long and short-term memory (TLSTM) for predicting exchange rates and stock prices and with a high level of accuracy and improvements in accuracy compared with a single model. The original study employed technical variables including moving averages and volatility to apply toward improving the model (Agrawal, Khan, & Shukla, 2019). Similarly, Wang et al. (2021) (Wang et al., 2021), proposed a CNN-TLSTM model for stock price prediction of the closing price of USD/CNY exchange rate. To enhance comprehensiveness of the results and the model stability to non-linear relations between the interacting factors, the authors used an ensemble of indicators, such as the stock indices, and historical exchange rates. The research results showed that the use of hybrid models allows to address the difficulties related to exchange rate fluctuations, especially within the unstable environment.

### 2.2. Gaps in Existing Literature

However, the following research gaps are evident from the recent existing models that have been developed First, it is often claimed that the forecast accuracy of many of the proposed models is heavily reliant on the availability of large computational resources in which also real-time forecasting environments. Second, these models depend on the quality and previous volume of data in estimating costs within the project. Further, where data has noise or is missing, the accuracy of the model could be considerably low. Furthermore, better predictive accuracy is gained through use of hybrid models, the model complexity enhances making interpretation difficult and time consumed in the hyperparameters tuning step. The chosen LSTM and XGBoost models manage to overcome several shortcomings inherent to conventional forecasting methods

Compared to other types of data, LSTM in time series data captures complex, non-linear relations that other models such as ARIMA may not factor. Additionally, LSTM overcomes the challenge of long-term dependencies by retaining relevant information across extended time periods, mitigating the vanishing gradient issue typical in recurrent neural networks. On the other hand, XGBoost reduces the need for extensive manual feature engineering by automatically selecting and weighting the most relevant features, thereby enhancing predictive accuracy. While LSTM is optimized for sequential data, capturing temporal relationships effectively, XGBoost incorporates built-in regularization techniques to control model complexity and minimize overfitting. Together, these models complement each other, ensuring accurate, scalable, and robust predictions in dynamic and high-dimensional financial data environments.

## 3. Methodology

### 3.1. Dataset

Although there are several websites and surveys that provide daily exchange rate data, I personally gather my data for this research via the Kaggle website. There are two variables in this data: US dollars and Chinese yuan. Our dataset comprises a time series of 36 months since we used daily data for this study, which was the Chinese Yuan and US Dollar exchange rate for the period between 2020.05.25 and 2023.05.26.

### 3.2. Preprocessing

This approach maintains the intervals of the time series, which is important for avoiding the disruption of the learning process of sequential models. Anomalies, sudden movements in the exchange rates may be due to a market disruption or economic crises, or fluctuations from actual data errors. To determine these outliers, a Z-score method was used which computes the difference of a data point to the mean. The concept used to select the outliers was the Z-score of their value where any value with Z-score of greater than 3 or less than -3 was considered an outlier. These outliers were then reviewed individually, actual market events such as financial crises were kept in while noise that arises from occasional large errors in the data was remove by averaging the data points in their local neighborhoods to keep the model clean.

Min-Max scaling was preferred for scaling the dataset in order to tune all the features between 0 and 1. This normalization technique is very important as it gives features of very different scales, such as exchange rates and macroeconomic indicators the same weight in the model during model training. Min-Max scaling was chosen instead of another normalization methods including Z-score normalization since it is simple and relation between values of series is preserved which is very important for the time series. Moreover, it is also observed that LSTM and XGBoost models are generally more accurate with the scaled data because this helps in converging faster in training also because feature with high variance does not over power low value features. To prevent having high dimensionality of dataset, and to consider only significant laboratory signs, Principal Component Analysis (PCA) was used. The aim was to maintain only those factors that account for at least 95% of the variance in the data set, thus excluding noise and nearly irrelevant variables. To test for stationarity, we used the Augmented Dickey-Fuller (ADF) test. This test checks the null hypothesis that a unit root is present in the time series, which indicates non-stationarity. A p-value less than 0.05 suggests that the series is stationary, while a higher p-value indicates the presence of a unit root, implying non-stationarity and the potential for trends or seasonal patterns. Stationarity is important because it ensures that the statistical properties of the data, such as mean and variance, remain constant over time. This stability allows models to learn from historical patterns effectively. Non-stationary data can lead to unreliable forecasts and misleading relationships. To achieve stationarity, we applied differencing as needed. Differencing involves subtracting the previous observation from the current observation to remove trends and stabilize the mean of the time series. If the ADF test indicated non-stationarity, we would use first differencing and, if necessary, second differencing until the data met the stationarity criteria before proceeding with model training.

### 3.2.1.Model Development

The LSTM and XGBoost models were then trained by using the preprocessed data as the input data to build a prediction model. The LSTM model of the present study was specifically aimed at modeling temporal dependencies and dynamics, and XGBoost helped to deal with structured features Both models were evaluated based on their ability to predict exchange rate fluctuations accurately.

### 3.2.2.Training and Testing

To make the division we have divided the dataset into 2 parts the first part used 80% data called as training data the second part used 20% data called as testing data.

### 3.2.3.Selection of Models

This study utilizes Long Short- Term Memory (LSTM) and Xgboost models to predict exchange rate of Chinese Yuan to US Dollar price. LSTM and XGBoost were chosen for this research because of their utility in handling the specific problems of currency exchange rate prediction. LSTM networks are specifically beneficial when there are long and long-term structures in sequential data in other words when the nature of data is temporal in which the structure of non-linear time series of data found in the financial market perfectly fits into this category. While the ARIMA method can only work with linear model, LSTMs can capture nonlinear trends hence can handle irregular time gaps in the exchange rate that LSTMs are particularly well when it comes to forecasting unpredictable movements in the exchange rates. However, XGBoost is good in feature selection and non-linearity as well. It does not overfit, which is an impending problem with models that use the financial data, and it is easily scalable to accommodate high dimensions. Compared with the more complex and sensitive to parameters indication SVM, XGBoost comes as a more effective and less demanding algorithm. Further, despite the potential benefits that can be attained by hybrid models, such models are relatively complex and computationally expensive to implement – especially when applied real-time forecasting. As this work focuses on furthering the development of the LSTM and XGBoost methods for exchange rate prediction, the efficiency of the algorithm and accuracy are proposed to trade in a manner that provides a strong positive exchange rate prediction with high computational velocity.(Vuong, Dat, Mai, & Uyen, 2022).

## 3.3. LSTM

Long Short-Term Memory (LSTM): This technique is popular in time-series forecasting issues and is used to Analyze the long-term dependencies that exist within data is sequential. It has multiple hyperparameters, such as batch size, number of epochs, number of dense layers, number of units in dense layer, number of LSTM layers, and number of units or memory cells in LSTM layers. The performance of the model is largely determined by each of these hyperparameters. The model's ability to learn and retain long-range dependencies is aided by the amount of memory cells and LSTM layers. To enable the LSTM to identify complex patterns and dependencies in the data, dense layers and the quantity of dense layer units serve to aggregate the data from all units or memory cells in the preceding layer. The quantity of samples processed prior to updating the model's weights is referred to as the batch size, and an epoch is a single iteration through the whole training dataset. LSTM models use an optimization algorithm to minimize the loss function in order to optimize the model parameters, such as weights and biases. RMSprop, Adam, ReLU, Tanh, and other optimization methods are a few examples of this type

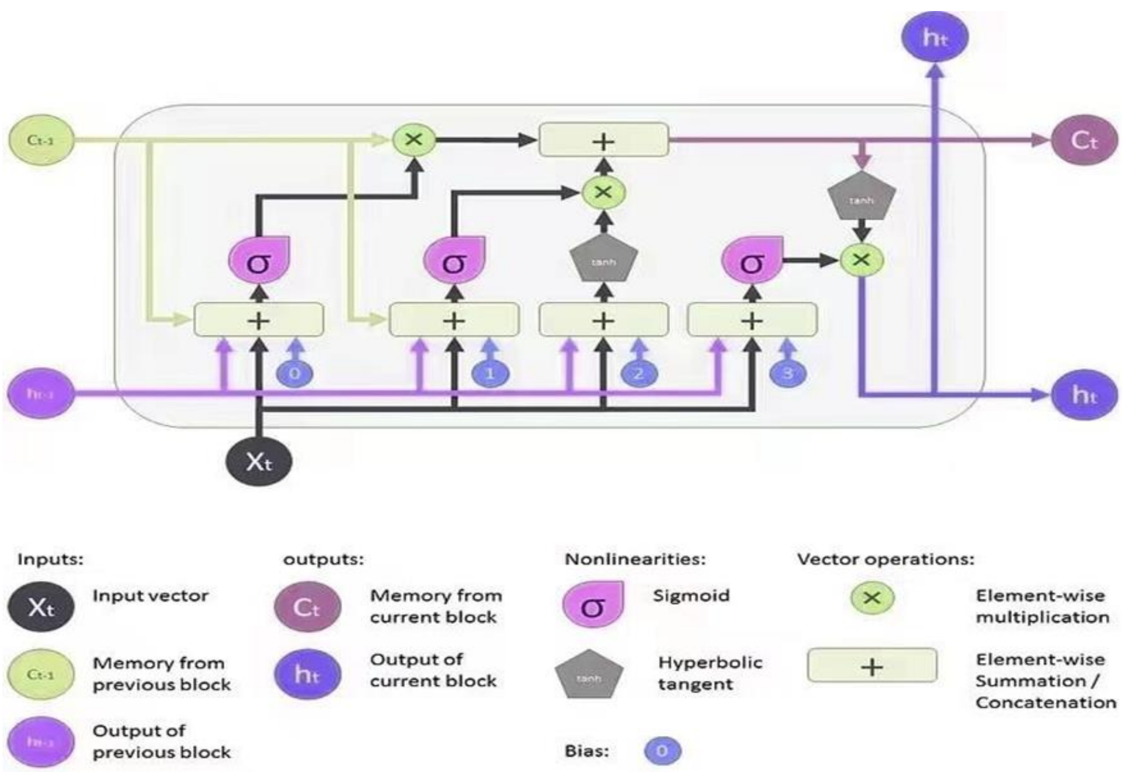


**Figure 1: The Structure of A Long Short-Term Memory (LSTM) Algorithm**

$it = \sigma\,(Wi\,[ht - 1, xt] + bi)$ (1)
$ft = \sigma(Wf[ht - 1, xt] + bt)$ (2)
$ct = ft * ct - 1 + it * tanh\,(Wc\,[ht\_1, xt] + bc$ (3)

$ot = \sigma\ (Wo[ht - 1, xt] + bo)$ (4)
$ht = ot\ *\ tanh\ (ct)$ (5)

where $xt$ is the contribution at time step $t$, ht is the secret state at time step $t$, $ct$ is the cell state at time step $t$, and $it$, ft, and $ot$ are the information entryway, neglect door, and result entryway, separately, at time step $t$. W and $b$ are the weight grids and inclination vectors, separately. The sigmoid capability and the exaggerated digression capability ($tanh$) are utilized to bound the result somewhere in the range of 0 and 1, and between - 1 and 1, separately.

### 3.3.1.XGBoost

Extreme Gradient Boosting is one of the ensemble techniques that has effectiveness in sequential decision tree machine learning algorithms is Extreme Gradient Boosting, or XGBoost. Although XGBoost is an advanced boosting algorithm implementation with regularization factors, it still makes use of most of the standard boosting method function. Boosting is the primary function of XGBoost. Trees are constructed one after the other in this boosting process, with each tree aiming to lower the mistakes of the one before it. This is done in a few of stages. It is defined that the target variable will be predicted by the initial model, F0. The residuals of earlier phases are fitted to a different model, h0. The result of combining these two models is F1, which will have a lower MSE than F0.

$$F_0(x) + h_0(x) = F_1(x) \quad (6)$$

With the release of the new F2 model, we can now further enhance performance.

$$F_1(x) + h_{n-1}(x) = F_n(x) \quad (7)$$

Until the required residual minimization is achieved, this can be done "n" times.

$$F_{n-1}(x) + h_{n-1}(x) = F_n(x) \quad (8)$$

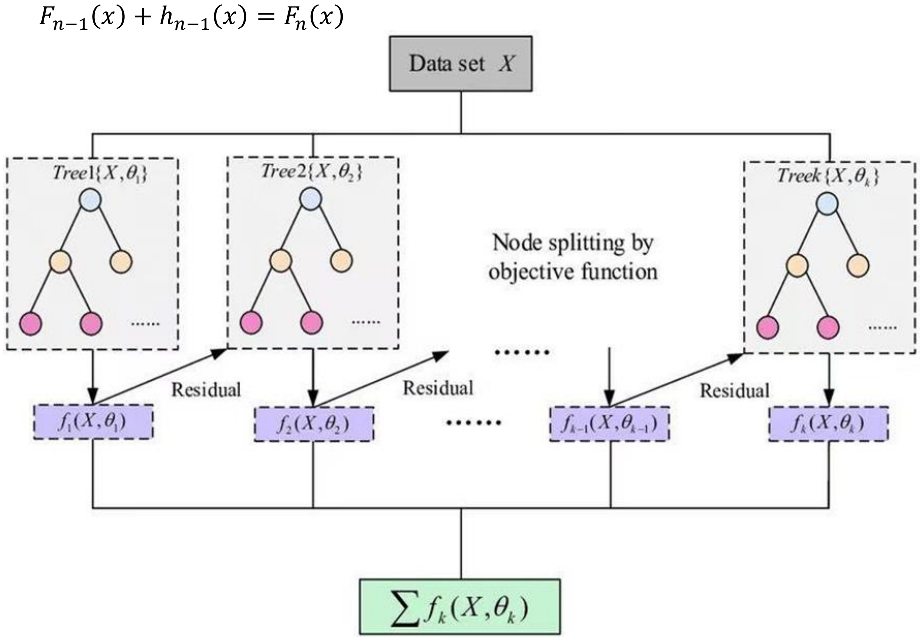


**Figure 2: The Structure of An Extreme Gradient Boosting (Xgboost) Algorithm**

### 3.3.2.Test accuracy

The test accuracy stage involves evaluating the accuracy of the trained models and comparison of the performance of LSTM and XGboost tested and trained by using some test parameters such as a MAE, MSE, RMSE, and MAPE.

### 3.3.3.Mean Absolute Error (MAE)

Absolute Mean Error (MAE). MSE operates in a similar manner. The squared error yields the value of the MAE. The distinction between the two, though, is whether or not absolute values are present. The MAE will convert any inaccuracies to an absolute value. The following is the formula for the MAE (Willmott & Matsuura, 2005). MAE = $\frac{\sum|Y'Y|^2}{n}$ With information: $Y'$ is represent predicted value, $Y$ is represent actual value and $n$ is represent amount of data.

## 3.4. Mean Square Error (MSE)

The error squared and divided by the average yielded the mean square error (MSE). Therefore, the MSE that is produced will increase with the size of the model's error. The following is the formula for the MSE (Raschka & Mirjalili, 2019). MSE = $\frac{\sum Y\prime\_Y^2}{n}$ with information: $Y'$ is represent predicted value, $Y$ is represent actual value and $n$ is represent amount of data.

### 3.4.1.Root Mean Square Error (RMSE)

The MSE result multiplied by the square root is the RMSE. Like MSE, the resulting RMSE number decreases with increasing error. The following is the formula for the RMSE (Hyndman, 2018).

RMSE = $\sqrt{\frac{\sum(Y'-Y)^2}{n}}$ With information: $Y'$ is represent predicted value, $Y$ is represent actual value and $n$ is represent amount of data.

### 3.4.2.Mean Absolute Percentage (MAPE)

The Mean Absolute Percentage Error (MAPE) is a metric used to evaluate the accuracy of a forecasting or prediction method. It measures the average percentage difference between the predicted values (Ý) and the actual values (Y) (Kim & Kim, 2016).

The following is the formula for the RMSE:

MAPE = $\frac{1}{n}\sum_{i=1}^{n}\frac{|y_i-\hat{\ }yi|}{yi}\cdot 100\%$ With information: $Y'$ is represent predicted value, $Y$ is represent actual value and $n$ is represent amount of data.

## 4. Results

This chapter will discuss the stationary, dataset results, preprocessing, modeling, and testing, which are the research stages.

## 4.1. Stationary test

The Augmented Dickey-Fuller (ADF) test is one of the often-used methods to check for stationarity. By analyzing if a unit root exists in the data, the ADF test determines whether a time series is stationary. The neural network model cannot be fitted with the non-stationary data. In

2023, Livieris tested the original training data's stationary state using the Augmented Dickey Fuller (ADF) test (Livieris, 2023). Thus, in this paper, the stationary of the original training data is tested using the ADF test. As a result, when I run the ADF test, the P value is less than 0.05, indicating that the data is probably not stationary. I then use difference to get the data to become stationary. Below is the difference test result. ADF Statistic: -28.83356512446317, p-value: 0.0. Now the data is likely stationary. The formula for calculation is $yn = xn - 1$.

Where, $yn$ is representing the value after the difference, $xn$ is represent the original value, $xn - 1$ is representing the previous data. In this section compares forecasts the Chinese Yuan and US dollar using LSTM and XGboost models. To make this comparison, different measures of prediction error are analysis such as mean square error (MSE), mean absolute percentage error (MAPE), rote mean square error (RMSE), Mean Absolute Error (MAE). The results of the study are described as follows:

The below table is showing the descriptive statistics overview of the data for the CNY/USD foreign exchange rates from 2020 to 2023.

**Table 1**
***Test Statistic***

| Mean | Std | Min | Max |
|---|---|---|---|
| 7.492 | 0.378 | 6.751 | 8.263 |

We used two models to estimate the CNY/USD exchange rate, and we used MAE, MSE, RMSE, and MAPE to quantify the model errors (Table 2). We have taken the R2 score into consideration while evaluating the fit of our models. Next, we created a figure (Fig. 2) showing the actual and expected values of the CNY/USD exchange rate. Next, in order to evaluate the suggested pipeline's efficiency, we applied it to our models. Lastly, we have contrasted our findings with those of two models, LSTM and XGboost.

**Table 2**
***Test comparison of LSTM and XGboost***

| Models | MAE | MSE | RMSE | MAPE |
|---|---|---|---|---|
| LSTM | 0.043 | 0.003 | 0.055 | 0.595 |
| XGboost | 0.111 | 0.701 | 1.119 | 0.330 |

Plotting the actual CNY/USD exchange rate against the forecasts made by our models: As the CNY/USD exchange rate is plotted against the predictions made by our models (Fig. 1It is evident that our models were able to generalize both the upward and downward trend of the exchange rate. Figure 1 shows the actual and predicted value of the Chinese yuan in relation to the US dollar using the LSTM model.

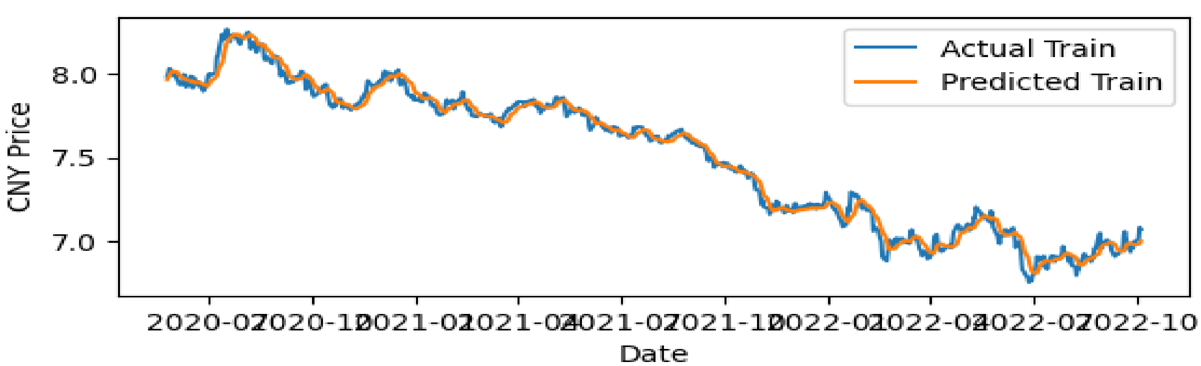


**Figure 1: The result of LSTM Training Data Shows the Actual Training and Predicted Training which is 2020 to 2022.**

The result of the actual and predictive value of Chinese yuan against US dollar by using LSTM model can be seen in Figure 2.

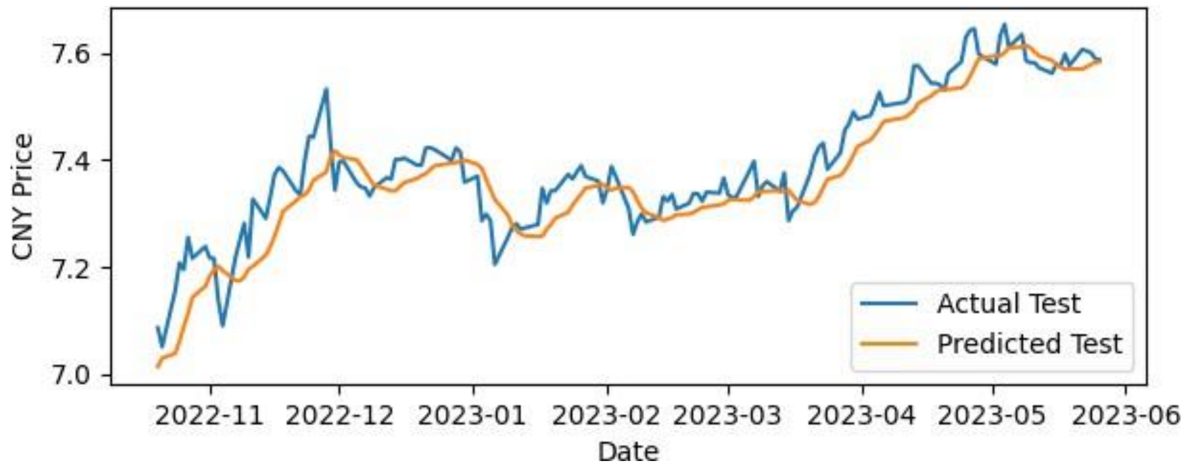


**Figure 2: The Result of LSTM Testing Data Shows the Actual Testing and Predicted Testing Which Is 2022 To 2023.**

The result of the actual and predictive value of Chinese yuan against US dollar by using XGboost, the model is seen in Figure 3.

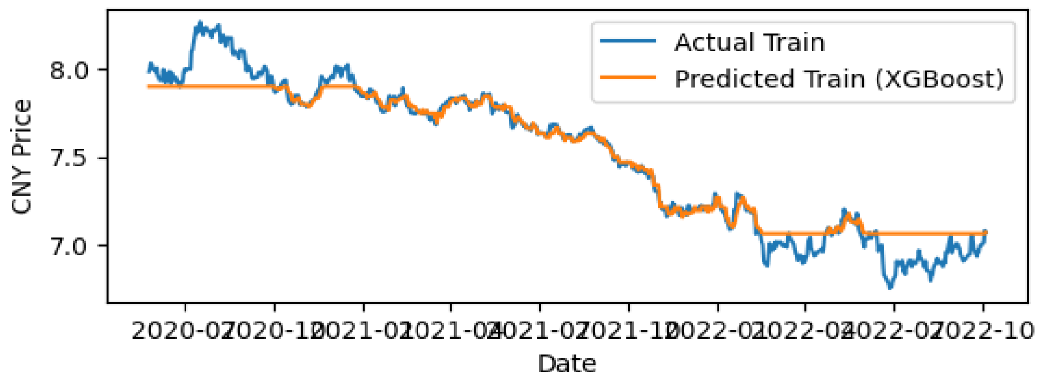


**Figure 3: The Result of XGboost Training Data Shows the Actual Training and Predicted Training which is 2020 to 2022.**

The result of the actual and predictive value of Chinese yuan against US dollar by using XGboost, the model is seen in Figure 4.

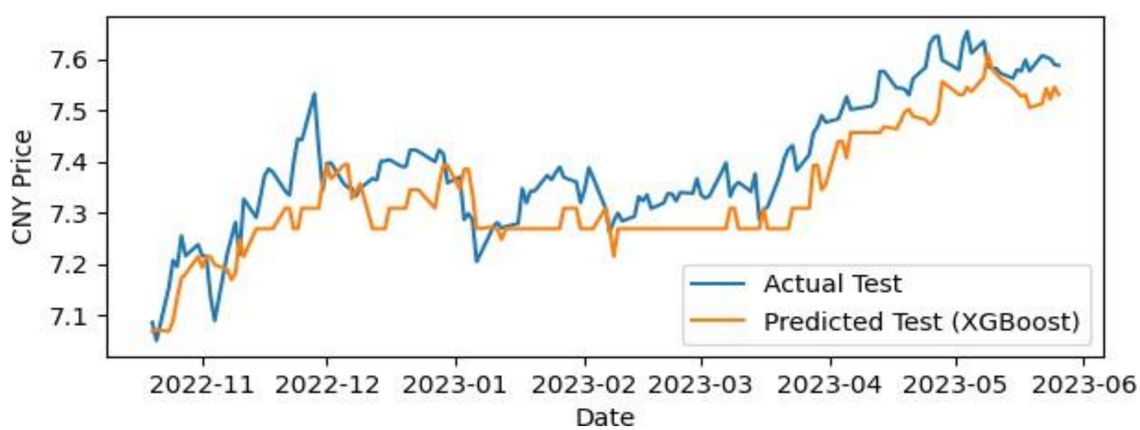


**Figure 4: The Result of XGboost Testing Data Shows the Actual Testing and Predicted Testing which is 2022 to 2023**.

**Table 3**
***Quantitative Comparison with State-of the Art Models***

| Model | MSE | MAE | MAPE | RMSE |
|---|---|---|---|---|
| ARCH | - | 0.350 | 0.228 | 0.468 |
| GRACH | - | 0.444 | 0.228 | 0.635 |
| ARIMA | 0.050 | 0.090 | 0.830 | 0.590 |
| Proposed Model LSTM | 0.043 | 0.003 | 0.055 | 0.595 |

Time Distributed MLP gives us the lowest RMSE of LSTM models, which is 0.055200, MSE is 0.003047, MAE is 0.043909, and MAPE is 0.059559, according to our final analysis of the CNY/USD exchange rate. Augmented Dickey-Fuller Test Data: we apply Dickey- Fuller test and the result confirmed that the data is non-stationary, as the p-value is greater than the significance level. To make it stationary, we apply the transformation. We take the first difference of the data, which make the data stationary. ADF test results: -28.83356512446317 p-value: 0.0 now the data is stationary. Previously, Mia MS, Rahman MS, and Das S (24) obtained an RMSE of 0.240281 using Artificial Neural Networks without any factors influencing the USD/BDT exchange rate. Without any factors, Alam M, Rahman MS, and Mia MS (Mia & Rahman, 2019) also completed the identical job and obtained an RMSE of 0.240. In our study, we used time-distributed MLP and obtained the best RMSE of 0.055200. We then used our suggested pipeline to lower the RMSE of time-distributed MLP to 0.055200.

Having performed the US dollar and Chinese yuan prediction using the two models, LSTM and XGBoost, I used the daily data to compare the models. In the anomaly's detection in the LSTM model, I used training and testing data to predict the best RMSE and MAPE value and I used the distribution of the data in the form of 80% training data and 20% testing data. It is known that the smaller the value of the RMSE, the higher the accuracy of the forecast in this work. LSTM with 50 neurons, batch of size of 1, epoch set at 100 was used and has an RMSE of 0.055200 as shown in the above tables.

From the results shown above it is clear that LSTM has a higher prediction accuracy using RMSE justification. Similarly, using MAAPE which measure the average percentage error, the LSTM model MAPE is 0.0595. This study has limitations because it only uses a few variables.

## 4.2. Model Comparison

We benchmarked both the LSTM and XGBoost models against simpler baseline models, including ARIMA and moving averages. The performance of these types of baseline models are used here to define to what extent how much the more complex models have actually performed better. The LSTM model yielded higher accuracy and less error rates in MSE and MAPE as compared to both ARIMA and moving averages. ARIMA faced difficulty in dealing with non-stationary features of the exchange rate data and, thus, had greater variability and errors which, however, were much greater than that of moving averages gave a fundamental method of forecasting without the sophistication that was required to predict in a highly unpredictable region of the market. In addition, even though a less accurate model in this case, XGBoost showed higher accuracy than the baseline models, showing its ability to handle structured data and create value even if it has weaknesses in time series data. This improvement highlights the benefits of employing complex methodologies in realistic conditions for machine learning and giving relevant players more accurate instruments for forecasting.

# 5. Discussion and Conclusion

This study employed two types of machine learning, LSTM networks and XGBoost, to predict fluctuations in the CNY/USD exchange rate. The forecast accuracy for all models was quantified and the results statically validated that the proposed LSTM is superior to XGBoost.

While XGBoost can work well in the case of such a structured data, it seems to miss temporal patterns absent in the exchange rate data which LSTM learns about due to its potential to learn long-term dependencies of the sequential data. The signification of these findings is meaningful for multiple stakeholders.

This is important for the formulation of database and models for monetary policy indicators such as changes in the interest rates, and operations in the foreign exchange markets. LSTM forecasts are particularly useful for business persons, especially those dealing with international trade where they may use the LSTM forecasts help them develop a pricing strategy and manage inventory proactively. It also has advantages for investors because such forecasts will enhance portfolio configurations and risks with respect to currency shifts. The findings of the LSTM model hold enormous potential and can be viewed as a strong base for implementing solutions in the sphere of the changing financial environment of the company and in the worldwide financial market as a whole. Comparing to XGBoost in aspects of performance indicators, RMSE, MAE, MSE and MAPE demonstrated that LSTM was more suitable for modelling financial time series data. This is especially important where the market price, for instance the exchange rates have a historical data and other nonlinear data that are so influential. The loss curves showing that LSTM has fine generalization throughout the training and testing phases also bear evidence for its reliability in actual practice. XGBoost is good performing in terms of structure data and overfitting issues but lacked the high-level temporal underlying patterns required in the forecasting problem in this domain to support its advancement.

A comparison between LSTM and traditional models such as ARIMA further highlights its advantages. Traditional models are most often slow and nonlinear besides which they don’t take into consideration the stochastic nature of high frequency financial data which LSTM as a sequential model being capable of retaining previous information is well suited to such tasks. The previous results indicated that LSTM achieved lower error rates compared to both XGBoost and ARIMA, which supports LSTM’s use for complex time series forecasting. However, it is important to enhance the effectiveness of identified LSTM by improving accuracy that; however, consume lots of computational resources. LSTM requires way more time and resources to train than other models such as the XGBoost. This compromise between computational speed and precision needs to be taken into account when choosing a model to be used in real time prediction tasks where timeliness of the result may be as valuable as, or even more than, the accuracy of the result. This paper shows that LSTM model is useful in giving forecasts for different financial data, especially exchange rates. They should also like the fact that, being an ARIMA model, it is capable of modeling long-memory processes and accommodating the non-linear nature of the examined financial data This is to mean that accuracy of the model can assist policymakers, businesses, and investors as they seek to understand and manage the vagaries of exchange rates in order to arrive at better decisions.

## Authors’ Contribution

Usman Ullah: Conceptualized and conducted the research, analyzed data, and drafted the manuscript.
Zhensheng Huang: Supervised the research, provided methodological guidance, and reviewed the manuscript.
Dawood Rehman: Contributed to the literature review and data analysis.
Sulaiman Khan: Assisted with data preprocessing and dataset structuring.
Haroon Rashid: Implemented and optimized the machine learning models.
Imran Ullah: Created visualizations for model comparison and results presentation.

## Conflict of Interests/Disclosures

The authors declared no potential conflict of interest w.r.t the article's research, authorship and/or publication.

## References


Agrawal, M., Khan, A. U., & Shukla, P. K. (2019). Stock Price Prediction Using Technical Indicators: A Predictive Model Using Optimal Deep Learning. *Learning, 6*(2), 7.

Fischer, T., & Krauss, C. (2018). Deep Learning with Long Short-Term Memory Networks for Financial Market Predictions. *European journal of operational research, 270*(2), 654-669. doi:https://doi.org/10.1016/j.ejor.2017.11.054

Hyndman, R. (2018). *Forecasting: Principles and Practice*: OTexts.

Kim, S., & Kim, H. (2016). A New Metric of Absolute Percentage Error for Intermittent Demand Forecasts. *International Journal of Forecasting, 32*(3), 669-679. doi:https://doi.org/10.1016/j.ijforecast.2015.12.003

Krugman, P. R. (2009). *International Economics: Theory and Policy*: New York: Prentice Hall.

Kumar, Y., Koul, A., Kaur, S., & Hu, Y.-C. (2022). Machine Learning and Deep Learning Based Time Series Prediction and Forecasting of Ten Nations' Covid-19 Pandemic. *SN Computer Science, 4*(1), 91. doi:https://doi.org/10.1007/s42979-022-01493-3

Li, J., Xu, C., Feng, B., & Zhao, H. (2023). Credit Risk Prediction Model for Listed Companies Based on Cnn-Lstm and Attention Mechanism. *Electronics, 12*(7), 1643. doi:https://doi.org/10.3390/electronics12071643

Livieris, I. E. (2023). A Novel Forecasting Strategy for Improving the Performance of Deep Learning Models. *Expert Systems with Applications, 230*, 120632. doi:https://doi.org/10.1016/j.eswa.2023.120632

Meese, R. A., & Rogoff, K. (1983). Empirical Exchange Rate Models of the Seventies: Do They Fit out of Sample? *Journal of international economics, 14*(1-2), 3-24.

Mia, M. S., & Rahman, M. S. (2019). Evaluating the Forecast Accuracy of Exchange Rate Volatility in Bangladesh Using Arch Family of Models. *American Journal of Mathematics and Statistics, 9*(5), 183-190.

Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag (Ardl) Cointegration Technique: Application and Interpretation. *Journal of Statistical and Econometric methods, 5*(4), 63-91.

Qonita, A., Pertiwi, A. G., & Widiyaningtyas, T. (2017). *Prediction of Rupiah against Us Dollar by Using Arima.* Paper presented at the 2017 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI).

Raschka, S., & Mirjalili, V. (2019). *Python Machine Learning: Machine Learning and Deep Learning with Python, Scikit-Learn, and Tensorflow 2*: Packt publishing ltd.

Rasheed, A., Ullah, M. A., & Uddin, I. (2020). Pkr Exchange Rate Forecasting through Univariate and Multivariate Time Series Techniques. *NICE Research Journal, 13*(4), 49-67. doi:https://doi.org/10.51239/nrjss.v13i4.226

Rossi, B. (2013). Exchange Rate Predictability. *Journal of economic literature, 51*(4), 1063-1119. doi:https://doi.org/10.1257/jel.51.4.1063

Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial Time Series Forecasting with Deep Learning: A Systematic Literature Review: 2005–2019. *Applied soft computing, 90*, 106181. doi:https://doi.org/10.1016/j.asoc.2020.106181

Vuong, P. H., Dat, T. T., Mai, T. K., & Uyen, P. H. (2022). Stock-Price Forecasting Based on Xgboost and Lstm. *Computer Systems Science & Engineering, 40*(1).

Wang, J., Wang, X., Li, J., & Wang, H. (2021). A Prediction Model of Cnn-Tlstm for Usd/Cny Exchange Rate Prediction. *Ieee Access, 9*, 73346-73354. doi:https://doi.org/10.1109/ACCESS.2021.3080459

Willmott, C. J., & Matsuura, K. (2005). Advantages of the Mean Absolute Error (Mae) over the Root Mean Square Error (Rmse) in Assessing Average Model Performance. *Climate research, 30*(1), 79-82.

Wu, J. M.-T., Li, Z., Djenouri, Y., Polap, D., Srivastava, G., & Lin, J. C.-W. (2021). *A Graphic Cnn-Lstm Model for Stock Price Predication.* Paper presented at the Artificial Intelligence and Soft Computing: 20th International Conference, ICAISC 2021, Virtual Event, June 21–23, 2021, Proceedings, Part I 20.

Zhang, C., Sjarif, N. N. A., & Ibrahim, R. (2024). Deep Learning Models for Price Forecasting of Financial Time Series: A Review of Recent Advancements: 2020–2022. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 14*(1), e1519.