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Predictive Powers of Carbon Emissions and Oil Price on Stock and Foreign Exchange (FX) Markets Using Multivariate Recurrent Neural Networks (RNN) Model

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Author's contribution

The sole author designed, analysed, interpreted and prepared the manuscript.

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ABSTRACT

The predictive power of environmental factors such as CO_2 levels and Brent oil price was evaluated on the stock market (S&P 500) and foreign exchange (FX) rates for market currency pairs (EUR/USD) and emerging market currency pairs (MXN/USD) with recurrent neural networks (RNN). The S&P 500 is a collection of well-established companies in the United States representing the macroeconomic health of the nation and the global economy. The FX market is a global decentralized over-the-counter (OTC) market used to determine the spot price of currency pairs. A highly leveraged market usually trades within a specific price range. Since stocks and FX pairs are

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highly correlated to macroeconomic factors, it was hypothesized that environmental factors such as CO_2 levels and oil prices also have predictive power due to their close causal relationship with anthropological economic activities. To verify the predictive power, an RNN model was built, and a bi-directional neural network with an internal state was used to process data sequences. The performance of RNN was quantified by measuring the residual prediction from the true value. Although the study at its current state might need further statistical rigor, it concluded that environmental factors increased the predictive power for the S&P 500 while decreasing it for the DM FX pair and the EM FX pair showed mixed results.

Keywords: Foreign exchange; Over-The-Counter (OTC) market; predictive power; Recurrent Neural Network (RNN) model, stock market.

1. INTRODUCTION

Foreign exchange (FX) trading, an integral component of global finance, is the over-the-counter (OTC) spot price trading of currency pairs [1]. It serves as a crucial mechanism for efficient and fast price discovery for currencies worldwide. The valuations of these currency pairs are significantly swayed by interest rates and macroeconomic indicators, underscoring the complex interplay between financial policies and global economic health. However, predicting FX is fraught with challenges, primarily due to the many variables influencing the pricing. And the complex and intricate relations between the variables shift unexpectedly [2]. Moreover, the trades are highly leveraged (10:1 to 50:1) to take profits at small price changes [3]. High-leverage trades amplify risks, making them considerably more prone to substantial loss than non-leveraged markets like stocks and bonds.

For the study, a hypothesis was set that variables related to fossil fuels, specifically CO_2 emissions and the price of Brent oil, significantly impact the prices of FX pairs. The hypothesis predates the global economy's dependence on fossil fuels for transportation and electricity generation [4]. Variations in fossil fuel prices and CO_2 emissions act as barometers for global market activity. To investigate the predictive capability of these variables related to fossil fuels, I developed a multivariate Recurrent Neural Network (RNN) model that can take traditional financial variables such as price data of other FX pairs, stock market, and environmental variables, for example, the CO_2 emission and Brent oil price. This model aims to evaluate the extent to which these environmental variables, alongside conventional economic indicators, affect FX price discovery.

The Recurrent Neural Networks (RNNs) are designed to identify patterns within sequential data. These networks use an internal state, or memory, to process sequences of inputs, rendering them exceptionally suitable for analyzing time series data [5]. The internal state allows RNNs to model temporal dynamics adeptly and handle arbitrary input sequences [6,7]. Consequently, the RNNs stand out for their proficiency in capturing the intricate temporal relationships inherent in data over time, making them a cornerstone in the field of sequence prediction and analysis.

Multivariate forecasting is an advanced predictive methodology that evaluates multiple input features concurrently to project future values [8]. Its success relies critically on the quality, rather than merely the quantity, of these inputs, as the relevance and accuracy of the features directly influence the model's predictive performance. This technique excels in delineating the complex relationships among various variables over time, a crucial aspect for accurately forecasting stock and foreign exchange (FX) prices [9]. Furthermore, it elucidates the intricate interactions between economic and environmental determinants affecting FX rates, highlighting the sophisticated interdependencies characterizing financial markets and the diverse factors influencing currency valuation dynamics.

This analysis employs a multivariate Recurrent Neural Network (RNN) model to forecast the movements of widely traded currency pairs from both developed (DM) and emerging markets (EM). A critical aspect of this research is synthesizing environmental factors and traditional economic indicators within the predictive framework. Accordingly, the dataset has been enriched with closing prices of various FX pairs and the S&P 500 index. Ultimately, this endeavor seeks to shed light on the potential for environmental variables to enhance our understanding of the financial markets.

2. METHODS

2.1 Data Acquisition

The daily CO2 measurement data [10] was downloaded from the Global Monitoring Laboratory (NOAA GML), which acquired the data from the Mauna Loa and Maunakea observatories. Brent oil price and S&P 500 price data were downloaded from Yahoo Finance [11]. FX pair price information was downloaded from FOREX.com broker, a US FX broker with a large daily trading volume [12].

2.2 Data Structure

The time series of 3521 data points was tabulated after removing all NAN entries as in Fig. 1. Then, 80% were split to the training dataset, and 20% were split to the testing dataset. For each dataset, 50 steps were taken out as input to the RNN model. The 50 step-window was pushed one data point at a time to advance the prediction time point.

The OHLC (open, high, low, and close) and volume of transactions were categorized as self-price data. OHLC + volume data for other FX pairs or stocks were categorized as peer-price data. Lastly, environmental variables such as CO_2 levels and Brent Oil were categorized as environmental data. For RNN models, three different input feature conditions were considered. The input conditions are given in Table 1.

Table 1. Input features conditions

Condition 1	Condition 2	Condition 3
Self-price data	Self-price data	Self-price data
	Environmental data	Peer-price data

2.3 RNN Model Development

The TensorFlow from Python was used for RNN [13]. The number of neurons in the input layer was determined by multiplying 50 steps by the number of variables as in Fig. 2. For instance, 250 input neurons are used if only self-price data is considered. Twenty neurons were in the Long-term, short-term memory (LSTM) layer and a single neuron was in the output layer for price prediction.

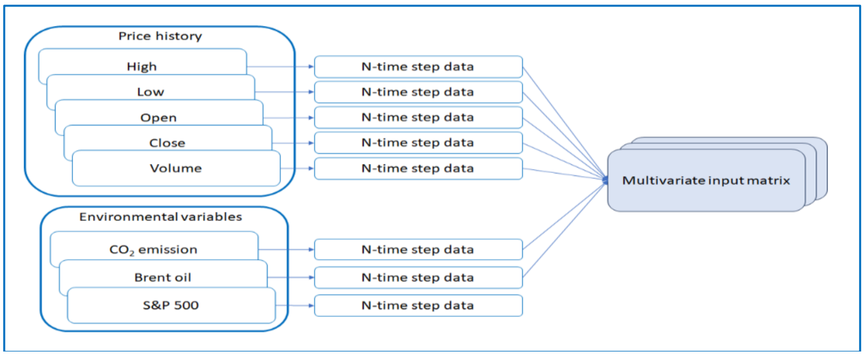

Fig. 1. Overview of data structure

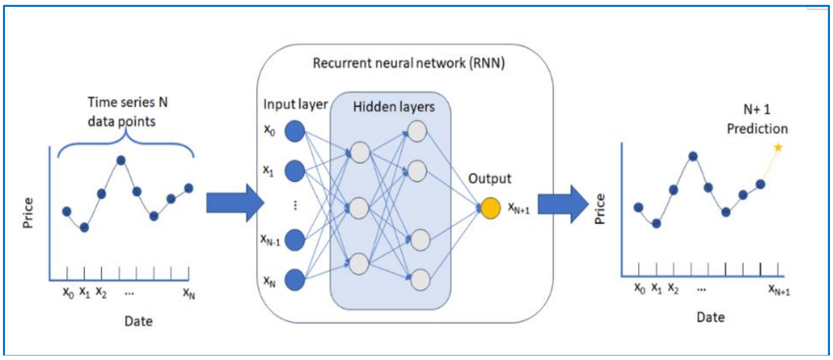

Fig. 2. Overview of the RNN model

3. RESULTS

3.1 Input Data

Input data were preprocessed to match the time stamps. Example input data are shown in Figs. 3 and 4. The CO_2 level shows seasonal fluctuations and increases steadily over time. Brent oil price does not have a particular direction but fluctuates between $150 and $20. For all financial data (both stock prices and FX pair prices), OHLC + volumes were considered. Example data from the EUR/USD pair is shown in Fig. 4.

3.2 Stock Price Prediction

Fig. 5 shows the price prediction with RNN. Condition 1 only has price information from itself, OHLC + volume. The inset shows the residuals from the prediction. The prediction had a few large errors, with an absolute median error of roughly 65.

Fig. 6 shows the price prediction with RNN. Condition 2 has price information from itself OHLC + volume and environmental features. The inset shows the residuals from the prediction. The prediction had a few large errors, with an absolute median error of roughly 63.

Fig. 7 shows the price prediction with RNN. Condition 3 contains price information from OHLC + volume and other FX pairs. The inset shows the residuals from the prediction. The prediction had a few large errors, with an absolute median error of roughly 64.

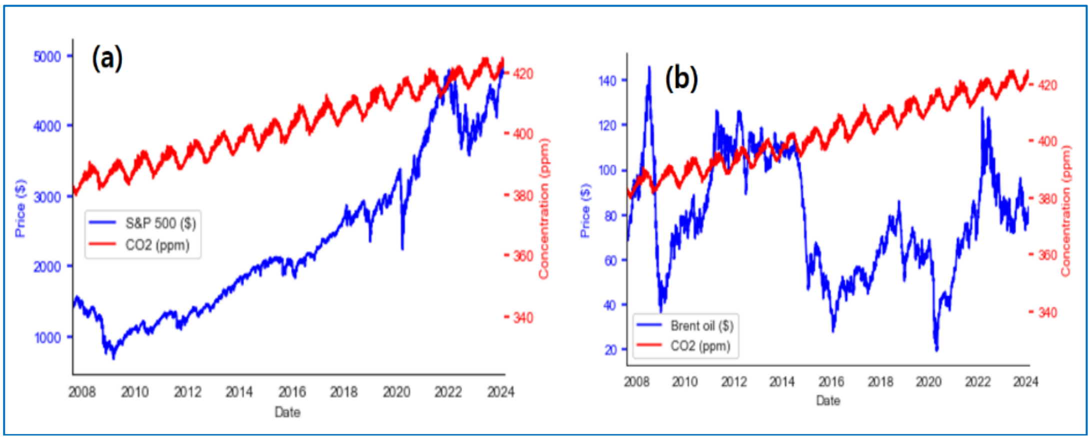

Fig. 3. Representative input data of (a) S&P 500, CO_2 levels, and (b) Brent oil price

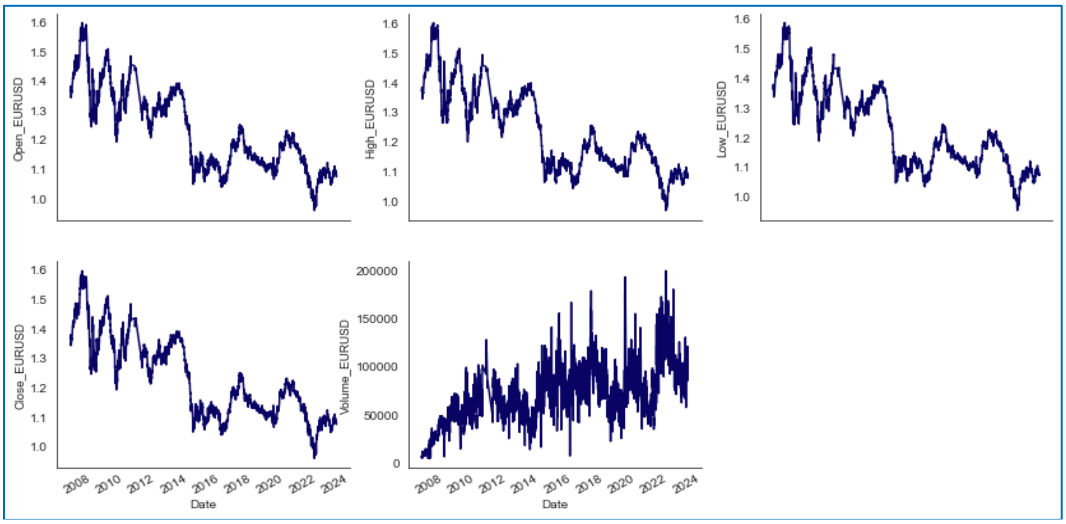

Fig. 4. Typical input data of FX pair (EUR/USD). Open, high, low, and close prices with volume data were input for the RNN model

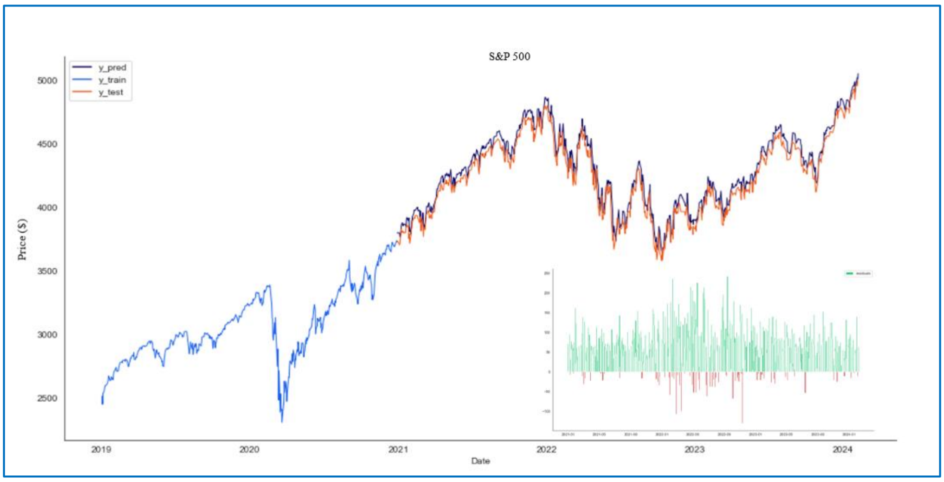

Fig. 5. S&P 500 price prediction with condition 1. The inset shows residuals of price prediction

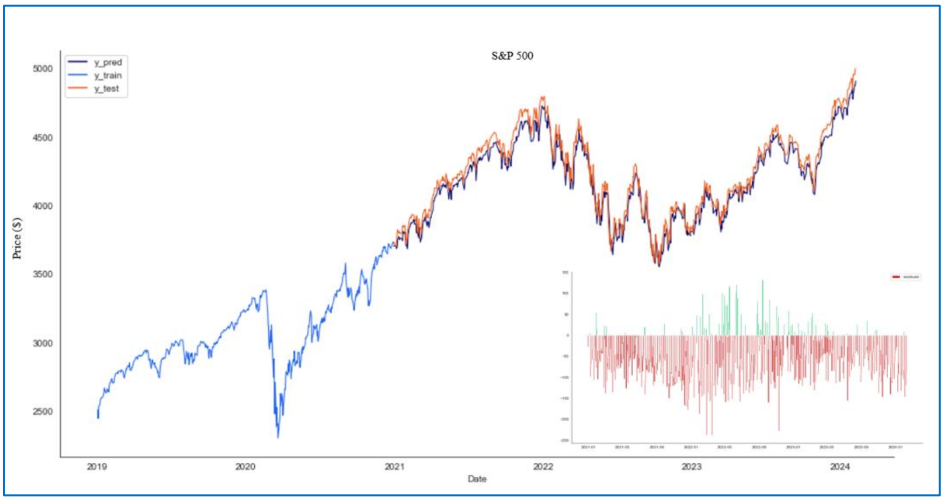

Fig. 6. S&P 500 price prediction with condition 2. The inset shows residuals of price prediction

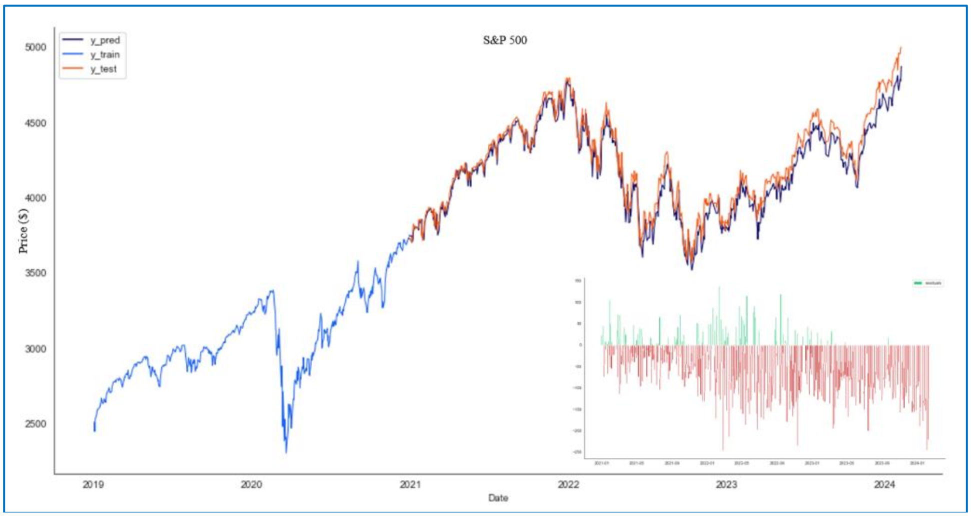

Fig. 7. S&P 500 price prediction with condition 3. The inset shows residuals of price prediction

3.3 DM FX Pair Prediction

In Fig. 8, the price prediction with RNN is shown. Condition 1 only has price information from itself, OHLC + volume. The inset shows the residuals from the prediction. The prediction had a few large errors, with an absolute median error of roughly 0.01. The low absolute error is due to the small absolute value of the EUR/USD pair (~1 to 1.2).

Fig. 9 shows the price prediction with RNN. Condition 2 has price information from itself OHLC + volume and environmental factors. The inset shows the residuals from the prediction. The prediction had a few large errors, with an absolute median error of roughly 0.01.

Fig. 10 shows the price prediction with RNN. Condition 3 has price information from itself OHLC + volume and other FX pairs. The inset shows the residuals from the prediction. The prediction had a few large errors, with an absolute median error of roughly 0.007.

3.4 EM FX Pair Prediction

Fig. 11 shows the price prediction with RNN. Condition 1 only has price information from itself, OHLC + volume. The inset shows the residuals from the prediction. The prediction had a few significant errors, with an absolute median error of roughly 0.12.

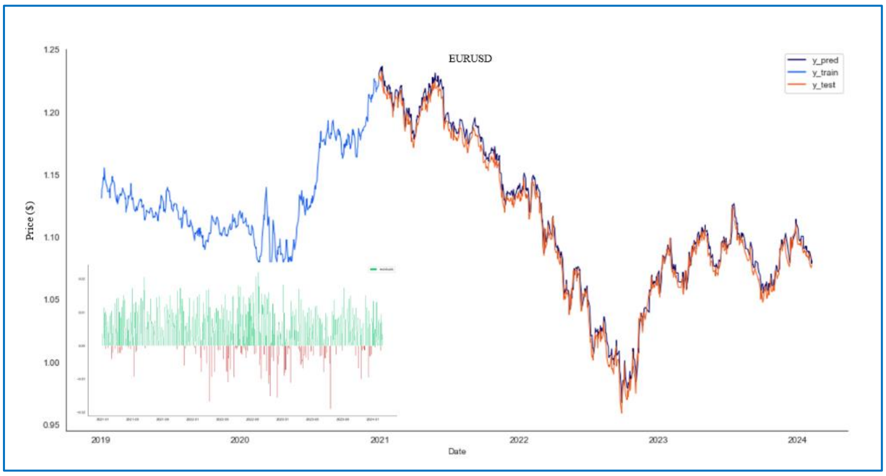

Fig. 8. EUR USD price prediction with condition 1. The inset shows residuals of price prediction

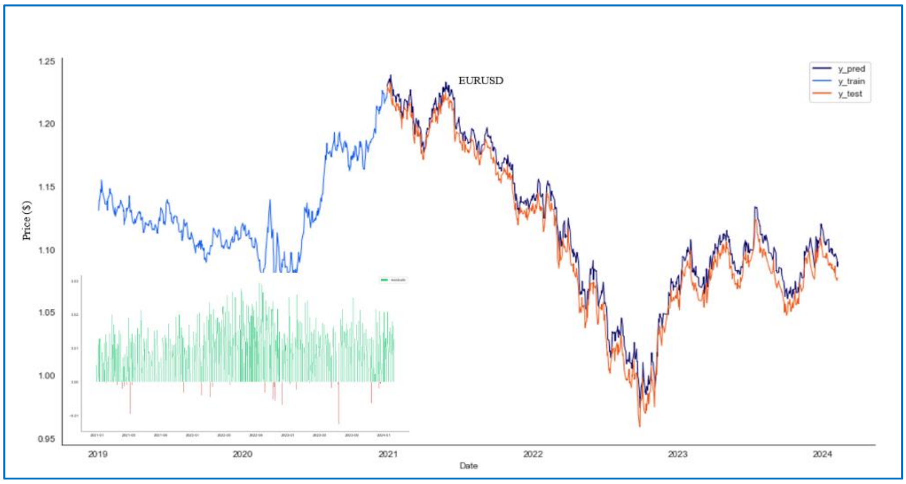

Fig. 9. EUR USD price prediction with condition 2. The inset shows residuals of price prediction

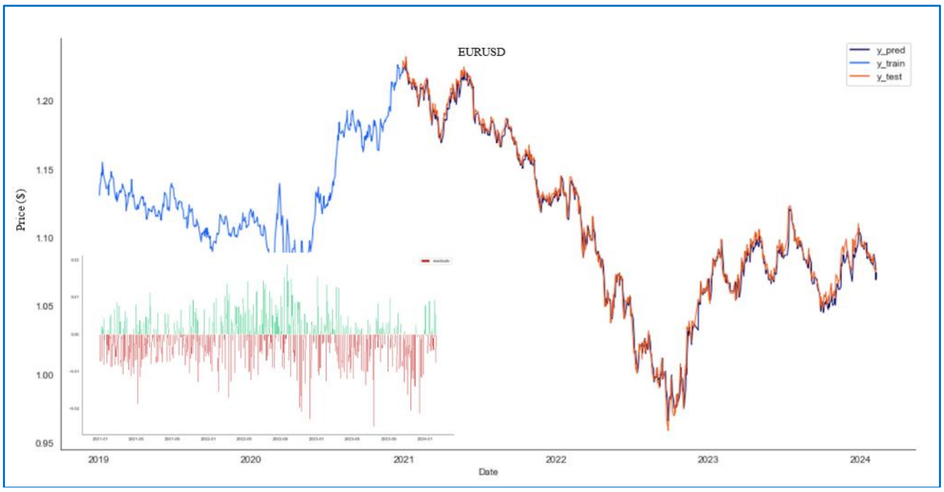

Fig. 10. EUR USD price prediction with condition 3. The inset shows residuals of price prediction

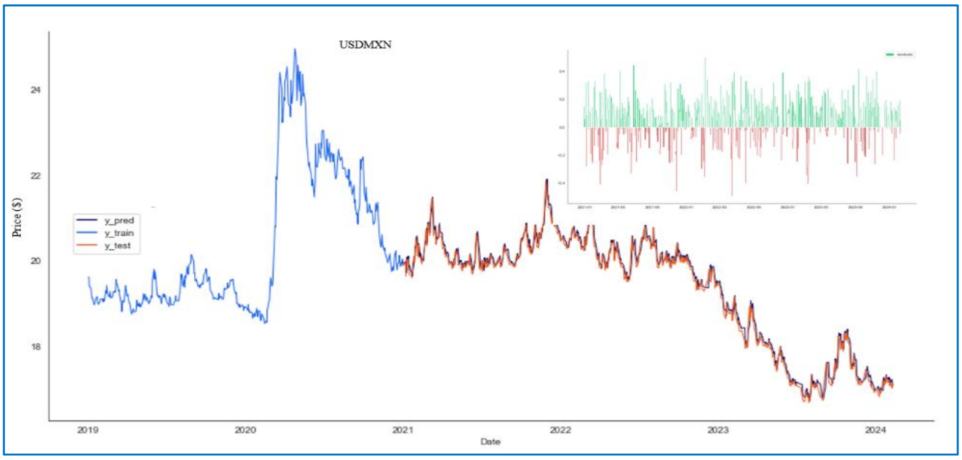

Fig. 11. EUR USD price prediction with condition 1. The inset shows residuals of price prediction

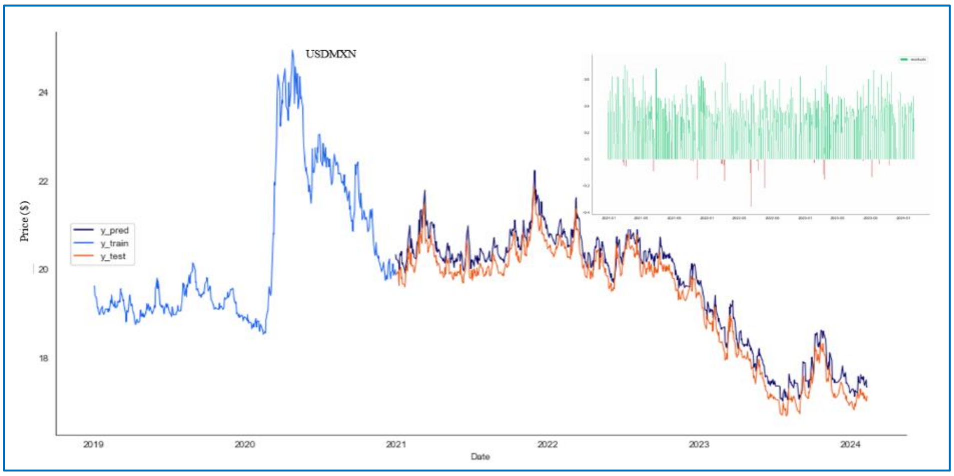

Fig. 12. EUR USD price prediction with condition 2. The inset shows residuals of price prediction

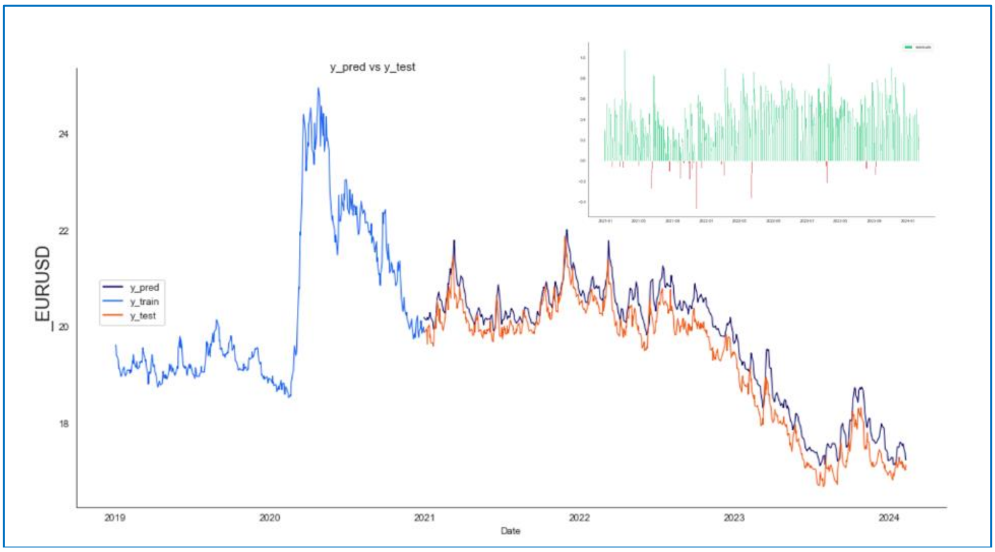

Fig. 13. EUR USD price prediction with condition 3

Fig. 12 shows the price prediction with RNN. Condition 1 only has price information from itself, OHLC + volume. The inset shows the residuals from the prediction. The prediction had a few significant errors, with an absolute median error of roughly 0.31.

Fig. 13 shows the price prediction with RNN. Condition 3 has price information from OHLC + volume and other FX pairs. The inset shows the residuals from the prediction. The prediction had a few large errors, with an absolute median error of roughly 0.38.

4. DISCUSSION

4.1 Stock Price Prediction

In the case of stock price prediction, condition 2 (self-price data & environmental data) outperformed all the other conditions, as in Table 2. Interestingly, the S&P 500 price was better predicted by CO_2 levels and oil prices than the peer financial information (FX pair prices). As a reason for higher predictive power, the general trend of CO_2 level could have helped the prediction. From the visual inspection of the data (Fig. 3), the CO_2 level has an upward trend that is very similar to the upward trend of the S&P 500. The cyclical price fluctuations of the S&P 500 could have been predicted by Brent oil price fluctuation. FX pairs, both DM and EX pairs, improved the price prediction but underperformed when compared to environmental factors.

4.2 DM FX Pair Prediction

In the case of DM FX pairs, environmental factors did not help explain the price. In fact, it was counterproductive for prediction. This could be explained by the fact that a developed economy is mostly a consumption-based economy with a heavy emphasis on the service sector. Moreover, unlike the S&P 500, FX pairs do not measure the cumulative growth of the economy. FX pairs are more relative strength indicators, which are counteractive to the cumulative growth of the CO_2 level (Fig. 3). Other currency pairs (both DM and EM) explained the DM FX pair better. This is most likely because of the prevalence of international trading and interconnected economies.

Table 2. Summary error table for stock price prediction

	S&P 500 Condition 1	S&P 500 Condition 2	S&P 500 Condition 3
Median Absolute error (MAE)	64.64	62.99	63.68
Mean Absolute percentage error (MAPE)	1.54	1.48	1.50
Median Absolute percentage error (MDAPE)	1.44	1.35	1.27

Table 3. Summary error table for DM FX pair prediction

	EURUSD condition 1	EURUSD condition 2	EURUSD condition 3
Median Absolute error (MAE)	0.01	0.01	0.07
Mean Absolute percentage error (MAPE)	0.58	0.98	0.45
Median Absolute percentage error (MDAPE)	0.51	0.93	0.34

Table 4. Summary error table for EM FX pair prediction

	USDMXN condition 1	USDMXN condition 2	USDMXN condition 3
Median Absolute error (MAE)	0.12	0.31	0.38
Mean Absolute percentage error (MAPE)	0.62	1.61	1.98
Median Absolute percentage error (MDAPE)	0.52	1.63	2.02

4.3 EM FX Pair Prediction

In the case of EM FX pairs, environmental factors did not help with the explanation of the price. In fact, it was counterproductive for prediction. Since FX pairs are more of relative strength indicators, the cumulative growth of CO_2 level (Fig. 3) probably worked against EM FX pair prediction. More interestingly, peer-price information from DM FX pairs performed worse than environmental factors. The USDMXN pair is mostly autocorrelated and not well connected to other pairs.

5. CONCLUSION

Since stocks and FX pairs are highly correlated to macroeconomic factors, we hypothesized that environmental factors such as CO_2 levels and oil prices also have predictive power from their close causal relationship with anthropological economic activities. In conclusion, our RNN model could predict the price fluctuations of stock and FX pairs. Further, the effect of environmental factors was compared with prediction, and the potential outcomes for the predictive power of environmental factors were discussed.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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