Bull’s Eye: A Deep-Learning-powered Intelligent Financial Trading Application

1st Ananya Sachan
Department of Artificial Intelligence & Machine Learning
Symbiosis Institute of Technology
Pune, India
ananya.sachan.btech2022@sitpune.edu.in

2nd Aparna Iyer
Department of Artificial Intelligence & Machine Learning
Symbiosis Institute of Technology
Pune, India
Aparna.iyer.btech2022@sitpune.edu.in

3rd Hevardhan S.
Department of Artificial Intelligence & Machine Learning
Symbiosis Institute of Technology
Pune, India
hevardhan.btech2022@sitpune.edu.in

4th Riya Shukla
Department of Artificial Intelligence & Machine Learning
Symbiosis Institute of Technology
Pune, India
riya.shukla.btech2022@sitpune.edu.in

I. INTRODUCTION

In Financial Markets, for increasing financial gain, and to reduce losses, analyzing optimal timing to perform trade is important. To handle this, the Intelligent Financial Trading Application, “Bull's Eye,” powered by Deep Learning techniques, has been designed to forecast accurate sales points, thus improving trading accuracy.

The Bull’s Eye application incorporates Long Short-Term Memory (LSTM) and Transformer models with financial indicators like the Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD). Through this, we advance towards the recognition of elaborate temporal patterns in stock prices, giving us helpful information about buy and sell signals depending on historical data and the dynamics of the stock market.

By capturing prices and analyzing trends, Project ‘Bull’s Eye’ provides a data-driven approach to provide precise insights to the investors, by encouraging successful management of risk and improving profit for the investors.

The Forex Market is rapidly growing. The stock market is a fluctuating market which results in obstacles for the traders and the investors to make financial decisions. Traditional approaches for analysing the stock market, which involve making linear assumptions, sometimes fail to capture the complex patterns and dependencies that are necessary for real-time trading. In response to this loophole , Machine Learning, specifically Deep Learning, has emerged as a powerful weapon for predicting and analysing stock market trends.

This report describes ‘Bull’s Eye’, a predictive model developed to analyse optimal sales points. In conjunction with LSTM and Transformer models, and with technical financial indicators, “Bull’s Eye” offers an advanced predictive framework that goes beyond the conventional approach. The application of financial indicators like RSI and MACD aids in refining the model analysis , improving the ability of the system to encounter even minute changes in stock market trends. The project empowers investors with reliable trade signals, which in turn results in reduced risk in investing, and increases the chances for positive outcome even in a highly volatile market. This report portrays how AI-driven forecasts can transform dynamic investment strategies using tools like Deep Learning and financial indicators .

All the models used in this Application were equipped with different strengths :

GRU: It was suitable to capture short term dependencies with easy-to- understand architecture.

LSTM: It helped in understanding long term dependencies in the time-series meta trader data.

Transformer: Used it to capture global patterns as it comes with an attention mechanism for enhancing the accuracy of the dynamic market trend.

II. APPLICATION DOMAIN- FINTECH

When finance and technology go hand-in-hand, the resulting domain is known as Fintech, short for ‘Financial Technology’. Technology gives financial services the added leverage of increased automation, which improves their delivery and use. The personalization and streamlining of financial applications through the use of technology, also helps companies working in the Finance and Banking (F&B) space to improve their operational efficiency and cut down on transaction costs.

Lately, Artificial Intelligence and Machine Learning (AI-ML) have had a transformative impact on the financial industry, giving rise to advanced applications for credit scoring, algorithmic trading, market forecasting and fraud detection. The primary reason for the penetration of AI-ML technologies in the financial domain is the latter’s reliance on large quantities of data. The strength of Deep Learning technologies lies in their ability to handle, process and interpret large amounts of data, which is the need of the hour in the financial domain.
Finance and Banking (F&B) application domains can be categorized into two main sub-groups:

1. Investment in the Financial Market, and
2. Banking and Credit Risk.

While applications in Banking and Credit Risk deal with credit-risk prediction or macroeconomic prediction, our project deals with the domain of Investment in the Financial

Market, which is divided into three sub-categories: Financial Prediction, Algorithmic Trading and Portfolio Management. Financial Trading refers to Stock Trading, while Financial Prediction encompasses the prediction of Exchange Rate, Stock Market or Oil Prices.
According to research and meta-analysis conducted on 40 research articles detailing the application of Deep Learning in Fintech, a substantial 18 articles (45%) were based on Stock Market Prediction, 12 articles (30%) on Stock Trading, and 5 articles (12.5%) on Exchange Rate Prediction.
Our research, 'Deep Learning in Forex Trading', focuses on the intersection of these three fields. It has limitless potential in accurately predicting buy and sell signals for investors, preventing fiscal losses and promoting gains through a thoughtful, well-informed navigation of the Forex (Foreign Exchange) landscape.

III. STATISTICAL ANALYSIS OF THE DATASET

Dataset Description:

Fig. (1): Overview of the Statistical Analysis of the Dataset

Descriptive Statistics:

A) Measures of Central Tendency and Dispersion

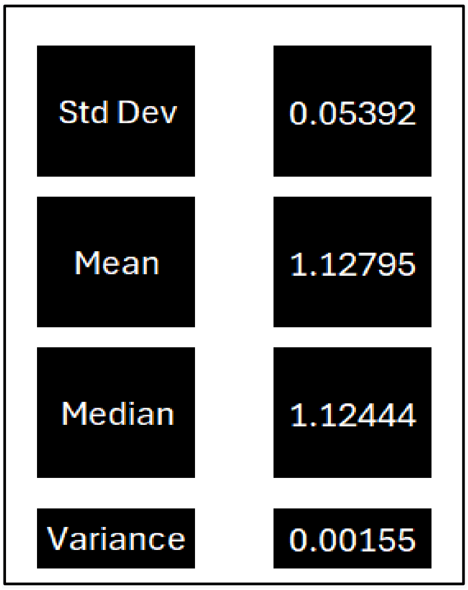

Fig. (2): Measures of Central Tendency (Mean and Median), and Dispersion (Variance and Standard Deviation), calculated on the Close Price.

B) Visualizing OHLC (Open High Low Close) and Tick Volumes:

Fig. (3): Month-wise sum of tick volumes; annual average of OHLC; trend of OHLC.

C) Candlestick Graphs:

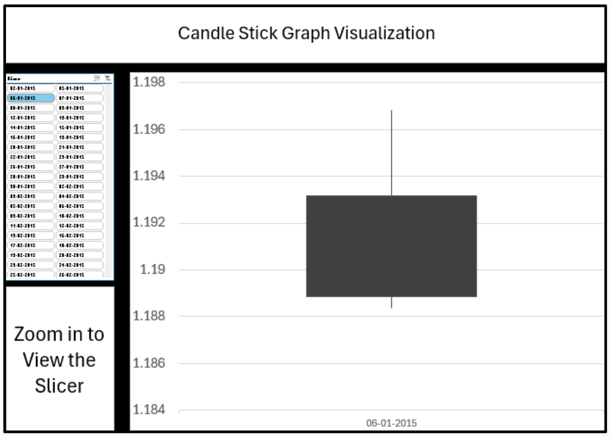

Fig. (4): Candlestick Graph used to visualize the Candlestick Graph of OHLC (Open, High, Low, Close) data, on a given day (i.e., filtered by date).

Inferential Statistics:

A) Linear Regression Analysis:

The linear regression line was calculated using

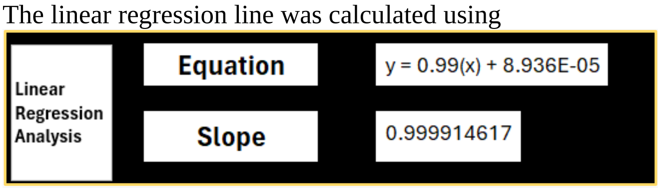

Fig. (5): Equation of Linear Regression Line, calculated using Linear Regression Analysis.

B) Technical Indicators - Moving Averages:

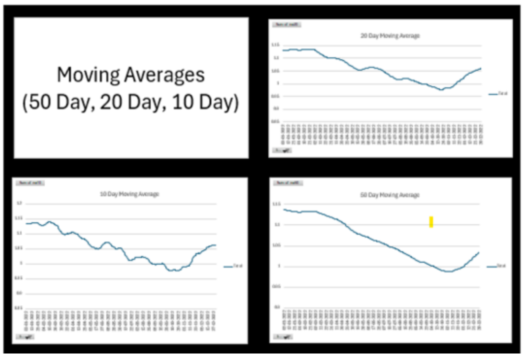

Fig. (6): Moving Averages over time, calculated over a period of (a) 50 days, (b) 20 days, and (c) 10 days.

IV. LITERATURE REVIEW

The following literature review analyses the different Deep-Learning-based approaches and methods to accurately place buy and sell signals, on OHLC Data for Foreign Exchange Markets. It is observed that initial approaches focused on using CNNs (Convolutional Neural Networks). Later, ANNs and ML Algorithms were used with substantial accuracy. Eventually, RNN variants such as LSTMs and GRUs began to be used. The research highlights the strengths and limitations of simpler architectures such as ML models and ANNs, the merits of more complex models such as CNNs and LSTMs, as well as the role of optimization techniques such as PSO (Particle-Swarm Optimization) in enhancing accuracy and performance.

Table (1).: Literature Review for Deep-Learning-powered Forex Trading

Sr. No.	Authors	Title	Method	Database	Result	Advantages / Dis-advantages
[1]	Svitlana Galeschuk, Sumitra Mukherjee	Deep Networks for Predicting Direction of Change in Foreign Exchange Rates.	-Utilises Deep CNNs to predict the direction of change in foreign exchange rates. -Compares CNNs against models like ARIMA, ETS, and shallow neural networks (ANN), as well as ML classifiers like Support Vector Machines (SVM). -Predicting the direction of change (up or down) , not the point estimates.	-The dataset includes daily closing exchange rates for three major currency pairs: EUR/USD, GBP/USD, and USD/JPY. -It contains 1565 observations from 2010 to 2015, with training data from 2010-2013 and testing data from 2014-2015.	Classification Accuracy in predicting the direction of change was calculated. -CNN Models achieved a high classification accuracy of over 75%. -ARIMA, ETS and ANN models showed lower accuracies-between 40% and 60%. -CNN outperformed other ML Classifiers, especially in short-term predictions.	-CNNs excel at learning abstract features from raw time-series data. This reduces the need for extensive feature engineering -However, CNNs require substantial computational resources and training time compared to simpler models. -They provide higher accuracy in predicting directional changes, which is crucial for developing profitable trading strategies. -However, complex architecture of CNN can lead to overfitting

						on smaller datasets.
[2]	Michael Ayitley, Peter Appiahane, Obed Appiah, Christopher Ninfaakang Bombie	Forex market forecasting using machine learning	Uses a Systematic Literature Review (SLR) and meta-analysis approach to evaluate the effectiveness of ML models in forecasting the Forex market. It reviews 60 research papers from 2010 to 2021. The focus is on ML algorithms, and their evaluation metrics used for Forex predictions.	The dataset includes major currency pairs like EUR/USD, which is the most commonly traded pair globally. It is drawn from reputable sources such as Google Scholar, IEEE Xplore, ScienceDirect, and other digital libraries, covering various Forex prediction studies.	Most commonly used assessment metrics are MAE, MSE, RMSE, MAPE. -EURUSD is the most traded in the world. -LSTM and ANN are the most commonly-used ML Algorithms for Forex Market Prediction. -Challenges and future scope to address these.	-Provides a comprehensive analysis of ML techniques, and how they can handle the volatile nature of the Forex market. -Since it is limited to publications from 2010-2021, it may exclude recent advancements in ML and DL models. -Offers insights into which models are most effective and guides future research. -The focus on only commonly traded pairs; potentially overlooks niche currency pairs.
[3]	Phuong Dong Nguyen et al.	Deep learning-based predictive models for forex market trends: Practical implementation and performance evaluation	Hybrid model with convolutional and LSTM layers, using multiple indicators and three-value-labelling for trend prediction	Yahoo Finance, Metatrader5.	High accuracy (97%) with 15% profit in simulated trading.	-Focus on high profitability. - It is beneficial for the practical trading utility.
[4]	Arisara Pornwattanavichai, Saranya Maneeroj, Somjai Boonsiri	BERTFOREX: Cascading Model for Forex Market Forecasting Using Fundamental and Technical Indicator Data Based on BERT	Cascading model combining BERT for fundamental data (FD) and technical indicator (TI) analysis with autoencoder aggregation	Forex dataset (2003-2020), USD/EUR pair	Achieved high accuracy, sensitivity, and specificity in predicting forex trends; correct direction rate of 84.38%	-Captures latent relationships between FD and TI -Avoids vanishing gradient in sequence models.

[5]	Nia Nuraeni, Puji Astuti, Oky Irnawati, Ida Darwati, Danang Dwi Harmoko	High Accuracy in Forex Predictions Using the Neural Network Method Based on Particle Swarm Optimization	Neural Network enhanced with Particle Swarm Optimization (PSO)	USD/IDR exchange rate data for 2019, 261 records	Neural Network alone achieved 90% accuracy; Neural Network with PSO achieved 100% accuracy	High prediction accuracy with PSO; effective for time series forecasting.

Review Methods Used: Through the course of our study, the research approaches that we have explored and that have been outlined in the above Literature Review, rely on meta-analysis- combining and analyzing data from multiple studies, scoping reviews - using the topic scope as the boundary for researching relevant literature, and Systematic Literature Reviews (SLRs) - the gathering of empirical evidence in the form of literature, to answer a research question.

V. USE-CASES OF DEEP LEARNING IN FOREX TRADING

The three tiers of Deep Learning in the Fintech Domain are data preprocessing, data inputs and evaluation rules.

Among the Deep Learning models in popular use in this domain, are the following:

1. Artificial Neural Network (ANN)
2. Multi-Layer Perceptron (MLP)
3. Gated Recurrent Unit (GRU)
4. Feedforward Neural Network (FNN)
5. Convolutional Neural Network (CNN)
6. Restricted Boltzmann Machine (RBM)
7. Recurrent Neural Networks (RNNs)
8. Reinforcement Learning (RL)
9. Deep Convolutional Models
10. Generative Adversarial Network (GAN)

Among these models, the ANN, CNN and RNN (specifically LSTM) dominate the literature studied.

Among these models, the ANN and LSTM are the most commonly-used models in Forex Market Projects. Our project leverages LSTM, GRU and TFT (Temporal Fusion Transformer), the last of which is a transformer-based model.

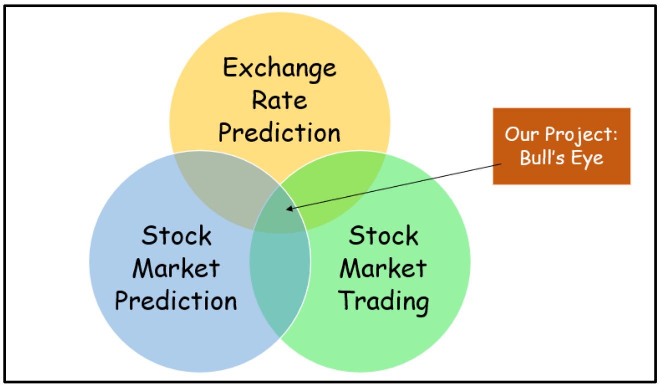

Fig. (7): Venn Diagram illustrating the intersection of 3 domains in Fintech.

The problem statement for Bull's Eye lies in the intersection of three domains: Exchange-Rate Prediction, Stock Market Prediction and Stock Market Trading. According to the study, 'Deep learning in finance and banking: A literature review and classification', published in 'Springer Open', of the total of 37 research papers published in these three domains, 40.54% (15) employ ANN/MLP/FNN; 27.03% (10) employ LSTM; 13.51% (5) are based on CNN; and 18.92% (7) rely on RNN.

VI. METHODOLOGY

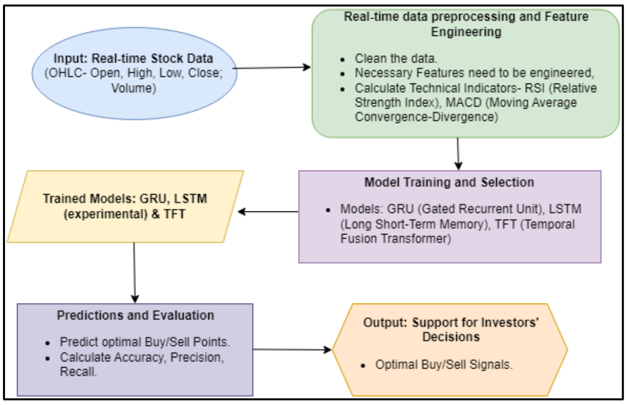

Fig. (8): Project Methodology Diagram for 'Bull's Eye'.

The input data is OHLC Data for Forex Markets (Euro-USD), scraped from MetaTrader5. Python is connected to MetaTrader5, and the OHLC data is imported into a Pandas

DataFrame. Next, the data is preprocessed, normalised and standardised. With the help of functions, the DataFrame is modified to display the corresponding RSI (Relative Strength Index) and MACD (Moving Average Convergence-Divergence) Technical Indicators based on the OHLC and Volume data. Following this, the data is split into training and test sets for training the Deep Learning Models: GRU (Gated Recurrent Unit), LSTM (Long Short-Term Memory) and TFT (Temporal Fusion Transformer) Models. The models are tasked with predicting optimal buy/sell points and generating accurate buy/sell signals on MetaTrader5.

The following Technical Indicators have been used:

$$RSI = 100 - \left(\frac{100}{1 + \frac{\text{Average Gain}}{\text{Average Loss}}} \right)$$

$$\text{MACD} = \text{EMA}_{\text{Fast}} - \text{EMA}_{\text{Slow}}$$

Figure. (9): Formulae for RSI and MACD Indicators
EMA: Exponential Moving Average

VII . CHALLENGES AND FUTURE WORK

Challenges: The inconsistency or gaps in the financial data due to OHLC (Open-High-Low-Close) affects the model accuracy.

Future Work: Implementation of optimization techniques such as Genetic Algorithm (GA) and Bayesian Optimization for fine tuning the hyper-parameters, can be useful for improving the accuracy of the model.

We can develop methods where the prediction for Forex trading can be done in real-time.

The project can be extended to be used on other financial markets such as cryptocurrency and commodities.

VII. CONCLUSION

Bull's Eye portrays the use of Deep Learning techniques to forecast signals (i.e., buy or sell) using real-time stock data from the trading tool, MetaTrader5. In order to gain valid insights from such a volatile and fluctuating market, we deployed Deep Learning models like GRU, LSTM and Transformer Fusion models, among which LSTM was the one with maximum accuracy, i.e., 76%, while GRU showed an accuracy of 57%. During classification on the test data, it was the LSTM Model that performed the best in classifying the signals for unseen data. This result was because GRU offered computational efficiency, while LSTM captured long term temporal dependencies .

The integration of financial indicators such as Simple Moving Average (SMA), SMA Crossover Strategy, Relative Strength Index (RSI), Rate of Change (ROC), Stochastic Oscillator, Moving Average Convergence Divergence (MACD), Average Directional Index (ADX), Average True Range (ATR), Heiken Ashi Candles, Williams %R, Commodity Channel Index (CCI), Ultimate Oscillator, Time Feature Extraction (minute, hour, day, month, year) was done to increase the volume of our dataset, in order to improve the accuracy of the models. Enhanced accuracy implied better ability to identify and interpret reliable signals. As this project-Deep-Learning-based Forex Trading with 'Bull's Eye'- deals with real-time data, the tool ensures that investors make informed decisions while performing live trade.

VIII. REFERENCES

[1] Galeshchuk, S., & Mukherjee, S. (2017). Deep networks for predicting direction of change in foreign exchange rates. Intelligent Systems in Accounting, Finance and Management, *24(4), 100–110.* doi:10.1002/isaf.1404

[2] Ayitey Junior, M., Appiahene, P., Appiah, O., & Bombie, C. N. (2023). Forex Market Forecasting Using Machine Learning: Systematic Literature Review and Meta-Analysis. *Journal of Big Data*, *10*, Article No.9. https://doi.org/10.1186/s40537-022-00676-2 https://link.springer.com/article/10.1186/s40537-022-00676-2

[3] Nguyen PD, Thao NN, Kim Chi DT, Nguyen H-Cuc, Mach B-Ngoc, Nguyen TQ. Deep learning-based predictive models for forex market trends: Practical implementation and performance evaluation. Science Progress. 2024;107(3). doi:10.1177/00368504241275370

[4] Arisara Pornwattanavichai, Saranya Maneeroj, Somjai Boonsiri, "*BERTFOREX: Cascading Model for Forex Market Forecasting Using Fundamental and Technical Indicator Data Based on BERT*", https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=9715051

[5] Nia Nuraeni, Puji Astuti, Oky Irnawati, Ida Darwati, Danang Dwi Harmoko," High Accuracy in Forex Predictions Using the Neural Network Method Based on Particle Swarm Optimization", November 2020, Journal of Physics Conference Series 1641(1):012067, DOI:10.1088/1742-6596/1641/1/012067

[6] Huang, J., Chai, J. & Cho, S. Deep learning in finance and banking: A literature review and classification. *Front. Bus. Res. China* **14**, 13 (2020). https://doi.org/10.1186/s11782-020-00082-6