EXPLORING THE PREDICTION ANALYTICS BY FORECASTING MODEL(ELM/NN) FOR EXCHANGE RATE CURRENCY PREDICTION

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Abstract - *We employ a cutting-edge technique to predict currency prices in financial markets that combines the Jaya optimization method with the Extreme Learning Machine (ELM) algorithm. This approach simplifies the process of currency price prediction and market analysis. While conventional neural network training methods tend to be computationally demanding and iterative, our method leverages the ELM algorithm's efficiency in randomly generating input-hidden layer weights and analytically determining output weights. This method speeds up neural network training considerably. Furthermore, the integration of the Jaya optimization approach aims to dynamically adjust hyperparameters, which further improves the performance of the ELM algorithm. Combining ELM with Jaya optimization promises to simplify neural network training, making it more efficient and effective in predicting currency prices in trading and market analysis.*

Key Words: **Extreme Learning Machines (ELM), Neural Networks (NN), Time-Series Data, Jaya Optimization, Economic Forecasting.**

1. Introduction

Due to the constantly shifting and unexpected nature of currency fluctuations, predicting trading costs in the foreign exchange market is complex and comprehensive. The forex market is characterized by sharp oscillations driven by many dynamic variables, in contrast to more static sectors such as climate prediction, where components change gradually over time. These variables include monetary policies, geopolitical events, market mood, and economic indicators, among many other economic, political, and social influences.

Even little departures from expected currency movements may have substantial financial ramifications in the forex market. Thus, it is critical to make precise and timely forecasts. Traders and investors use predictive models to anticipate future changes in exchange rates and help themdecide whether to purchase, sell or hold onto their currency. However, to fully account for the subtleties and complexity present in forex trading, typical forecasting techniques often need assistance, resulting in subpar performance and lost chances.

Innovative methods like Jaya Optimization and Extreme Learning Machines (ELM) have developed as potential tools for currency exchange rate prediction in response to these issues. The machine learning algorithm ELM is notable for its ease of use, effectiveness, and adaptability. ELM has a strategy different from traditional neural network training algorithms, which call for iterative optimization using methods like gradient descent. This method eliminates the need for time-consuming and repetitive training by calculating output weights through analysis and assigning random values to input weights. This method enables quick adaptability to shifting market circumstances, essential in the volatile and fast-paced forex market. It also cuts down on training time and computing complexity.

Jaya Optimization provides a robust framework for optimizing predictive models to improve performance when combined with ELM. Jaya Optimization is inspired by the cooperative behavior seen in social contexts, simulating how people pick up on and modify the behaviors of their peers to better the group as a whole. When used to forecast currency exchange rates, Jaya Optimization may optimize network architecture and hyperparameters, among other ELM model characteristics. Jaya Optimization helps enhance the efficacy and accuracy of ELM-based forecasting models by repeated refining based on observable performance indicators, which eventually results in more accurate forecasts and improved trading outcomes.

Trading professionals and financial analysts may use cutting-edge methods to understand the dynamics of the forex market better and improve their trading judgments by combining ELM with Jaya Optimization. By enabling traders to see hidden patterns and trends in exchange rate data, these tools provide insightful predictions that guide trading strategies and approaches to risk management. All things considered, the combination of ELM with Jaya Optimization marks a noteworthy breakthrough in forecasting currency exchange rates, with the possibility of improving trading profitability, efficiency, and accuracy

2. Literature Survey

[1] Minakhi Rout, Babita Majhi, Ritanjali Majhi and Ganapati Panda titled "Forecasting of currency exchange

rates using an adaptive ARMA model with differential evolution-based training". Previous research has offered methods using soft computing and evolutionary algorithms to overcome limitations of statistics based foreign exchange rate forecasting techniques. To further advance the study in this field, this work proposes a straightforward yet effective hybrid prediction model by successfully combining an adaptive autoregressive moving ave-rage (ARMA) structure with the training of its input and feed-back parameters using differential evolution (DE). The prediction model's internal coefficients are trained using the DE optimization technique by extracting surface statistical features for each exchange rate from a sliding window of past data. The prediction accuracy is confirmed by utilizing past exchange rates not used for training. Three different exchange rates are shown by simulation results using accurate world data, with estimates ranging from one to fifteen months ahead. This analysis looks at how well a sugge-sted forecasting model predicts exchange rates compare-d to four other common approaches: ARMA combined with particle swarm optimization (PSO), ARMA combined with forward backwards least mean square (FBLMS), ARMA combined with bacterial foraging optimization (BFO), and ARMA combined with cat swarm optimization (CSO). The model that performs the worst is the derivative-based combination of ARMA and FBLMS. When considering training length and other performance measures, the recommended ARMA differential evolution exchange rate prediction model out performs the other two evolutionary computing-based models both in the short term and long term.

[2] Svitlana Galeshchuk titled "Neural networks performance in exchange rate prediction". To find the most instructive characteristics for input into neural network models, input selection entails examining variables like economic indicators, geopolitical events, and market sentiment after data collection and preprocessing. To increase performance, model training and optimization include experimentation with various topologies, such as feedforward, recurrent, or convolutional neural networks, along with hyperparameter tweaking and optimization methods like gradient descent or genetic algorithms. Model performance is measured using evaluation metrics, and their generalizability is confirmed by testing data that is not in the sample. Time series and scatter plots are examples of visualizations that show how effectively the models represent underlying patterns and trends in exchange rate data. By comparing the outcomes oftraining and testing, disparities may be analyzed, and possible areas for improving the modelling strategy can be found. Overall, the construction of reliable neural network models for exchange rate prediction is made possible by this iterative process of data gathering, preprocessing, model training, assessment, and analysis.

[3]SalimLahmiri titled "Modeling and predictinghistorical volatility in exchange rate markets". Forecasting how much currency exchange rates change is important for several financial tasks. These include checking portfolio risk, pricing financial contracts, and managing company money risk. This study looks at a simple¬ way to predict exchange rate¬ volatility in the past. The suggested method works well by using a few common technical indicators as inputs for artificial neural networks (ANN). It focuses on the US/Canada dollar rate and the US/euro rate. The results show that our low-complexity method does better than usual volatility models. These include versions of GARCH and EGARCH combined with ANN based on errors like average absolute error, average squared errors, and Theil's inequality measure. This technique can improve US currency volatility prediction efforts due to its simplicity and efficacy, demonstrating its usefulness in practical applications and financial decision-making scenarios.

3. Project Goal

This research will combine the speed and efficiency of extreme learning machines with the extensive pattern recognition capabilities of neural networks to provide more precise and accurate exchange rate fluctuation estimates.

4. Problem Identification

The complex dynamics of currency values are challenging for conventional forecasting techniques to fully capture due to their unpredictable character, which is impacted by many other factors, including market emotion, geopolitical events, and economic data.

5. Dataset Description

The dataset we're working with for forex exchange rates has many data: 12 different types of information and 3392 separate records. By performing the data preprocessing and removing the null values and other garbage values, the dataset record count was changed to 3366.
So, the dataset size 3366 x 12 of data has a timestamp that tells us when it was recorded and other information like how much was traded, the price at the beginning and end of trading, the highest and lowest prices, and other economic factors that affect how currencies change.
This lets us take a close look at how the forex market changes and what trends are happening.
In addition, we looked at datasets that had information from different financial instruments, such as essential currency pairs like USD/EUR and USD/INR.

The dataset is further described as follows.

S.No	Attribute	Description
1.	Price	Closing Price
2.	Open	Opening Price
3.	High	Price hike on that certain day
4.	Low	Price low on that certain day
5.	Chg%	Change%
6.	SMA	Simple Moving Average
7.	TR	True Range
8.	ATR	Average True Range
9.	EMA 12	Exponential Moving Average 12
10.	EMA 26	Exponential Moving Average 26
11.	MACD	Moving Average Convergence Divergence
12.	Output	

Table 1: Dataset attributes and Description

6. Proposed Method

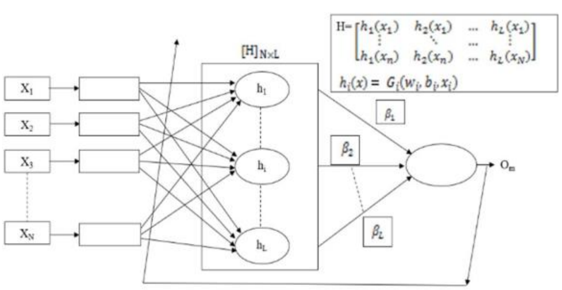


Fig 1: ELM Model

6.1 Architecture

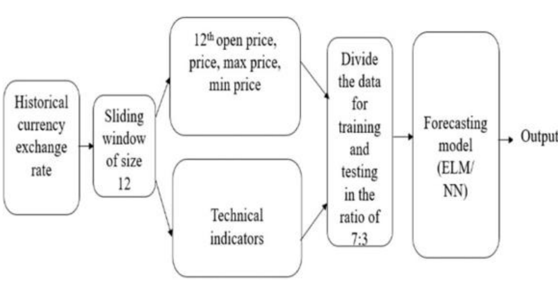


Fig 2: Architecture

- The Exchange Rate Currency Prediction project emerges as a pivotal tool with wide-ranging implications.
- We consider time series data, which indicates the opening price, closing price, and high and low values on that particular day.
- The described methodology considers the sliding window size 12 for the attributes open price, max price, and min price for that specific data.
- Our methodology incorporates technical indicators including: Simple Moving Average (SMA), True Range (TR), Average True Range (ATR), Exponential Moving Average (EMA), Moving Average Convergence Divergence (MACD).
- Once data is split into training and testing subsets, machine learning models can be applied to the training data. Techniques like extreme learning machines or neural networks allow these models to generate predictions for new data, utilizing their learned patterns from the training data.

6.2 Working of Model

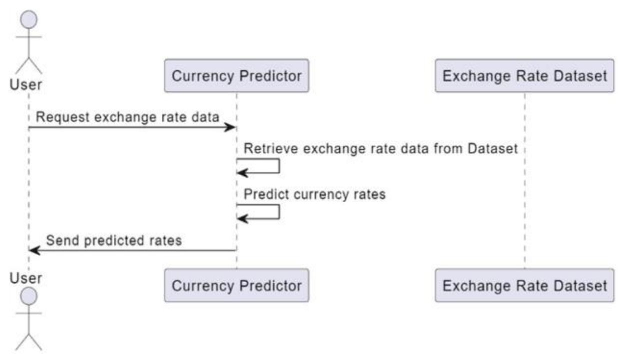


Fig 3: Process of working

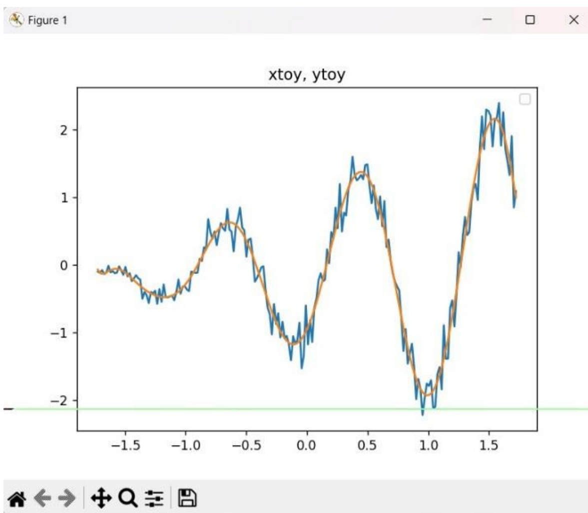
- The user requests the Currency Predictor for information about the exchange rates.
- The Currency Predictor gets the exchange rate data from a collection of data called the Exchange Rate Dataset.
- The Currency Predictor uses the collected data to estimate how much currencies will be worth.
- The Currency Predictor sends the estimated rates back to the user.

6.3 Technical Indicators

- Simple Moving Average (SMA): The average price of an investment over a given timeframe. This is calculated by totaling the prices over that period and dividing the sum by the number of time periods.
- True Range (TR): A volatility indicator that calculates the largest of three values: 1. Difference between current High and Low 2. Absolute difference between current High and previous Close 3. Absolute difference between current Low and previous Close.

- Average True Range (ATR): The Average True Range (ATR) is a volatility indicator that gauges market volatility by calculating the average True Range over a specified time period.
- Exponential Moving Average (EMA): This moving average prioritizes the most recent data, allowing it to react swiftly to changes and provide more up-to-date insights compared to a regular moving average.
- Moving Average Convergence Divergence (MACD): This indicator tracks trends and momentum by comparing two moving averages of a stock's price. It calculates the difference between the moving average over the past 12 periods and the moving average over the past 26 periods.

7. Results



The model predicting exchange rates between the US dollar (USD), the Euro (EURO), and the Indian Rupee (INR) is very accurate. This is shown by the close alignment of the lines on the graph, indicating that the model accurately reflects the factors that influence the exchange rates. The stable economic conditions in the US, Eurozone, and India contribute to this accuracy. All three countries have well-managed policies, low inflation, and consistent economic growth. These stable economic environments lead to predictable changes in exchange rates, making them easier to forecast. The model is also accurate because it includes many important factors that affect currency exchange rates, such as interest rates, inflation gaps, economic growth, trade balances, and political stability. The success of the model shows that these variables can effectively predict movements in currency exchange rates. During the time frame studied, there were few economic surprises, which helped keep predicted and actual exchange rates aligned. By continually refining our models, we can forecast currency exchange rates more accurately. The model shows that it is essential to take into account many different things and do a thorough analysis in order to make accurate predictions.

8. Conclusion

A critical instrument with broad consequences is the Exchange Rate Currency Prediction project. Its application is widespread in essential fields like government policy, corporate finance, trade, and finance. By giving precise forecasts, the project helps businesses plan ahead and hedge currency exposure, investment managers make well-informed decisions, central banks and governments with economic planning, and financial institutions optimize portfolios and reduce risks.

9. Future Work

The Exchange Rate Currency Prediction project has a bright future ahead of it, full of chances for strategic applications, innovation, and optimization in a variety of fields and businesses. Its value proposition and effect on the global financial scene may be further enhanced by ongoing developments in prediction methodology and technological integration.

10. Reference

[1] Minakhi Rout, Babita Majhi, Ritanjali Majhi, Ganapati Panda: Forecasting of currency exchange rates using an adaptive ARMA model with differential based evolution.
[2] Svitlana Galeshchuk: Neural networks performance in exchange rate prediction.
[3] SalimLahmiri: Modeling and predicting historical volatility in exchange rate markets.