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Convolutional Neural Network – Based Algorithm for Currency Exchange Rate Prediction

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Abstract— The foreign exchange market is one of the complex monetary markets in the world. Each day trillions of dollars are traded in the FOREX market by banks, retail traders, corporations, and individuals. It is very challenging to predict the price in advance due to the complex, volatile and high fluctuation. Investors and traders are constantly searching for innovative ways to outperform the market and increase their profits. As an outcome, forecasting models are continually being developed by scholars around the globe to accurately predict the characteristics of this nascent market. This study intends to apply the Random Forest (RF) approach to Convolutional Neural Networks, which involves two key steps. The first step is starting with feature selection using Convolutional neural network.The attention layer is then employed to assign weight.The random forest strategy is designed in the second stage to generate high-quality feature subsets. Thus the better result generated by CNN-RF model. Actually, this strategy combines the advantages of two different strategies to produce an outcome that is more consistent with what exchange market decision-makers anticipate happening in the exchange market.The main currency pairs considered in this study's proposed model for predicting exchange rates five and ten minutes in advance are the British Pound Sterling (GBP) against the US Dollar (USD), the Australian Dollar (AUD) against the US Dollar (USD), and the European Euro (EUR) against the Canadian Dollar (CAD) are also used to evaluate the performance of the proposed model. In compared to the other three models (Multi-Layer Perceptron, Autoregressive Integrated Moving Average, and Recurrent Neural Network), CNN-RF yields better results. This conclusion has been backed by a large body of empirical research, which also suggested that this methodology be regularly used due to its high efficacy.

Keywords-: Foreign Exchange Rate, Convolutional Neural Network, Deep Learning, Random Forest Regression, Attention layer,.

I. INTRODUCTION

The Foreign exchange rate (Forex) is the value of one country's currency expressed in terms of another. Exchange rates are very essential parts in financial sectors and foreign currencies are unique financial assets. The FX market has an impact on everyone's daily lives, not only those working in the financial sector but also business owners and decision-makers.

To forecast the currency exchange rate might be challenging. For predicting foreign exchange rates many academics were employed several methods. Terms of trade, public debt, interest rates, and current account deficit have an impact on exchange rates [1].The two main methodologies such as basic approach and the technical approach used in Forex [2]. This paper presents a highly helpful Convolutional neural network (CNN) technique.CNN is also used in a variety of other applications, with face identification [3], medical imaging such as radiologic image analysis [4], document analysis [5], and autonomous driving [6]. Yet, predicting currency exchange rates is not frequently done. As finance market is chaotic in nature. So, various methods used for currency exchange rates prediction. This paper suggests a Convolutional neural network with random forest regression technique to address the problem of foreign currency exchange rate prediction.GBP/USD, AUD/USD, EUR/CAD three pair of datasets had taken into consideration which is trained and tested in 80:20 ratio. The aim of the research focused to achieve two main objectives –

- Short term (5mins and 10mins ahead) Currency exchange rate prediction.
- The proposed model provides better accuracy by using some measuring criteria.

The present piece of work has the following structure. Part II covers the related topic of projecting currency exchange rates. Section III, describes the data utilized for tests and the existing models with our proposed methodology used to predict currency exchange rate. Performance evaluation is described

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in Section IV. The outcomes of our experiment are given in Section V. The conclusion described in section VI.

II. LITERATURE REVIEW

This section contains the most relevant articles, which concentrate on forecasting foreign exchange rates using various techniques. So many techniques used for exchange rate forecasting. One of the author proposed a hybrid foreign exchange rate forecaster model which is the combination of the shuffled frog leaping learning method with a recurrent legendre polynomial neural network. A technique which provides a superior level of daily prediction precision for currency exchange rates is the combination of RLPNN network with ISFL learning technique [7].The author suggested gradient boosted decision trees and artificial neural networks in the form of multilayer perceptron models for prediction of exchange rate fluctuations. Furthermore, the research points to temporal information as a critical factor in forecasting performance [8].The proposed Bi-lstm Br technique combines bagging ridge regression (Br) with bidirectional long short-term memory (Bi-lstm) neural networks. During the pre-covid-19 and covid-19 periods tthe exchange rates of 21 currencies relative to the USD done using the Bi-lstm BR technique. The suggested model was compared to many established machine learning methods, including random forest regression, regression tree, and support vector regression. When predict forecasting exchange rates, the suggested approach ensemble deep learning hit the evaluated models in terms of error [9]. Using the Australian dollar as a case study and the US dollar as the reference currency, forecasts of currency exchange rates for the following day, week, two weeks, and month were studied. Comparing the suggested attention-based LSTM model to common models like ARIMA, SARIMA, SLP, and traditional LSTM. As a result of the accumulated errors based on a single model, the freshly trained models beat the next-day model, according to the results [10].The two additional methods used to forecast the exchange rates are Deep learning and the Nsga-II based dual-objective measurement optimization algorithm. The deep learning model has more accurate findings when compared to more conventional traditional exchange rate prediction algorithms additionally optimizing the selection of investment portfolios is the Nsga-II-based model, which recommend shareholders a more suitable savings portfolio plan [11]. In this study, the author coupled economic models that outperform the random walk model with contemporary machine learning approaches. For the one-period-ahead forecast, JPY/USD experiment analysis was used. The core machine learning models outperform the random walk, as evidenced by the Root mean square error results (this result was further supported by the Mean absolute percentage error)[12].In order to project future movement a linear regression technique was applied to the Eur/Usd exchange rate and the daily, hourly data prediction compared in the global market. Based on the outcome of the error, the proportion of the daily data is superior to hourly data prediction at the test phase [13].The exchange price is successfully predicted using the author's proposed reptile search algorithm—deep predictive coding network model. The accuracy has been measured using Rmse, Mape, Mae, Mare, R^2, and Theils'U, and its recital has been evaluated with Flann and Elm [14]. For the purpose of predicting exchange rates, the author used various currency pairs. To get better prediction outcomes, the suggested model integrated Q-learning with the M-RNN sensing network. For projections, many currency rates as well as key variables are taken into account. The entire simulations demonstrated the efficacy and efficiency of the suggested approach and the model's average accuracy in predicting forex rates is 94.36 percent [15]. The Fspsosvr algorithm allows pso to optimize svr parameters and so increase the precision of exchange rate predictions while FS is able to choose the key features. The carry trade strategy using Fspsosvr, which offers superior trading performance. Based on the result of monthly rate predicting of Fspsosvr model, It might be feasible to use it to analyze small, high-dimensional datasets [16]. To anticipate exchange rates of USD against INR,EURO data for odd days like one, three, five, seven ,fifteen and one month ahead an integrated technique combination of Elm with Tlbo, Jaya, Pso, and De has been suggested. For predicting the open price the proposed technique is contrasted with FLANN and neural network with Tlbo, Pso,Jaya and DE which display evidently the suggested technique is capable of guiding the depositor to make investments in the Forex market [17].The empirical approach entails estimating a model developed by Ols and System Gmm that uses measurements of domestic and global economic, political, and financial uncertainty as explicative variables. The main findings indicate that the measure of internal political uncertainty has a favorable and statistically significant impact on the volatility of the MXN/USD exchange rate. Additionally, during recessionary times, the impact of the domestic economic uncertainty measure on the volatility of the MXN/USD exchange rate is magnified. These findings hold up well to various parameters, econometric methods, and global Epu indexes as well as various measurements of the MXN/USD exchange rate volatility [18].The closing price of the next trading day of the US dollar/Chinese yuan exchange rate was predicted using Cnn-Lstm model. The combination of convolutional neural network and tanh long short-term memory applied in the suggested model. Comparisons with various models, such as the multilayer perceptron, recurrent neural network, Cnn-lstm, and Lstm, were used to assess the model's precision after getting the outcome the suggested

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model is appropriate for next day trading of US dollar/Chinese yuan exchange rate [19].

III. EXPERIMENTAND METHODOLOGY

Three machine learning models—MLP, ARIMA, and RNN—are also contrasted with the CNN-RF prediction model to demonstrate its efficacy.

A. *Dataset*

The datasets used for the experiment are from the http://www.forextester.com/data/datasources database. The data of the GBP/USD, AUD/USD, EUR/CAD were collected between January 2001 and May 2020. Where, the data of GBP/USD, AUD/USD, EUR/CAD exchange rate includes highest price, opening price, closing price and lowest price. Where Open denotes the currency rates starting price, High the highest price, Low the lowest price, and Close the exchange rate's ending price.

B. *ARIMA*

The ARIMA model, also referred to as the Box-Jenkins method, is a statistical model for analyzing and forecasting time series data [20]. It involves analytical and predictive statistical techniques. These models seek to explain how the data are correlated with one another. Based on previous observations and forecasting errors, utilise these correlations to estimate future values.

The general ARIMA formula, Equation (1), illustrates how the parameters are used.

$$W_t=V_t+\beta_1 X_{t-1}+..........+\beta_i X_{t-i}+\alpha_k R_{t-1}+ \ ....+ \alpha_k R_{t-j} \quad (1)$$

W_t= Point predicted at time t

V_t=Height at time t (Time smoothing constants are applied using the mean of the difference data.)

X_{t-i}= Prior data point with a difference

R_{t-j}= Prediction error based on earlier data points

The smoothing constants are α and β.

C. *Multi Layer Perceptron*

The common method used for time series forecasting involves neural network architecture with hidden layers between the input and output layers. In a neural network's hidden layer, each neuron multiplies the input signals by their corresponding weights and then computes their sum [21]. Based on their output, the neurons are computed. A prior study that anticipated time series data using MLP had successful outcomes with a 50% accuracy rate [22].

D. *Random Forest Technique*

Two criteria can be used to categories the ensemble learning method known as random forest. The first is more efficient computationally than the second, which is more efficient statistically. Both classification and regression methods have been applied. The classifier and training methods worked great. Random forest is a high-speed classifier that is often used to address high-dimensional problems [23]. When the output is continuous, it is known as random forest regression, and when it is discrete, it is known as random forest classification. It can be used for both classification and regression [24].

E. *Recurrent Neural Network*

The output from the previous step is used as the input for the recurrent neural network (RNN) phase that is now being performed. In a typical neural network, all of the inputs and outputs are unrelated to one another, yet in order to predict the future word, the prior word must be remembered. To solve the issue the RNN used the hidden state. To remember some information about a sequence RNN use hidden state. The previous input of the network remembered by the memory state. Since it does the same operation on all inputs or hidden layers to produce the output, the same parameter is used for each input [25].So, the complexity reduces like other neural networks. Equations (2) , (3) and (4) were used to calculate the current state ,activation function and output. The current state calculating formula is:

$$X_t=f\ (x_{t-1},I_t) \quad (2)$$

X_t->Present state

X_{t-1} ->earlier state

I_t-input state

Equation (3) applies the activation function (tanh) as follows:

$$X_t=\tanh\ (R_{hh}\ X_{t-1} + R_{xh} I_t) \quad (3)$$

R_{hh}-> Recurrent neuron weight

R_{xh}-> Input neuron weight

Calculation formula for the result indicated in Equation (4):

$$O_t=R_{wh} X_t \quad (4)$$

O_t-> Output

R_{wh}->weight of output layer

F. *Proposed Model*

CNN offers an easy resolution to the problem of computational complexity, making it a computationally efficient option. . By using specialized convolution and pooling algorithms and parameter sharing, CNN can significantly reduce the amount of computational resources required. Moreover, CNN models are now able to run on a wide range of devices, making them a highly attractive option on a global scale.CNN also provides a better result for a huge amount of data. In Between the input and output layers of CNN, there are multiple hidden layers [26] Basically CNN has a total of three layers: A Convolutional layer, a pooling layer, a fully connected layer. It is a type of neural network that uses a grid-like architecture to process data. The convolution layer is the fundamental element of CNN that handles the majority

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of computation. Pooling reduces both the amount of computation required and the spatial size of the representation. However, the Prior Layer and the Recent Layer are both connected to the Fully Connected Layer. The pooling layer was used to reduce each feature map's extent. Mean-pooling and max-pooling are the two types of pooling that are employed. The most significant value was chosen by max-pooling, and the fewest feature maps by mean-pooling. The flowchart of the proposed model shown in fig.1. The proposed model having four Convolutional layers, three pooling layers, four attention layers and one fully connected layer. 1-minutes exchange rates of 24 hours are (24 x 24) is the input of the model. Then the one minute data resampled to 1 hour or 1 day data. Using a pre-processor technique the data were normalized to (0,1).For giving the weight to the feature the attention layer was used. With Convolutional tool the feature extraction had done. To extract few possible features from the dataset the CNN feature extraction model used. Max pooling layer is the next layer. The main goal of this layer in the convolution process known as "Max Pooling," the Kernel extracts the maximum value from the region it convolves. The main component of Max Pooling is the feature map. Between the Convolutional Layer and the fully linked Layer, the Pooling Layer frequently acts as a bridge. Until the optimized weight arrives, the attention layer is employed to assign weight. Finally as a readout layer, a random forest regression strategy is used. The training dataset may typically overfit due to all features associated to the FC layer. Over fitting is the procedure of a particular model execute so well on training data but it impairs the model's performance with fresh data. To address this issue a dropout layer was employed, eliminating a few neurons from the neural network by shrinking the size of the model during training. In the neural network 20% of the nodes are arbitrarily eliminated at a dropout threshold of 0.2. The optimization algorithm used for the proposed model is ADAM. While only 20% of the data were used for testing, the remaining 80% were for training.

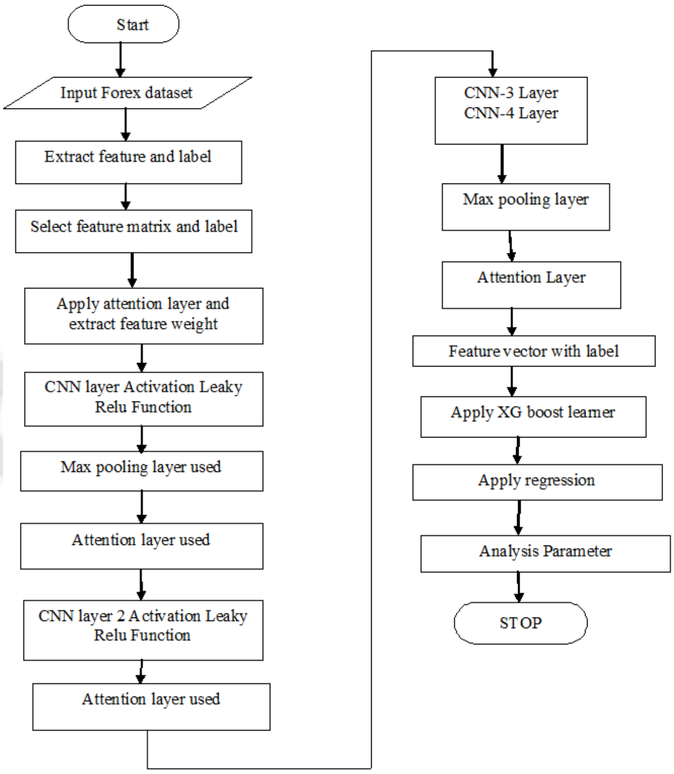

Figure 1. Flowchart of the proposed Model

G. Settings for experimental parameters

Table 1 displays the CNN-RF model's ideal settings for each layer. The following is an explanation of the parameter settings:

Table 1: Table with the best parameters for each layer of the CNN-RF model.

Parameter	Value
Optimization technique	Adam
Pooling layer(Max pooling)	3
Attention Layer	3
Activation function	LeakyRelu
Epoch	10
Batch size	256
Dropping rate	20%
Learning rate	0.003
Loss function	MAE,MSE

The main parameters of the CNN-RF model include optimization technique, pooling layer, attention layer, and Activation function. Epoch, Dropping rate, Learning rate, Batch size and loss function are the parameters for training data are described in the above table.

Non-linear factors are introduced using the convolution layer's activation function. LeakyRelu, Relu, Sigmoid and tanh are frequently used activation functions. Update parameters and

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optimize goal functions are done via an optimizer or optimization technique. The feature maps' dimensions are reduced by the pooling layer. A neural network can benefit from the attention layer's assistance in memorizing lengthy data sequences. A neural network can memorise lengthy sequences of information or data with the aid of the attention mechanism. One loop across the entire training dataset is referred to as an epoch. There are one or more batches in an epoch. The quantity of samples to be processed before updating internal model parameters is specified by batch_size. Dropout contributes to a reduction in over fitting by reducing the squared weight norm. Whether the neural network can converge to the global minimum depends on the learning rate. The forward propagation computation yields the loss function, which also serves as the origin of reverse propagation.

The proposed model contains four convolutional layer, three pooling layer and one read out layer. The model is first fed with the training set data. Attention layer is used for giving optimized weight. The feature extraction had done with Convolutional layer. Each feature map's size will always be reduced by the pooling layer. Finally as a readout layer, a random forest regression strategy is used.

IV. PERFORMANCE ASSESSMENT

Six indices : R^2, Mean Absolute Error (MAE), Mean Square Error (MSE), Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Cumulative Explained Variance (CEV) are used to assess the model's recital. The R^2 coefficient gauges how well the projected values match the starting points.

R^2 is a coefficient that measures how well the predicted values fit the original values.R^2's mathematical expression is found in Equation (5).

$$R^2(\mathrm{v},\mathrm{w}) = 1 - \frac{\sum_{x=1}^{s}(\mathrm{v}_x - w_x)^2}{\sum_{x=1}^{s}(\mathrm{v}_x - \overline{\mathrm{v}_x})^2} \qquad (5)$$

The symbol's' represents the total number of samples in a dataset, w_x is the x^{th} sample's predicted value, and v_x is the x^{th} sample's actual value. R^2, which ranges from 0 to 1, is used to assess the fitness of a prediction model. More accurate the model, if the result is superior.

MAE (Mean Absolute Error) –The variance among the actual value and the expected value is considered by the Mean absolute error. Equation (6) contains the mathematical formula for MAE.

$$MAE(v,w) = \frac{1}{s}\sum_{x=1}^{s}|v_x - w_x| \qquad (6)$$

MSE (Mean Square Error)-The Mean square error is a statistical measure used to evaluate the precision of a model. It calculates the average squared difference between the predicted and actual values. The mathematical formula for MSE is given by Equation (7).

$$MSE(\mathrm{v},\mathrm{w}) = \frac{1}{s}\sum_{x=1}^{s}(\mathrm{v}_x - w_x) \qquad (7)$$

MAPE (Mean Absolute Percentage Error)-Statistics' measure of forecasting method prediction accuracy is MAPE . Equation (8) contains the mathematical formula for MAPE .

$$MAPE(\mathrm{v},\mathrm{w}) = \frac{1}{s}\sum_{x=1}^{s}\left|\frac{v_x - w_x}{v_x} \times 100\right| \qquad (8)$$

Root Mean Square Error (RMSE) -Root Mean Square Error (RMSE) is a useful metric when a large number of errors affect the performance of a model. The mathematical formula for RMSE is shown in Equation (9).

$$RMSE(v,w) = \sqrt{\frac{1}{s}\sum_{x=1}^{s}(v_x - w_x)} \qquad (9)$$

CEV(Cumulative Explained Variance)-The Cumulative Explained Variance (CEV) is a metric used to evaluate the accuracy of the expected outcome. It is widely used in various industries, including banking and healthcare.

V. TEST RESULTS AND ANALYSIS

This section aims to evaluate and analyze the performance of the suggested CNN-Random Forest (CNN-RF) prediction model used for currency exchange rates. The implementation of the CNN-RF model was carried out using Python 3.7 on a machine with a Pentium dual-core CPU, 4 GB of memory, and Windows 10 operating system. The experiment makes use of the most recent data on the GBP/USD,AUD/USD,EUR/CAD exchange rates. For the project, data sets spanning from January 2001 to May 2020 were utilized. The whole data was divided into two sets, 80% of the entire data was utilized for training and 20% utilized for testing. The algorithm is utilized to forecast the currency pair's closing price five and ten minutes beforehand. In the experiment, the daily high, low, opening, closing, and volume of currency exchange rates were considered as input variables for the proposed CNN-RF model. The recital of the model was estimated using various indices including R^2, MAE, MAPE, MSE, RMSE, and CEV.

CNN is a highly effective predictor for complex data, and it can successfully handle the computational challenges associated with such problems. Factual metrics include R^2, which is the variance of the independent variable divided by the variance of the dependent variable in this context refers to the measure used to evaluate the quality of the prediction, whereby a larger value indicates a better prediction. The

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accuracy of the predicted outcome is assessed using the CEV metric, where a higher value indicates better accuracy. To quantify the magnitude of the model's forecast errors the MAE values used. It is a way to compare errors in two observations that both describe the same phenomenon. MAPE is the metric used to assess the forecasting system's precision. For the dependent variable in this context refers to the measure used to evaluate the quality of the prediction, whereby a larger value indicates a better prediction. The accuracy of the predicted outcome is assessed using the CEV metric, where a higher value indicates better accuracy. Table 2 displays the performance of the various currency pair conversion using several methods for the anticipated five-minute future.

TABLE 2: ERRORS CALCULATION FROM DIFFERENT ALGORITHMS OF 5 MINUTES AHEAD PREDICTION.

Variable	Algorithms	R^2	MAE	RMSE	CEV	MAPE	MSE
GBP/USD	MLP	0.37025	0.654	0.5733	0.5875	0.0791	0.8675
	ARIMA	0.6045	0.544	0.5368	0.59	0.0856	0.788
	RNN	0.93205	0.133	0.27215	0.76375	0.0324	0.322
	CNN-RF	0.9665	0. 122	0.2329	0.97	0.0223	0.2334
AUD/USD	MLP	0.2875	0.545	0.71005	0.58875	0.09235	0.92775
	ARIMA	0.453	0.675	0.65325	0.66	0.074	0.8325
	RNN	0.8976	0.233	0.407525	0.866875	0.0424	0.3777
	CNN-RF	0.9665	0.2275	0.3879	0.97	0.03735	0.3334
EUR/CAD	MLP	0.8015	0.8046	0.80001	0.9195	0.05984	0.9001
	ARIMA	0.786	0.5227	0.69831	1.0189	0.04443	0.71218
	RNN	0.965	0.353	0.61035	1.0765	0.0424	0.42438
	CNN-RF	0.97	0.3523	0.6079	1.08	0.04176	0.344

The outcome graphs displayed in fig.2 (a), 2(b) and 2(c). The results illustrate the precision of predictions generated by the CNN models compared to the ARIMA, MLP, and RNN models. The analysis findings reveal that the CNN model outperforms its competing counterparts.

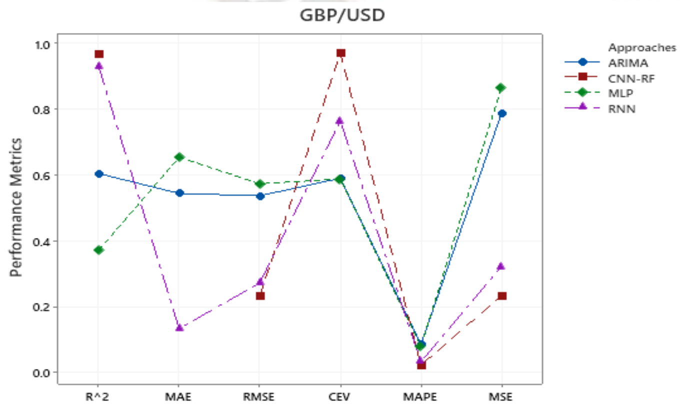

Figure 2: (a) Five minutes ahead Prediction of GBP/USD

The performance of the currency exchange rate (prediction of the next 10 minutes) is shown in Table 3 utilizing a variety of methodologies and performance markers. The four approaches for forecasting are MLP, ARIMA, RNN, and CNN-RF. The various measurement standards for performance prediction include R^2, MAE, MSE, RMSE, MAPE, and CEV.

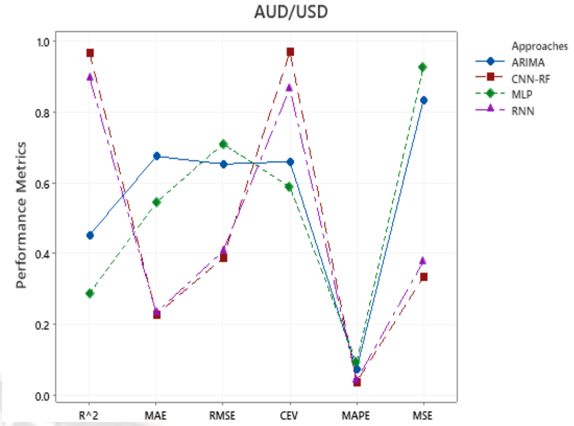

Figure 2: (b) Five minutes ahead Prediction of AUD/USD

The resultant graphs depicted in fig.3 (a), 3(b) and 3(c). The effectiveness of the CNN-RF model, the recital of the MLP model, and the recital of the RNN model and the performance of ARIMA were compared in the evaluation. The results were represented using different colored lines, with the red line indicating the effectiveness of the CNN-RF model, the blue line representing the performance of ARIMA model ,the green line representing the performance of MLP, and the RNN model's performance shown using purple line.

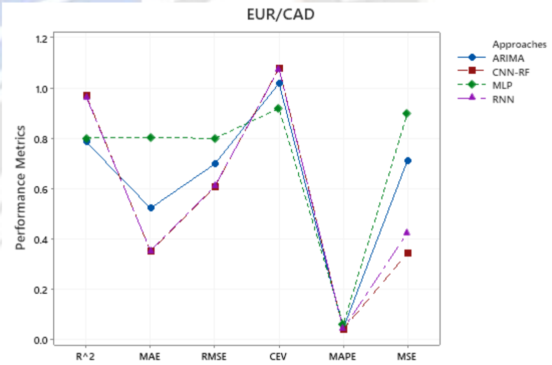

Figure 2: (c) Five minutes ahead Prediction of EUR/CAD

TABLE 3:VARIOUS ALGORITHMS' CALCULATIONS OF ERRORS OF 10 MINUTES AHEAD PREDICTION.

Variable	Algorithms	R^2	MAE	RMSE	CEV	MAPE	MSE
GBP/USD	MLP	0.497375	0.68	0.56505	0.59875	0.09235	0.8377
	ARIMA	0.72565	0.8495	0.50825	0.67	0.074	0.7425
	RNN	0.889425	0.5205	0.3759	0.756875	0.04235	0.5095
	CNN-RF	0.9765	0.1375	0.2429	0.98	0.03735	0.2434
AUD/USD	MLP	0.38025	0.839	0.69165	0.634375	0.093175	0.890125
	ARIMA	0.6145	0.70925	0.597088	0.713438	0.068175	0.726
	RNN	0.8368	0.429	0.474225	0.816875	0.04985	0.4986
	CNN-RF	0.9765	0.24025	0.3979	0.98	0.039875	0.3434
EUR/CAD	MLP	0.692756	0.673708	0.7591	0.904766	0.062141	0.8161
	ARIMA	0.669	0.462802	0.6751	0.81	0.052469	0.6563
	RNN	0.8695	0.377583	0.6311	0.865	0.052084	0.5124
	CNN-RF	0.98	0.362656	0.6191	0.997	0.051134	0.3941

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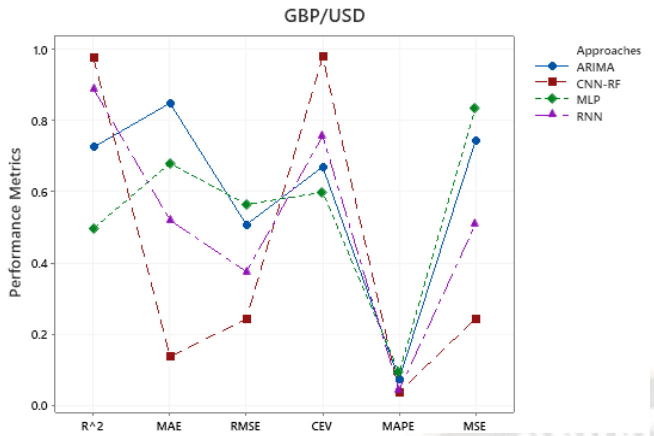

Figure 3(a): Ten minutes ahead prediction of GBP/USD

The CNN-RF model was compared to the ARIMA, RNN and MLP models in order to assess its efficacy. To evaluate the CNN-RF model's efficacy the suggested model was compare with ARIMA, RNN and MLP models. The CNN-RF model was compared to the ARIMA, RNN and MLP models in order to assess its efficacy. To evaluate the CNN-RF model's efficacy by forecasting GBP/USD the suggested model was compared with ARIMA, RNN and MLP models. The MAE values of CNN-RF model are 0.122 and 0.1375 which is less than other models. The RMSE values of 5 minutes and 10 minutes predictions are0.2329 and 0.2429 which are also less than other models. The forecasting values of CEV using ARIMA are.0.59 and 0.67. The predicted values of CEV using the MLP algorithm are 0.58 and 0.59. The CEV values predicted by RNN are 0.76 and 0.75. But the values predicted by CNN-RF are 0.97 and 0.98 which are very close to 1. The best score of CEV is 1.0. So, CNN-RF model is better than other models.R2's top rating is 1.0.The R^2 values of 5 minutes and 10 minutes ahead prediction of GBP/USD using MLP algorithm are 0.37 and 0.49, using ARIMA algorithm the outcomes are 0.60 and 0.72, with RNN the predicted values are 0.93 and 0.88 but the forecasting result of CNN-RF model are 0.96 and 0.97 which are very nearer to 1. So, the CNN-RF model is better than other models. In MAPE (the least value is the better) and MSE (the least value, is the better) values are less than the model is better than the other model. Based on the 5 minutes and 10 minutes ahead MAPE results using CNN-RF model are 0.02 and 0.03, less than other model's values. The MSE results using CNN-RF model are 0.23 and 0.24 .These values are also less than other models.

The suggested model was also used to predict the Australian Dollar's value versus the US Dollar five and ten minutes in advance, with results that were also compared to those of other models. R2 values for forecasting 5 and 10 minutes in advance using the MLP algorithm are 0.28 and 0.38, 0.45 and 0.61 using the ARIMA algorithm, 0.89 and 0.83 using the RNN, and 0.96 and 0.97 using the CNN-RF algorithm. The suggested model's MAE values for predictions made after five and ten minutes are respectively 0.22 and 0.24, which are likewise lower than those of other models. The model is superior to others if the MAE values are lower. The MLP algorithm's RMSE values are 0.71 and 0.69.The expected values using the ARIMA model are 0.65 and 0.71, whereas using the RNN model, the forecasted values are 0.86 and 0.81. RNN offers accurate prediction results. However, the anticipated RMSE values using the CNN-RF technique are 0.97 and 0.98. The MLP algorithm's CEV values are 0.58 and 0.63.The expected values using the ARIMA model are 0.66 and 0.71, whereas using the RNN model, the forecasted values are 0.86 and 0.81. RNN offers accurate prediction results. However, the projected CEV values using the CNN-RF technique are 0.97 and 0.98.These numbers are quite near to one. The CNN-RF model's 5-min and 10-min forecasts yielded MAPE values of 0.03 and 0.03, respectively, which were lower than those of the other three models. Additionally, the CNN-RF model's MSE values for predictions made five and ten minutes in advance were 0.33 and 0.34, respectively, which were lower than those achieved by the other three models.

The CNN-RF model was also used to compare the European Euro to the Canadian Dollar for predictions made five and ten minutes in advance, and the results were compared to those of other models. R2 values for forecasting 5 and 10 minutes in advance using the MLP algorithm are 0.80 and 0.69, 0.78 and 0.66 using the ARIMA algorithm, 0.96 and 0.86 using the RNN, and 0.97 and 0.98 using the CNN-RF algorithm. The suggested model's MAE values for predictions made after five and ten minutes are respectively 0.35 and 0.36, which are likewise lower than those of other models. The model is superior than others if the MAE values are lower. The MLP algorithm's RMSE values are 0.80 and 0.75.The expected values using the ARIMA model are 0.69 and 0.67, whereas using the RNN model, the forecasted values are 0.61 and 0.63. RNN offers accurate prediction results. However, the projected RMSE values using the CNN-RF technique are 0.60 and 0.61.Better is a larger value, or CEV. Using the MLP technique, the CEV values are 0.91 and 0.90.The expected values using the ARIMA model are 1.01 and 0.81, while using the RNN model, the forecasted values are 1.07 and 0.86. RNN offers accurate prediction results. However, the projected CEV values using the CNN-RF technique are 1.08 and 0.99.These numbers are quite near to one. For forecasting 5mins and 10 mins ahead prediction using MLP the MAPE values are 0.05 and 0.06.By applying ARIMA the values are 0.04 and 0.05.The values using RNN are 0.04 and 0.05.The CNN-RF model's 5-min and 10-min forecasts yielded MAPE values are 0.03 and 0.03, respectively, which were lower than those of

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the other three models. The MSE values using MLP model are 0.91 and 0.81.After applying ARIMA the MSE values are 0.71 and 0.65.0.42 .With RNN the values are 0.42 and 0.51.Additionally, the CNN-RF model's MSE values for predictions made five and ten minutes in advance were 0.33 and 0.34, respectively, which were lower than those achieved by the other three models. As a result, the suggested model's precision is judged to be superior to that of all three of the others.

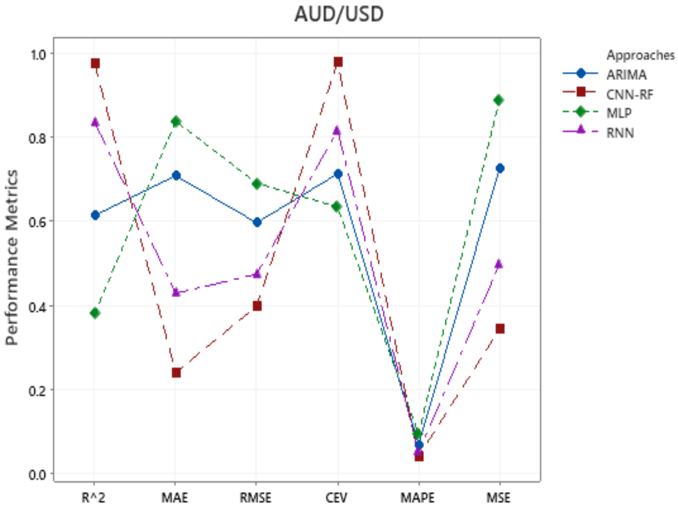

Figure 3(b): Ten minutes ahead prediction of AUD/USD

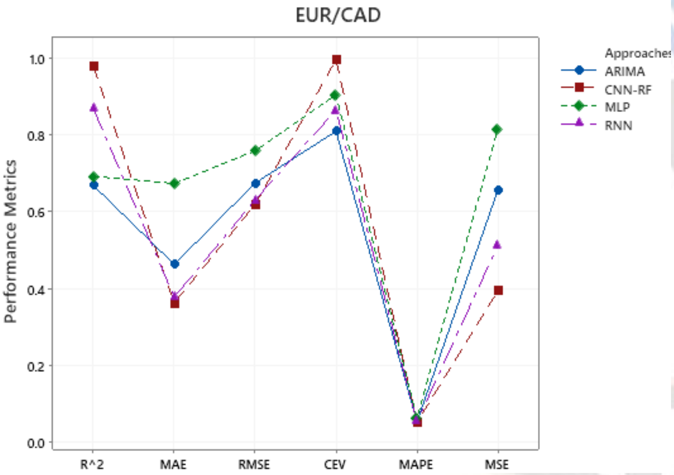

Figure 3(c): Ten minutes ahead Prediction of EUR/CAD

VI. CONCLUSION

This study utilized a new approach by combining CNN and RF models to predict FOREX currency pairs, with GBP/USD, AUD/USD, EUR /CAD being the primary pair of interest. For forecasts generated at intervals of five and ten minutes, the presentation of the suggested model in predicting exchange fluctuations was contrasted to that of existing models including ARIMA, RNN and MLP. The performance of the proposed model was assessed using a number of performance metrics, including R^2, MAPE, CEV, MSE, RMSE, and MAE. The CNN-RF model fared better than all three models in terms of accuracy in predicting short-term FOREX exchange prices, according to the experimental results. Future studies will primarily focus on two areas:

- Due to the numerous variables influencing the currency rate's closing price, this article solely takes into account historical data for the GBP/USD, AUD/USD, and EUR/CAD exchange rates. However, neither the worldwide pandemic nor governmental policy had been taken into account.
- Creating and implementing a framework for analyzing dynamic data sets and predicting performance.

REFERENCES

[1] T.N.Pandey et al.,"A novel committee machine and reviews of neural network and statistical models for currency Exchange Rate prediction: An experimental analysis", Journal of King Saud University–Computer and Information Sciences, vol.32, no.9,pp.987-999, 2020.

[2] S.K. Chandra, M. Sumathi, S.N. Sivanandam, Foreign exchange rate forecasting using Levenberg-Marquardt learning algorithm, Indian J. Sci. Technol. 9 (8),1–5,2016.

[3] K.o.Shea, R.Nash, "An Introduction to Convolutional Neural Networks", arXiv:1511.08458v2,2015.

[4] Y.A.,Andrade-Ambriz, ,S., Ledesma, M.A. Ibarra-Manzano, M.I.Oros-Flores, and D.L. Almanza-Ojeda, . Human activity recognition using temporal convolutional neural network architecture. Expert Systems with Applications, 191,2022.

[5] N.S. Rani, P.N.Rao, P.Clinton," Visual recognition and classification of videos using deep convolutional neural networks", International Journal of Engineering & Technology, 7(2.31), pp.85-88,2018.

[6] Y.L.Chang, T.H. Tan, W.H.Lee, L.Chang, Y.N. Chen, K.C. Fan, and M. Alkhaleefah, Consolidated Convolutional Neural Network for Hyper spectral Image Classification. Remote Sensing, 14(7), p.1571,2022

[7] Z.Hu. Y.Zaho., M.Khushi," . A survey of forex and stock price prediction using deep learning", Applied System Innovation, 4(1), p.9,2021.

[8] J.F. Pfahler, Exchange rate forecasting with advanced machine learning methods. Journal of Risk and Financial Management, 15(1), p.2,2022.

[9] M.Z.Abedin, M.H.Moon,M.K..Hassan, P.Hajek," Deep learning-based exchange rate prediction during the COVID-19 pandemic", Annals of Operations Research, pp.1-52,2021.

[10] I.C.Lee, C.H.Chang, F.N.Hwang," Currency exchange rate prediction with long short-term memory networks based on attention and news sentiment analysis", In 2019 International Conference on Technologies and Applications of Artificial Intelligence (TAAI) (pp. 1-6).2019, IEEE.

[11] J.Chen et al.,"Exchange Rate Forecasting Based on Deep Learning and NSGA-II Models", Computational Intelligence and Neuroscience, 2021.

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DOI: https://doi.org/10.17762/ijritcc.v11i10.8525
***Article Received:** 10 August 2023 **Revised:** 30 September 2023 **Accepted:** 18 October 2023*

[12] Y.Zhang, S.Hamori," The predictability of the exchange rate when combining machine learning and fundamental models", Journal of Risk and Financial Management, 13(3), p.48,2020.

[13] M.S.A. Sarkar and U.M.E. Ali," EUR/USD Exchange Rate Prediction Using Machine Learning", I. J. Mathematical Sciences and Computing, 1, 44-48, 2022.

[14] S.Dash et.al,"A Novel Algorithmic Forex Trade and Trend Analysis Framework Based on Deep Predictive Coding Network Optimized with Reptile Search Algorithm", Axioms, 11(8), p.396, 2022.

[15] T.S. Madhulatha, M.A.S Ghori," Foreign Exchange Rates Prediction for Time-series Data using Advanced Q-sensing Model", 2022.

[16] M.L.Shen et.al," An effective hybrid approach for forecasting currency exchange rates", Sustainability, 13(5), p.2761, 2021.

[17] S.R.Das, M. Rout.," A hybridized ELM-Jaya forecasting model for currency exchange prediction", Journal of King Saud University – Computer and Information Sciences, vol.32, no.3, 2017.

[18] J.Wang, X.Wang, J.Li, H.Wang," A prediction model of CNN-TLSTM for USD/CNY exchange rate prediction", Ieee Access, 9, pp.73346-73354, 2021.

[19] K. Bataineh," USD Exchange Rate Cycles Using Developed and Developing Currencies and Risk Factors", Journal of Advances in Humanities Research, 1(1), pp.42-59,2022.

[20] T.M.U.Ngan," Forecasting foreign exchange rate by using ARIMA model: A case of VND/USD exchange rate. Methodology, 2014, p.2015",2013.

[21] F.Mansour, M.C.Yuksel, M.F.Akay,"Predicting Exchange Rate by Using Time Series Multilayer Perceptron", 3rd International Mediterranean Science and Engineering Congress, IMSEC 2018, October 24-26, Adana/Turkey, 2018.

[22] M.Karim," The Forecast of Exchange Rates using Artificial Neural Networks, and their comparison to classic models", UEL, Royal Duck Business School, 2014.

[23] M.Savargiv, B. Masoumi, M.R.Keyvanpour," A New Random Forest Algorithm Based on Learning Automata", Hindawi, Computational Intelligence and Neuroscience, V. 2021, 2021.

[24] X.Gao, J.Wen, C.Zhang," An Improved Random Forest Algorithm for Predicting Employee Turnover", Hindawi Mathematical Problems in Engineering, Volume 2019, ,2019 .

[25] S. A. Zargar," Introduction to sequence learning models: RNN,LSTM, GRU", April,2021.

[26] M.M.Panda, S.N.Panda, P.K.Pattnaik,"Exchange Multi currency exchange rate prediction using convolutional neural network", Materials Today: Proceedings, 2021.