Cross Asset Market Timing Using Deep Learning Algorithms.

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Abstract

Virtual trading complexity is influenced by applying more than one trading equipment at the same time, a concept that we generally describe as cross-asset market trading. The aspect of time comes in when we need to have precise timing within a market for our applied equipment to realise maximum profit. This comes surrounded by challenges like complex global market dynamics, non-uniformity of data infrastructure, inadequate risk management protocols and emotional inclusivity by traders.

These intense demands have led to the application of machine learning which basically means the application of complex algorithms and advanced statistical models to identify patterns and use them to make predictions of future market movements. This, however, has its fair share of challenges including data overfitting, data under-fitting, the complexity of models, and accuracy among others. The deep learning algorithm applied for this project, looks to solve this issues and provide a reliable and simple model that can be used by both starters and gurus in cross asset market timing.

The models applied include the Prophet Model, famous for the Facebook application, the XGBoost Model, and a hybrid of CNN and LSTM. These are known for their ability to handle large data and high accuracies from previous tests. They will be provided with historical data of about 10 years which will serve as their prediction source for future predictions.

Keywords: Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM)

Project Track

The current world has many avenues of making money that do not necessarily involve the sale of physical goods to make transactions. The world is swiftly transforming into a digital platform an evolution that has closed a few doors but has certainly opened channels to online exchange. In this process, new anonymous currencies have been devised and embraced even though partially, opening people's eyes to trading non-tangible assets that generate mouth-watering profits.

Individuals and organizations in the finance sector have certainly capitalized on this trend, an action that has popped some key questions that serve as the fuel of this project.

The questions revolve around the scope of:

1. What exactly are these markets?
2. For whom are they made and how?
3. When should I be in these markets?
4. While in the market what should I pay attention to?
5. What should I do to guarantee maximum profits?
6. What are the risks involved and how do I avoid them?

We would certainly like to answer these questions in one go, but we have to appreciate that financial knowledge and investment takes time, and we can only handle these issues in bits. In this case, we assume that you already have a financial background and are looking to manoeuvre your way around the virtual platforms more accurately. We will focus mostly on the third, fourth, and fifth questions.

Solving these problems has just been like the history of Agrarian Evolution with everything beginning with manual steps until today where computers can be trained to solve the problem. We are settling on the machine learning approach where the model in question will "get the job done" intellectually when we simply subject it to a series of historical data.

Our project is based on a practical track where we seek to develop and implement a deep learning framework that can be used in market forecasting. The value of this model is to serve as a platform for efficient and reliable prediction of market trends based on historical information and seasonal timing. The end goal is a vehicle that can be used by both financial gurus and starters in the virtual markets. In layman's language, it is convenient to say that we want to create a car, give it a set of instructions and the vehicle shows us the way to go. Our key interest is to arrive at the destination accurately.

The area of study is Quantitative Finance and Machine Learning; the former being the primary asset field and the latter being the digital statistical solution. Within this, we will be focusing on trading stocks and currencies since these two form the most familiar assets to the majority of the financially knowledgeable population. We believe that upon the success of this project, it could be used as a basis of the creation of others in the future as the world devices more currencies.

INTRODUCTION

The idea of transacting and making money virtually has become an irresistible global trend due to promising outcomes and dependable profit. You acquire what you did not have or dispose of what you don't need by pressing a button. The realisation of a good trade, however, does not come anyhow, anywhere and anytime. Instead, it operates from simple business concepts that we use to determine "where" the niche is and "when" it is valuable. In simple terms, we say "There are many markets with a variety of commodities and we need to know the time I should be selling or buying goods in a market."

Virtual trade is carried out in a financial market. A financial market is broadly referred to as a marketplace where securities trading occurs including the stock market, bond market, forex markets and derivatives markets. Just like any buy-and-sell stall, a financial market has different commodities including stock, currencies and many others. In this case, we focus on these two since they are considered the most liquid forms of trading equipment and are used by the majority of the market.

A currency can be defined as a standardization of money in any form that is in circulation in an economy and is actively used as a medium of exchange. Stock also called equities, is a form of security representing a fraction of the issuing corporation. These two commodities vary in value depending on the time factor as a result of the external business environment.

These influencers cause a certain behaviour in stock price variation as it follows the rules of demand and supply. While demand increases, price will tend to increase and supply decrease. The stock value then operates within the obtained equilibrium. The ultimate result is what is housed within our financial markets where a trader's ability to analyse and predict future trends will determine their reward.

Their monitoring process however doesn't come easy. The application of traditional methods demands an intense understanding of almost all the trends and global happenings, a quest that becomes very challenging and time-consuming. This has led to a transition from traditional methods of prediction and monitoring to machine learning techniques.

This trading concept could either be quantitative or algorithmic. Quantitative trading consists of trading strategies that rely on mathematical computations and number crunching to identify trading opportunities. In this case, price and volume are the most common data inputs. Its advantage is that it allows for optimal use of available data and eliminates the emotional decision-making that can occur during trading. It also allows for the application or use of multiple data. Algorithmic data on the other hand only analyses charts patterns and organizes data exchanges to find trading positions (Prachi). In other words, it bases its approach of trading on traditional methods.

Machine learning by definition is the use and development of computer systems that can learn and adapt without following explicit instructions by using algorithms and statistical models to analyse and draw inferences from patterns in data. The patterns are what we are describing as *market behaviours*.

According to (Azaz Hassan Khan1) Different ML models perform differently on the same historical data. Their performance depends on the type of data and the duration for which the past data is available. Another important term to understand is Deep learning. It is a subset of machine learning that uses multi-layered neural networks, called deep neural networks, to simulate the complex decision-making power of the human brain (Jim Holdsworth). With context to financial markets, it serves as a toolkit that takes in various financial information analyses it and uses the patterns it picks up to make predictions (Lit.AI). They continue to explain that, with enough data at its disposal, deep learning can also highlight irregularities and anomalies that signal a shift in the stock market is likely to occur before the occurrence giving its human counterparts an edge. Due to market sensitivity to news and historical data, it can capture shifting sentiments among consumers and investors and use this insight to inform trade execution.

Even though we celebrate these milestones, new inventions and innovations do not come without weaknesses. Most of the algorithms today, still prove to be substandard and subject to regular conditions such as quality data scarcity, overfitting and under-fitting, monitoring and maintenance and complexity of models for anyone to use. In addition, the most widely employed algorithms such as linear regression, logistic regression, random forest and support vector machines bring with them fall-backs that still render their results extremely unreliable.

Secondly, the global development of the financial markets is growing exponentially. To catch up, there is a need to assess more than one market and more than one trading tool at the same time. This brings about the idea of cross-asset market timing. According to (Caringal) cross-asset timing is a sophisticated strategy that savvy investors use to build their portfolios and manage their risk more effectively. By trading across different asset classes, such as stocks, bonds, commodities, and currencies, investors can spread their risk and take advantage of varying market conditions. This approach helps mitigate the impact of poor performance in any single asset class, leading to more stable returns over time. Essentially, cross-asset trading allows investors to navigate economic cycles with greater confidence, leveraging the strengths of different assets to offset potential weaknesses in others.

With that said, and reliable support from deep learning we look to create a robust model, whose predictions and analysis will be ultimately reliable and easy to use by anyone interested in the financial markets. We will have a deep dive into the algorithms used and their purpose and a test of the model to meet its function.

Problem statement

In both the physical and virtual markets, profit maximization is a thin but satisfying goal craved by all, that relies heavily on the time factor. For example, a carrot-selling season is likely to yield thinner returns compared to a standout trader who could have the same product out of its season. Similarly, in the virtual world, a stock rate could escalate or deteriorate in a moment of global economic change. This helps us to understand the importance of the time factor in the market world.

Precise market timing is instrumental to maximising returns in today's dynamic financial markets and managing risk accordingly. Experts ranging from portfolio managers to investment analysts would certainly appreciate a robust model that can correctly predict the best times to enter, trade and exit the markets. In simple terms, "trading made easier." This model simply considers complex patterns in historical data and their resultant reactions in terms of market fluctuations and rates and gives a likely trend of the markets now, based on present conditions.

Just to give you some perspective, there is a genuine noticeable struggle, restriction and limitation experienced by a majority if not all financial institutions today when navigating market behaviours and setting up strategies. This can be attributed to the application of conventional models which are usually based on linear assumptions and basic indicators. These methods are not robust enough to capture complex relationships between different assets. Moreover, they have limited generalization capabilities and hence will experience difficulties in adjusting to sudden market shocks or regime changes.

This gap that exists between ideal multi-asset timing models and the challenges of conventional methods is likely to put investors at risk. Investors are not only likely to miss on very good opportunities but also become very vulnerable in volatile market environments.

Our project therefore aims to bridge this gap by **creating an advanced deep learning system** to help in predicting the best times to enter the market with a focus on major trading currencies and stocks.

Goals and Objectives

The main objective of this project is to develop a robust deep-learning model capable of forecasting the best times of holding, entering or exiting financial assets based on historical financial data.

Specific Objectives

a) To determine the correlation between major trading currency pairs
b) To design and implement various machine learning and deep learning models for forecasting the markets.
c) To evaluate the performance of various models in market forecasting.

d) Back-testing the best-performing model on historical data.

e) Refining and optimizing the forecasting model.

Literature Review and Competitor Analysis

Market timing can be described in simple terms, as an investing strategy through which a market participant (trader) makes buying or selling decisions by making a prediction of the price movements and utilizing this to identify a perfect moment for a purchase or sale. It involves anticipating market movements based on both internal and external economic factors to enhance investment decisions and has been a fundamental topic in financial research for many years.

It is a strategy used to maximize profits and offset the associated risks with high gains. It is the classic risk-return trade-off that exists with respect to investment – the higher the risk, the higher the return. It enables traders to curtail the effects of market volatility. It also enables them to reap the benefits of short-term price movements. It is an intense strategy that involves consistent follow-up of the markets, higher transaction costs and commissions and includes a substantial opportunity cost. (CFI)

Given this state, any Investment manager (professional or individual) needs to master certain asset price predictions and utilize the forecasts to either buy, hold or sell a security for a specified period before switching to another one as determined by the investment strategy. Metcalfe G. (2018) refers to this process as market timing. He describes it as an effort to anticipate price changes of securities and switch investment funds to assets with anticipated higher returns, away from those with expected lower or negative returns.

Traditionally, market timing strategies were built around technical indicators and econometric models. However, with recent developments in machine learning, particularly deep learning, more advanced methods have emerged for designing and testing market timing strategies across various asset classes. This review explores the current literature on cross-asset market timing using deep learning, outlines key trends and research gaps, and discusses how emerging studies may redefine market timing strategies. Cross asset in this case means the ability to trade multiple asset classes simultaneously through those systems. (Spotters).

Stock market directions can be analysed in different approaches or techniques which include among others; Fundamental analysis, which is explained by Segal T (2022) as a process to be undertaken by focusing on the company's fundamentals such as financial reports, future projects and economic conditions in which the business operates. Second, is the Technical analysis which according to Oğuz R. et al. (2019) predicts asset prices by analysing asset price charts and volume's evolution over time. The third one is machine learning (ML) based analysis which does prediction of future prices by finding the underlying patterns within the historical dataset. Finally, we have Sentiment analysis which does the prediction of asset price direction using sentiments or emotions of other market players or individuals obtained from social media activity or financial news websites as outlined by Jariwala G. et al (2020).

Extensive research has been conducted by a lot of researchers on the subject of financial asset price prediction to inform market timing strategy using traditional methods, machine learning and sentiment analysis. Some research has shown evidence of no value in undertaking market timing, such as Metcalfe G (2018) who utilized basic mathematics of market timing which invests in US bonds and equities. The results came out indicating that most likely, market timing led to below median return even before accounting for transaction costs. Khan AH. et al (2023) also used traditional prediction methods to predict Tesla Inc. stock prices. Logistic regression was more accurate at 86% while the Naive Bayes model came out last recording 73% accuracy.

The frustrations realized from the old techniques, prompted the discovery and application of machine learning. Different algorithms were obtained each taken through the test of time and data, to assess their viability. Researchers assessed the performance of multiple ML models during different periods. They came in handy when there was a need to know which model to rely on during periods of high volatility and that of low volatility to ensure a successful market timing strategy.

Omar AB. et al (2022) for instance, did wonderful research to assess the performance of ML models for global stock markets. The model accuracy testing results indicated that autoregressive deep neural network (AR-DNN (1, 3, 10)), AR-DNN (3, 3, 10) and autoregressive random forest (AR-RF (1)) performed well for the whole period, pre-Covid-19 and during the Covid-19 respectively. Khan AH. et al (2023) used multiple ML models to predict the stock price of Tesla Inc. of which the random forest model saw a superior performance at 91.93%, followed by XGBoost and ADABoost, while the lowest performance was seen in the K-nearest neighbour model registering 80.83%.

Zhao R. et al (2024) utilized a deep learning approach based on convolutional neural network (CNN), bidirectional long short-term memory networks (BiLSTM) and attention mechanism for the prediction of the stock market. The deep learning models which combine the three methods achieved the best performance when assessed with all metrics. Qiu M and Song Y (2016) studied the prediction of stock market index using the ANN model using genetic algorithm (GA-ANN). The results showed poor performance (60.87%) when Type 1 inputs were utilized and 81.25% for Type 2 inputs. Lin Y. et al (2021) identified candlestick patterns to make informed investment decisions using pattern recognition with machine learning (PRML). The strategy attained average annual return, annual Sharpe ratio and information ratio as high as 36.73%, 0.81 and 2.37 respectively on Chinese stock markets.

Literature indicates that, ML models outperform traditional models in terms of forecasting financial asset prices which inform investment decisions with consideration of the direction of movement. Different ML models have performed differently in various studies undertaken with some performing poorly while others showed superior performance. Inconsistency in the performance of the ML models leaves room for further research to understand its performance in the prediction direction of the movement of major five stocks and global currencies. Literature in combination of stocks and currency is limited so the research will contribute to that area of study.

What contributions have been offered so far in this field?

Researchers as well as industry professionals have contributed to the advancement of deep learning's role in financial markets, especially in market timing. Traditionally, finance relied on simpler models like support vector machines (SVMs), logistic regression, and random forests. However, with the invention of deep learning, there was a shift of focus toward using deep neural networks (DNNs) to address complex non-linear interactions in the financial data, thereby resulting in more accurate predictions.

Prominent individuals in deep learning, including Yann LeCun, Geoffrey Hinton, and Yoshua Bengio, have significantly influenced the modelling of financial data. Their work has been adapted in financial applications with promising observations and results. Their initial successes in other areas such as natural language processing have also contributed to the success of financial applications of those techniques they developed.

To contribute a piece to these trends, statistical experts such as Gu et al. (2020) added to the ideas of deep learning capability to asset pricing. This entails formal treatment and development of two interrelated pricing principles. In their research, traditional linear models were outperformed by the neural networks under the task of forecasting stock returns. This contributed greatly to the research advancement of market timing in the quest to show that DL can uncover non-linear patterns in assets compared to conventional models.

In addition, Fischer and Krauss (2018) applied long short-term memory (LSTM) networks to predict the stock market. According to their research, LSTMs demonstrated superiority in terms of profits acquired and the accuracy of their model in comparison to others was significantly greater.

Recent Trends

In the recent past, research related to deep learning has evoked several trends in the market timing sector. One of these milestones is the use of reinforcement learning (RL) for timing strategies. In principle, RL models learn the optimal trading strategies through interaction with market environments, unlike supervised learning which predicts prices or returns. In their paper, Moody and Saffell (2001) applied reinforcement learning to asset allocation, while Zhang et al. (2020) explored the use of RL in cryptocurrency markets. RL is well-suited for market timing because it allows traders to be involved in the decision-making process based on evolving market conditions.

The combination of deep learning with traditional financial models including the Fama-French factors and Capital Asset Pricing Model (CAPM) is another emerging trend. Li and Kazemi (2021) demonstrated that incorporating traditional financial factors into deep learning models has the potential to improve predictive performance. This hybrid approach integrates established financial theory with the flexibility of deep learning, which is ideal in finding non-linear relationships in financial data.

In as much as most of the research has focused on equity markets, there exists a growing interest in the application of deep learning to other asset classes, including commodities, bonds, and cryptocurrencies. Benth and Saltyte-Benth (2021) utilized deep learning for market timing in energy commodities, while Makarov and Schoar (2020) applied similar techniques to cryptocurrency price forecasting. The two studies highlight the versatility of deep learning across different asset classes, thus paving the way for more comprehensive cross-asset market timing strategies.

What Research Gaps have been identified so far?

Just like any other field, growth in finding reliable methods and models does not mean that the problem is nearly solved. Despite the great advances, gaps still exist in the application of deep learning for market timing strategies. One of the main challenges is the interpretability of the model. Financial professionals most often require models that can clearly explain their decision-making process, especially in regulated environments. Traditional models offer transparency as they are capable of showing how each variable makes an influence while on the other hand, deep learning models are harder to interpret their predictions as they function as "black boxes." With the ongoing work of exploring attention mechanisms in neural networks to enhance model interpretability, more work is still needed in this area.

Secondly, limited research exists on multi-asset strategies. With the notable success of deep learning in single-asset market timing, only a few studies explore how these models time multiple asset classes in a simultaneous manner. Borovkova and Tsiolkovski (2020) noted that an understanding of cross-asset dependencies could potentially lead to more robust strategies. Despite this being such a crippling challenge to the application of DL, very little has been done to remedy this.

Another interesting crevice is the challenge of model overfitting. This is a situation where the model demonstrates excellent performance with training data but fails to demonstrate similar reliability when subjected to new data. This challenge is mostly attributed to the sparsity of data. With this cause, Heaton et al. (2017) argue the need to apply regularization methods and cross-validation to boost the robustness of these models. Slight developments have been applied to remedy this challenge but there remains an urgent need to research on techniques to cure this challenge.

Other limitations include, Data Quality and quantity, where most models are intense data consumers of high quality. If this is not availed, the situation becomes garbage in, garbage out. Secondly, a prevalent issue is generalization, which is very difficult to achieve. Models should be able to perform with new and unseen data but this is a challenge. These among others leave great to explore these fields.

How does this project contribute to the field and assist in addressing the gaps?

In the field of Quantitative Finance and Machine Learning, this project advances the ongoing development of market forecasting by employing cutting-edge deep learning techniques in market timing strategies. Although machine learning models are increasingly being used in the financial sector, particularly in equity markets, the application of deep learning frameworks to multi-asset market timing remains relatively unexplored. My work seeks to contribute to this field by extending the utility of deep learning beyond single-asset models to accommodate multiple asset classes. This includes key trading currencies and stocks—an area that is still underdeveloped. This multi-asset approach allows for more robust and adaptable framework for market forecasting, thus enhancing the understanding of cross-asset correlations and trends. Moreover, the project aligns with the current industry shift towards incorporation of AI in financial decision-making, with the aim to improve the precision and flexibility of predictive models.

This project addresses the gap existing in the traditional market timing, which often depends on linear assumptions and basic indicators. Conventional methods struggle due to the complexity of financial markets and fail to fully account for the complex relationships between asset classes. They are also less adaptable to sudden market shifts or regime changes. In addition, reliance on individual expertise in these traditional strategies brings the risk of inconsistency, especially when such key personnel exit the organization.

In this project, the development of a deep learning framework seeks to address the challenges brought about by conventional methods. This will be achieved by replacing the linear and static models with an advanced system to capture non-linear relationships and cross-asset dependencies. This approach will make it more effective at identifying market timing opportunities across multiple asset classes. The proposed framework offers a more versatile and automated solution and the ability to adapt to market fluctuations occurring abruptly, thus mitigating the risks associated with human decision-making and inconsistent performance. In the long run, this project bridges the existing gap between conventional methods and the demand for a comprehensive multi-asset market timing model that is capable of navigating complex modern financial markets.

Project Design and Methodology.

As stated earlier, the basis of our project is Quantitative Finance. This involves algorithms and pair trading. Pair trading means taking simultaneous long and short positions of two related assets. The objective is to capitalize on the price difference between the two assets or exploiting the relative performance of two securities at once (Composer).

The key elements of pair trading are:

- Correlation Analysis
- Risk management strategies
- Entry and exit points.

The models used in our project are:

a) **The Prophet Model**. Its application is famous through Facebook. It is known for its great speed and works best with time series data that has great seasonality and a great chain of historical data. (Athanasopoulos)
Prophet can be considered a nonlinear regression model, of the form:

$$\boldsymbol{yt = g(t) + s(t) + h(t) + \varepsilon t,}$$
$$\boldsymbol{yt} = g(t) + s(t) + h(t) + \varepsilon t,$$

Equation 1

where g(t)g(t) describes a piecewise-linear trend (or "growth term"), s(t)s(t) describes the various seasonal patterns, h(t)h(t) captures the holiday effects, and (εt, εt) is a white noise error term. (Athanasopoulos).

b) **XGBoost Model**. This describes the Extreme Gradient Boosting machine learning library. According to (Ferraz), this is a model that uses decision-making trees. The model produces a forecast by using binary rules in the form of a tree. For each tree, the error is computed, which will be used sequentially in the next trees. The trees are created sequentially, hence the error improves after each tree. (Ferraz)

$$\mathbf{F}{*}(x)=\mathrm{argmin}\,\mathbf{E}_{(x,y)}[\mathbf{L}(\mathbf{y},\mathbf{F}(x))].$$

Equation 2

The solution of XGBoost is a process of minimizing the loss function, that is, the process of finding the minimum error between the true value and the predicted average value. Equation (**2**) shows the process of minimizing the loss function. (Qin).

c) **CNN and LSTM.** This is a hybrid model that utilizes CNN to interpret visual patterns from stock market charts while LSTM analyses the temporal patterns in trading data (SAHIB Mohamed Rida). This hybrid capitalizes on the weaknesses of using one model, leverages CNNs for robust feature extraction from complex input formats, such as images or transformed time series, and LSTMs to interpret these features over time, enhancing the predictive accuracy for various financial applications.

Dataset

Financial assets data, particularly, major trading currencies and stocks data was used in this project. The data which span from 1st January 2014 to 30th September 2024 was extracted from Yahoo Finance.

Main trading currency pairs explored in this project include: Euro/US Dollar, Great British Pound/US Dollar, US Dollar/Japanese Yen, Australian Dollar/Japanese Yen and the US Dollar/Canadian Dollar.

The stocks used include: Apple, Microsoft, NVIDIA, Google and Amazon.

Project Methodology

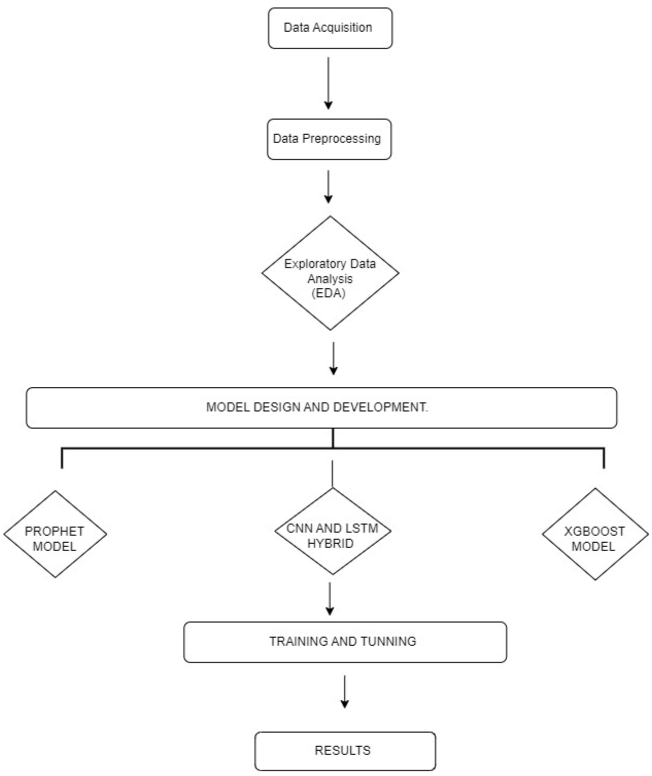

Figure 1 Project Methodology

Results

The aim of this project was to develop a robust machine (deep) learning model capable of predicting the best times of entering, holding or exiting financial markets based on historical data. To achieve this core objective, we sought to address 4 specific objectives using the currency pair and equities prices data.

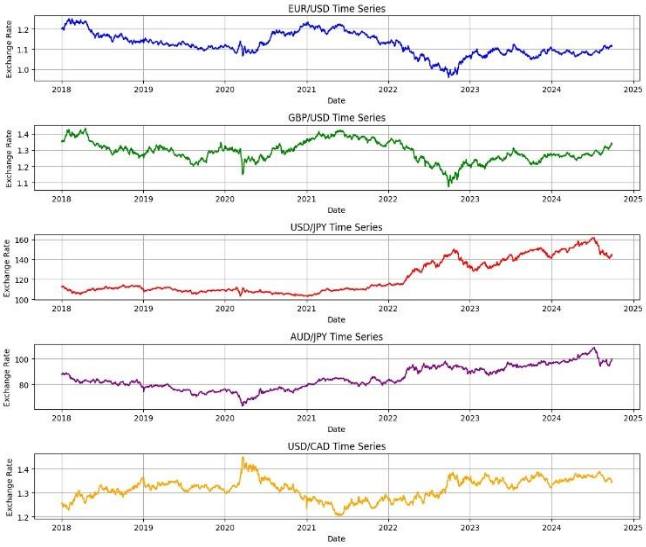

Figure 2 Historical Currency Pair Time Series Plot

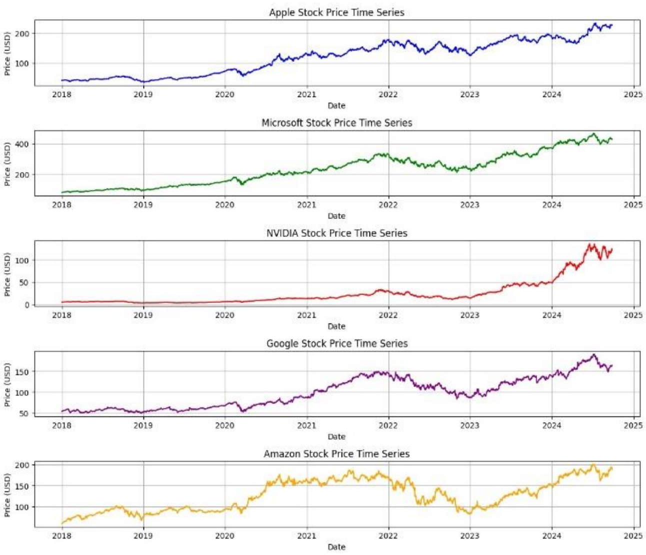

Figure 3 Historical Stocks Time Series Plot

Objective 1: Determining the Correlation Between Major Trading Currency Pairs: Understanding the association that exists between different currency pairs is very important for any trader. First of all, it helps one to manage risks appropriately. For instance, if two currency pairs are highly correlated, taking positions in both will result to overexposure to the same market conditions, hence increased risk. For the case where the currency pairs are negatively correlated, there is diversification. If one position results in losses, the losses will be offset by the other position. Moreover, an investor can take advantage of correlated currency pairs to hedge. This strategy is common in volatile markets.

To understand correlation between the major trading pairs, we conducted correlation analysis and summarise the findings in a heat map as shown in figure 4 below.

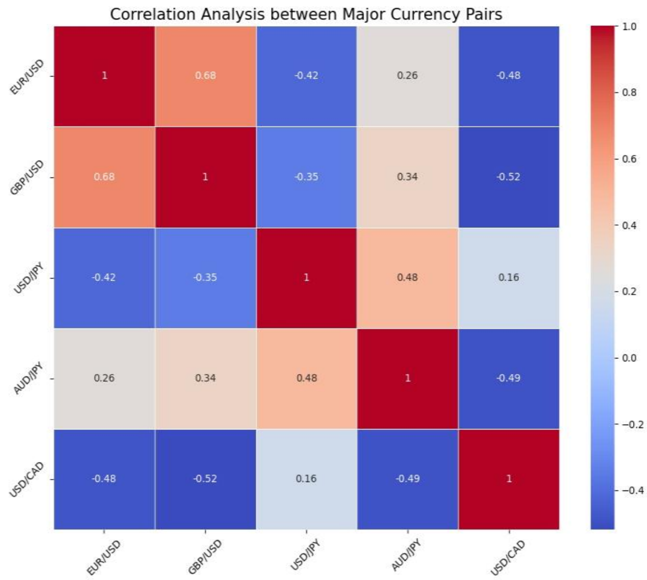

Figure 4 Heat Map showing correlation between major currency pairs

From the heat map of correlations, it can be observed that AUD/JPY and USD/JPY, and EUR/USD and GBP/USD are positively highly correlated with correleation values of 0.53 and 0.6 respectively. There is negative correlation betweeen GBP/USD,EUR/USD against USD/CAD. A negative correlation also exists between AUD/JPY and USD/CAD.

Objective 2: Implementation of the various machine and deep learning models. Three machine (deep) learning algorithms were fitted on the historical data. These are Prophet model, Extreme Gradient Boosting model and a hybrid of CNN-LSTM. The models were fit on all the asset classes to forecast for a 30 day ahead window.

Objective 3: Evaluation of Model Performance in market forecasting: Model evaluation is key in the field of machine (deep) learning as it ensures that the models being developed are accurate, reliable and suitable to use for making predictions in the real world. It helps us understand by quantifying how well a model can perform on unseen data. Evaluating model performance also helps us to avoid overfitting.

For our model evaluation, we used Root Mean Square deviation (RMSE) and Mean Absolute Error (MAE) measures to evaluate how the three models performed on the 10 financial assets (major trading currencies and major trading stocks). The table below summarizes how the models performed with respect to the 2 performance metrics.

Asset Class	Prophet Model		XGBoost		CNN-LSTM HYBRID	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
EUR/USD	0.0175	0.0135	0.0171	0.0089	0.0098	0.0075
GBP/USD	0.0228	0.0177	0.0194	0.0095	0.013	0.0095
USD/JPY	2.6973	1.9416	17.6899	14.0765	1.7463	1.2551
AUD/JPY	2.2165	1.7775	1.2471	0.7589	1.2676	1.0115
USD/CAD	0.0188	0.0147	0.0059	0.0046	0.009	0.0071
Apple	7.0018	5.085	42.71	35.7979	5.2964	4.2143
Microsoft	10.9765	7.2734	83.6558	60.8584	10.3251	8.39
Amazon	8.7348	6.1067	7.0611	4.9959	5.4545	4.2834
Google	5.6751	3.8805	21.5404	14.8245	4.4998	3.5217
NVIDIA	5.8892	3.6017	39.5443	23.8151	4.6762	3.0219

Table 1 Model Performance

It can be observed from the performance table than CNN-LSTM model consistently demonstrated lower RMSE and MAE values, making it the best performing model in market forecasting for both the stocks and the currency pairs. Higher error rates were showed by XGBoost model especially in stocks forecasting. The Prophet model had intermediate performance though fell short in comparison to the CNN-LSTM hybrid model.

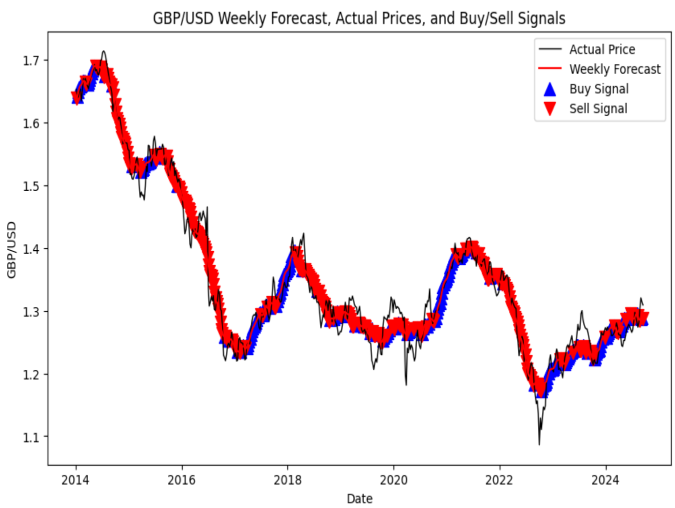

Figure 5 Prophet Model in Forecasting GBP/USD prices

Figure 6 XGBoost Model in Forecasting AUD/JPY

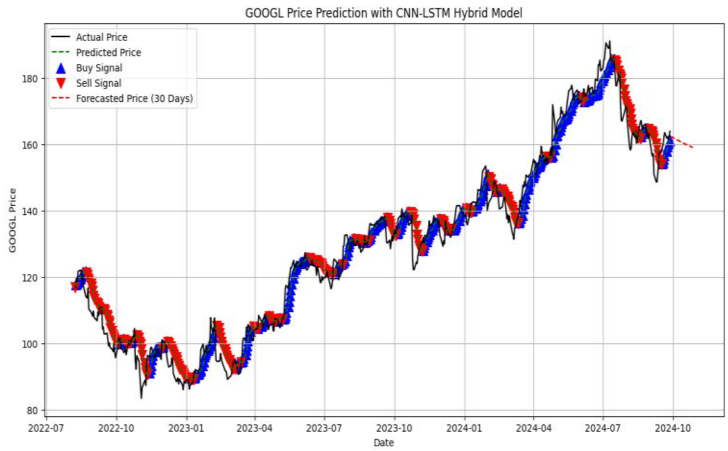

Figure 7 CNN-LSTM Model forecast of Google stock prices

Figures 5, 6 and 7 gives a high level view of how the models practically performed.

Objective 4: Back-testing the best-forming model: We conducted back-testing on the CNN-LSTM model which was the best performing among the 3. In the back-test, we simulated a trading strategy based on buy/sell signals which were generated from forecasted prices. Starting with a portfolio value of $ 100000, we implemented the strategy based on the signals generated considering EUR/USD currency pair prices over time. The portfolio grew over time demonstrating CNN-LSTM hybrid model's ability to effectively generate actionable signals. The final portfolio value reflected a positive return of 19.14% on the total investment. This further affirmed the robustness of CNN-LSTM hybrid deep learning model in market forecasting.

Figure 8 below shows the model's prediction on the currency pair while figure 9 shows the portfolio performance over time.

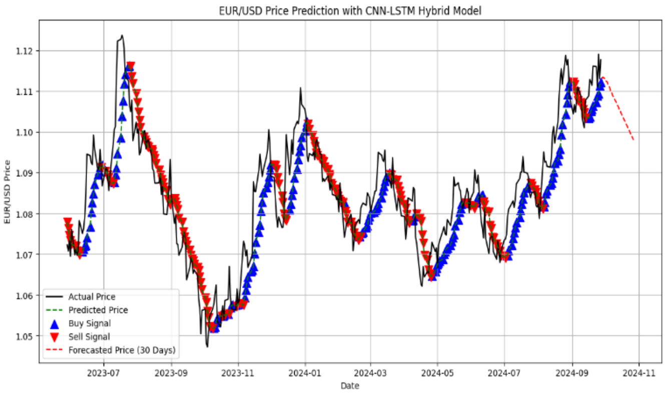

Figure 8 CNN-LSTM Model Prediction on EUR/USD

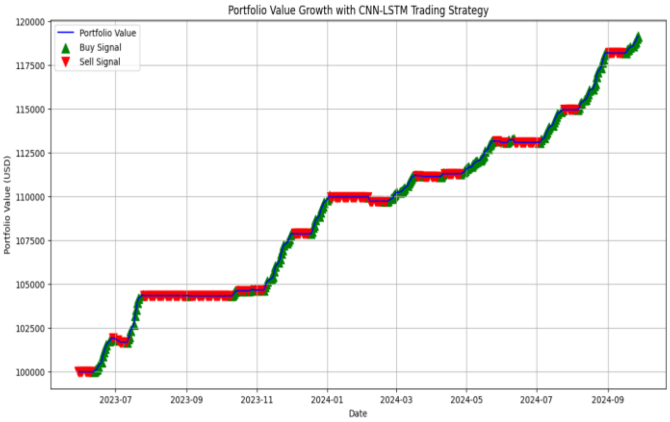

Figure 9 Portfolio Performance based Back-Testing

Objective 5: Refining and Optimizing the model: CNN-LSTM hybrid model is a robust model capable of capturing complex relationships in market dynamics. We tuned the model adjusting for the number of epochs to attain reliable results.

Further refinements may involve integrating external factors like the macroeconomic indicators to enhance market forecasting.

Conclusion

This project focused on developing a robust machine (deep) learning model capable of forecasting the financial markets particularly the currencies and stocks asset classes. Three models were fit on historical data fetched from yahoo finance to predict on the market. CNN-LSTM hybrid model was found to be the best performing model in market timing strategies. Furthermore, back-testing on the CNN-LSTM model yielded promising returns of 19.6% on the total value invested.

Despite the fact that the CNN-LSTM model performed well both in training and testing, and also when it came to back-testing, it could be observed from the forecast plots that in volatile markets, the model struggled a bit. However much the robust model is able to learn from historical data capturing the complex relationships, there is need to consider macroeconomic data especially when one is trading for the short run. Overall, the model is good for long term investing as it adjusts according to the shocks in the market.

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