of experimental comparisons had been conducted between ELM core algorithms and the state-of-the-art learning algorithms, e.g., Back Propagation Neural Network (BPNN) and Support Vector Machine (SVM). The conducted experiments have been performed on the intraday intervals using 23 stocks data in the H-share market (i.e., H-share market regulations in 2001 defined the trading sessions from 10: 00 to 12: 30, and from 14: 30 to 16: 00) and the selected stocks' historical news.

The obtained results showed that (1) both kernelized ELM and SVM outperformed BPNN and the B-ELM in terms of prediction accuracy and prediction speed; (2) K-ELM achieved the same accuracy as the kernelized SVM (i.e., RBF-SVM) and (3) K-ELM outperformed the kernelized SVM (i.e., RBF-SVM) in the prediction speed. Moreover, the authors carried out the proposed trading strategy simulations with the signals, the achieved results showed that in the presence of more accurate trading signals, the proposed trading strategy could gain more profits with less risk.

In [40], the authors explored the benefits of using of Deep Deterministic Policy Gradient (DDPG) in optimizing stock trading strategy and so maximize investment return in the complex and dynamic stock market. The authors selected 30 trading stocks with their daily prices from 01/01/2009 to 09/30/2018 as the training and trading market environment. They trained a deep reinforcement learning agent and got an adaptive trading strategy using the 30 stock trading data. The trained agent's performance evaluation was compared against two baseline benchmarks; the Dow Jones Industrial Average and the traditional min-variance portfolio allocation. The proposed DDPG approach outperformed the two baseline benchmarks in terms of cumulative returns and Sharpe ratio.

In [31], the authors presented a stock trading recommender system based on an optimized genetic algorithm, namely Symbolic Aggregate approXimation (SAX). The proposed system adopted the stock price dataset in mining the temporal association rules to generate stock trading recommendations. The performance of the system was optimized using Genatic Algorithm (GA). The proposed system was validated on 12 different datasets on stocks from two different markets; an emerging market (India) and a mature market (the United Kingdom). For each stock, the system was validated over three-time frames. Based on the defined objective functions for identifying the optimal temporal association rules, two different variants of the proposed system were presented.

From the obtained results, it was observed that the proposed system significantly outperformed the buy-and-hold strategy. The proposed system was able to learn patterns from the stock price data and to execute profitable trades resulting in higher profits than that generated by the traditional strategy. Hence, it can be said that the proposed stock trading recommender system can be successfully used to generate stock trading recommendations that can help any one in a successfully trading in the stock markets.

In [25], in the same context; portfolio management, where an optimal asset allocation at a different time for high return as well as low risk. The authors explored several categories of portfolio management approaches including "Pattern-Matching", "Follow-the-Winner", "Follow-the-Loser" and "Meta-Learning Algorithms". They explained that deep reinforcement learning is the combination of "Pattern-Matching" and "Meta-Learning" and can somehow capture the different patterns of market movements in the presence of limited observed data and features, also it can self-improve its performance.

The authors implemented three state-of-art continuous reinforcement learning algorithms, Proximal Policy Optimization (PPO), Deep Deterministic Policy Gradient (DDPG), and Policy Gradient (PG) in portfolio management. PPO has interesting properties that are hopefully potential in portfolio management. They adopted different settings for performance evaluation, including different learning rates, feature combinations, objective functions in order to provide insights regards parameter tuning, features selection, and data preparation. Moreover, the authors conducted intensive experiments in the China Stock market and showed that PG was more desirable than DDPG and PPO in the financial market, although both of them are the state-of-art learning algorithms. Furthermore, the authors proposed Adversarial Training method and showed its great impacts on promoting the average daily return and the Sharpe ratio.

4.2 Interest Rate

Interest rate is one of the important lagging indicators of economic growth. It represents the cost of borrowing money; it is mainly related to the federal funds rate. Federal fund rate represents the rate at which money is lent from one bank to another and is determined by the Federal Open Market Committee (FOMC). It is well known that this rate changes as a result of economic and market events.

In [9], the author proposed and developed a hybrid model for forecasting the 3-month T-bill interest rates. The proposed model structured in two stages; Multiple Regression and Fuzzy Inference Neural Network model. In the first stage, the authors adopted multiple regression analysis that reduced the number of the used variables while keeping only the variables that are highly correlated with interest rate and also have strong prediction ability as well. In the second stage, the selected variables from the first stage were fed to the Fuzzy Inference Neural Network model for performing the future interest rate returns prediction. The proposed model adopted 20 different variables, including economic indicators and non-linear historical interest rate data in the regression analysis. The data used for training the model covered the period from June, 1960 to January, 2011 in a quarterly basis, for a total of 208 data points.

The authors demonstrated that all the existing research in this context was based on either technical or fundamental factors, i.e., factors that are determinants of the future returns (e.g. various economic and financial variables). The authors stated that the combination of the aforementioned factors differentiate their work from other existing works to get more precise results. Moreover, the authors illustrated that a Differential Evolution-based (DE) Fuzzy Inference Neural Network was utilized to mitigate the drawbacks of the Artificial Neural Networks (ANN). As a result, the proposed hybrid model with its techniques provided an outstanding prediction system to the mentioned conventional statistical techniques.

The authors performed their proposed model experiments using 5 fundamental and 2 technical factors as input to the second stage, i.e., the Fuzzy Inference Neural Network for interest rate returns prediction. The obtained results from the first phase showed that the significance level was much less than 0:05 (5% false-positive rate), while R2 = 0:9377, this implied that the model provided a good fit (R = 0:9683, adjusted R2 = 0:9351). For performance evaluation, the proposed model achieved a good performance with an Root Mean Square Error (RMSE) value of 0:3877.

In [18], the authors demonstrated the recession forecasting in the period 2007 to 2009. They compared the interest rate spreads using neural network against regression models in the prediction. The authors explained that recent research agreed on the important role that the spread had in predicting real economic growth e.g., real Gross Domestic Product (GDP), Real Total Business Sales (RTBS), and industrial production. Moreover, the authors stated that spread can also forecast consumption and inflation. The authors mentioned that the monthly average yield on the 10 year U.S. Treasury Bond and the monthly average yield on the 3 month U.S. Treasury bill were the interest rate variables that constructed the spread in their proposal.

Both datasets were obtained from the Federal Reserve Economic Data (FRED) database of Saint Louis Federal Reserve Bank, and the variables used in describing the the U.S. economy recession was monthly data of RTBS. It is worth mentioning that, the adopted variables were reported by the Bureau of Economic Analysis and U.S. Department of Commerce and known as real manufacturing and trade sales. The authors stated that RTBS was one of the indicators that predicted recessions with correlation of 0:99 to the real GDP. Furthermore, RTBS provided monthly data series, while the real GDP was reported quarterly that represented fewer observations.

The experimental work illustrated that the adopted neural network modelwere trained using data from April 1969 to December 2005 and tested on data from January 2006 to November 2007, while the regression models were trained on data from April 1969 to November 2007 and tested on data from December 2007 to June 2009. The authors evaluated the proposed model performance using the R-squared and Mean Square Error (MSE) of in-sample model estimations as well as out-of-sample testing and out-of-sample forecasts. The obtained results showed that the neural network models outperformed the multiple regression models, this ensured the superiority of adopting neural network models over regression models in the prediction.

4.3 Currency Exchange Rate

Recently, many forecasting models have been proposed and applied in forecasting several currency exchange rate. Existing forecasting models can be classified in two main categories, qualitative and quantitative models [22]. Timeseries models is considered as one of the most important quantitative models in forecasting currency exchange rate.

In time-series models, historical observations (of the same variable) were collected and analyzed for training the developed model. Then the prediction process achieved using the trained model. This modeling approach was successfully applied in case of few knowledge was available from the data generating process or when there was no satisfactory relational model between the prediction variable and other explanatory variables [22].

In [36], the authors presented the adoption of ANN in forecasting the US Dollar (USD) / Indian Rupee (INR) exchange rate. Because of the existing unpredictability behaviors and data volatility in current markets, many research groups paid their attention to predict the currency exchange rates using various techniques. Moreover, ANN as one of the well-known forecasting models, has recently shown its applicability in time-series analysis and forecasting as well. The authors aimed to examine many important neural network factors impacts on in-sample fit and out-of-sample neural networks forecasting capabilities, e.g., number of inputs nodes, number of hidden nodes, and the training sample size.

The authors discovered that the number of input nodes has a great impact on the forecasting performance over the number of hidden nodes, moreover, a large number of observations reduced the forecasting errors. Furthermore, both in-sample fitting and out-of-sample predictive performance have been evaluated using three metrics, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The authors adopted the random walk model as a benchmark for comparison. Random walk model used the current observation to predict the next one since it is a one-step forecasting model. The obtained results showed the robustness of ANN model towards the achieved changes in the models structures, also, ANN model could easily handle the inaccuracy and the non-linearity degree in the trained data.

In [5], the authors applied Artificial Neural Network (ANN) in predicting Indian Rupee (INR) exchange rates against four other currencies such as Pound Sterling (PS), United States Dollar (USD), EURO and Japanese Yen (JYEN) using their historical data. The data used in this study for the foreign currencies was made available for Reserve Bank of India. A total of 1205-day data were considered, 80% out of the data was used in training and the remaining 20% for evaluating the trained model. Five different ANNs based models using existing learning algorithms were considered in order to evaluate the general performance of each algorithm in different problems as follows:

- GD: traingd- Batch gradient descent
- GDM: traingdm- Batch gradient descent with momentum
- GDA: traingda- Variable Learning Rate Back-propagation
- RP: trainrp- Resilient Back propagation
- LM: trainlm- Levenberg-Marquardt

The Back Propagation Neural Network (BPNN) algorithm was chosen for this application, since it is capable of solving variety of problems and it was commonly used in forecasting. The performance evaluation of the proposed forecasting technique was carried out using popular statistical metrics; RootMean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

The obtained results showed a remarkable difference between the performances of the different learning algorithms, it was observed that GD, GDM, and GDA algorithms were very slow. Also, the results showed that RP and LM algorithms consistently performed better than other models for all currencies. However, LM based model converged quickly and also has smaller MSE for all currencies. Furthermore, the authors explored that a well-designed network structure played a great role in the forecasting performance. It is worth mentioning that BPNN could be used in foreign exchange rate accurate prediction, thus decreasing the risk of making unfair decisions.

In [30], the author demonstrated the adoption of deep learning models in predicting the top-traded currencies ex-change rates. The author applied ANN, Support Vector Regressor (SVR), Long Short-Term Memory (LSTM), and Neural Network (NN) with one and two hidden layer neurons to predict the multi-currency exchange rates. The adopted models predicted the exchange rate of the world's top-traded currencies; USD/GBP, USD/EUR, USD/AUD, USD/JPY, USD/CAD, USD/CHF, USD/CNY, USD/SEK, USD/NZD, USD/MXN and USD/INR from the daily currency exchange rate data collected in the period from 1980s to December 2018 (30 - 39 years). The authors obtained the data from investing website from appx. 30 - 39 years' data for each currency with more than 11250 total data. The obtained data was partitioned into training and testing data into the proportion of 80-20%. After performing the models training, the outcomes were profoundly promising. The performance evaluation results showed that the prediction model average accuracy exceeded 99%. The authors in this research proved the applicability of using deep learning in multi-currency exchange rates prediction.

In [42], the authors proposed a deep learning-based model in forecasting foreign currency exchange rate. The authors incorporated event sentiments in the proposed model to achieving accurate prediction, since the exchange market is a volatile market that always affected by the ongoing social and political events. Moreover, the authors considered in their exchange forecasting model other volatile factors that had highly impacts e.g., gold and crude oil prices since the currency market is heavily dependent upon them. The proposed model was tested over 3 currency exchange rates; British pound sterling to US dollar (GBP/USD), Hong Kong Dollar to US dollar (HKD/USD), and Pak Rupee to US dollar (PKR/USD).

The proposed model used the daily exchange rate data ranging from early 2008 to late 2018 taking into consideration additional explanatory factors in the prediction model such as crude oil prices and gold price index. Moreover, the authors also explained the importance of incorporating investor's sentiment to local and foreign events for accurate exchange rate forecasting. The events were divided into global and local event; local events like Hong Kong Protest (2014), Pakistan Lahore Blast 2016, UK Brexit, while global events were US Election 2012. It isworth noting that, around 5:9 million tweets were processed to extract considerable events' sentiment.

The proposed model validity was tested against linear regression and support vector regression models. For performance evaluation, MAE and RMSE were the most commonly used metrics in evaluating the foreign exchange rate prediction accuracy. The obtained results without sentiment showed that the proposed deep learning-based model outperformed the commonly used statistical techniques in the prediction of foreign currency exchange rate. Moreover, the authors compared the predicted exchange rate results in the presence of sentiments with linear model as well as support regression model. The comparison results showed that deep learning-based methods outperformed other methods. Moreover, incorporating sentiment analysis in the proposed model enhanced the prediction results.

As a conclusion, incorporating the social media sentiment related to events happening in the US in the prediction model contributed significantly on the currency exchange rate prediction accuracy of Hong Kong, Pakistan, and the UK. Thus, these countries are affected by mega-events happening across borders.

In [11], the authors aimed to achieve two objectives; the first objective was to explore the deep neural networks prediction accuracy in currency exchange rate compared with the well-known models of neural network and time-series analysis. The main key feature in using the deep neural network model was its ability to learn abstract features from raw data. This feature suggested that deep networks may achieve good prediction results in foreign exchange rates based on the available raw time-series data.

In this research, the authors adopted raw exchange rate data of US dollar against developed countries currency e.g., Euro (EUR/USD), British Pound (GBP/USD), and Japanese Yen (USD/JPY) as input features to the model. The authors adopted data from 2000 to 2015 in training and testing the proposed models. Preliminary results using the dailyclosing exchange rates and three major currencies suggested that indeed deep convolution networks outperformed other existing methods. For emerging currency markets, the authors adopted the exchange rates of Eastern Partnership (EaP) countries e.g., Armenia, Azerbaijan, Belarus, Georgia, Moldova, and Ukraine to US Dollar: AMD/USD, AZN/USD, BYR/USD, UAH/USD, GEL/USD, and MDL/USD. The proposed models were trained for each dataset for daily, monthly, and quarterly predictions.

Furthermore, the authors explained that their research was focused on adapting deep neural network models for predicting currency exchange rates in emerging markets as a second objective. The authors claimed that in EaP countries' economies, the stability if the currency exchange market considered as one of the most important indicators in achieving sustainable development and growth on those countries. They added that accurate exchange rate prediction was critical concern in formulating a robust monetary policy on those countries.

In achieving the first objective that aimed to perform a better exchange rate prediction on the macroeconomic level, the authors included the real sector economic indicators e.g., (GDP growth, unemployment, wages), current and capital account, public and private foreign debt, capital flows, international variables (interest rates and price ratios), and others. Furthermore, they considered some additional factors including money growth, fiscal growth, and a measure for the degree of political instability and market liberalization. However, the authors discovered that because of the emerging markets volatility as well as its political instability as in the case of EaP economies, improving the exchange rate prediction models was particularly a challenging task to achieve.

In performance evaluation, the authors adopted the following baseline models: random walk model, two time-series models (ARIMA and ETS), and a single-layered neural network model. The adopted models parameters were tuned by cross-validating the parameters ranges. The authors intended to use Stacked Long Short Term Memory (LSTM) deep network for exchange rate prediction as well.

Preliminary results confirmed that in the developed currency market, the proposed deep neural network model achieved significantly higher prediction accuracy than the baseline models. For emerging currency market, the authors also proposed a novel set of input features that may help improve the prediction accuracy of such models.

The same authors in [12] presented the usage of deep convolution neural networks in predicting directions of change in foreign exchange rates. They demonstrated the significant contribution of deep neural network that outperformed time-series models and neural networks when the inputs to the models are the raw data. The authors claimed time-series models provided point estimates for short-term prediction currency rates, while econometric models worked well for long-term predictions. Furthermore, the obtained time-series prediction accuracy were with acceptable error levels but were unreliable in predicting the change direction.

The authors explained that when using raw Forex rate data as inputs, a multilayer perceptron with a single hidden layer had the same aforementioned problem. Moreover, they claimed that both Support Vector Machines (SVM) and neural networks with single hidden layers did not perform significantly well as classifiers even when using derived input features such as moving averages. It is worth mentioning that, using moving average as derived feature were widely used in the financial statistics since they are able to filter out random noise. In their experiments, the authors used 3 different time-series datasets of the daily closing currency exchange rates between 3 popular currency pairs: Euro and US Dollar (EUR/USD), British Pound and US Dollar (GBP/USD), and US Dollar and Japanese Yen (USD/JPY) for training and testing their models. The adopted currency pairs were the most and highly traded currencies in the Forex market.

The authors defined the baseline models using a naive method, two time-series models (ARIMA and ETS), and a single-layered neural network. The authors named the adopted naive method as Majority Class (MC) model, in which the the majority class in the training set was predicted as the output for any test example, i.e., the class of a test example was predicted as 1 if the exchange rate direction increased in at least 50% of the training examples, and 0 otherwise. The time-series models (ARIMA and ETS) provided the exchange rates point estimates that predicted the change direction. The ANN model had a single hidden layer contained 10 hidden neurons performed good results.

Although the authors' main objective was to predict the exchange rate direction, they trained the baseline models to provide point estimates. Thus, for a fair comparison, the authors trained the ANN and SVM models as classifiers using the true direction of change as output labels. Also, they trained the deep networks as classifiers as well. Moreover, to improve the classification accuracy, they adopted derived features as inputs in training the models e.g., moving averages. For discrimination, they referred to the ANN model trained on Moving Averages as ANNMA to differentiate from the ANN model trained on raw time-series data.

For performance evaluation, the authors presented the prediction MAPE of ARIMA, ETS, and ANN for the 3 currency pairs. They illustrated that the baseline models were poor in predicting the exchange rate change direction although they achieved relatively low absolute errors for point estimates. Furthermore, the point estimates classification accuracy that were obtained by the baseline models (MC, ARIMA, ETS, and NN) varied between 40% and 60% using raw time-series data. This indicated that they were not significantly different from random guesses. Also, the adopted classifiers ANNMA and SVM that were trained using derived features (moving averages) achieved classification accuracies around 65% better than aforementioned models. Moreover, the proposed deep convolution neural networks resulted in more than 75% average classification accuracies. As a conclusion, the performed experimental results showed that deep convolution neural networks achieved significantly higher classification accuracy in predicting the change direction in foreign exchange rates.

In [6], the author stated that any exchange rate movements and forecasting studies should include explanatory variables from the payments balance current account as well as capital account. The authors in this work included such explanatory factors to forecast the value of the Indian Rupee against the US Dollar. They mentioned other factors that should also be considered in the forecasting process like political instability that can impact direct foreign investment as well as portfolio investment.

The authors adopted ANN-based models and time-series econometric models as two different forecasting models classes. In ANN-based models, they adopted the Multilayer Feed Forward Neural Network (MLFFNN) and Non-linear Autoregressive Neural Network with Exogenous Input (NARX). While in the time-series econometric models, they adopted Generalized Autoregressive Conditional Heteroskedastic (GARCH) and Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) techniques.

The authors explained the added features values that enhanced the future exchange rate movements forecasting task. First, they used the daily exchange rate data and the other explanatory variables, no macroeconomic variables have been added. Then, they adopted explanatory variables such as forward rate that were represented in term of current account and capital account factors. The authors incorporated explanatory variables that reflected the economy instability in terms of economic, political, and financial. After that they defined multivariate framework that incorporated machine learning techniques and econometric techniques. The defined framework enabled them to compare the efficiency of these two types of forecasting models. Finally, the authors implemented the NARX model.

The authors performed their experiments using daily exchange rate data within the period from 1:1:2009 to 8:4:2016 with 1783 observations. These data were partitioned into training, validation, and testing dataset 70%; 15% & 15% respectively. Moreover, they defined the Rupee Dollar exchange rate (FX1) as the dependent variable. Also, they defined the Rupee-Dollar futures exchange rate (FX4), Dow Jones Industrial Average returns (DJIAR), NIFTY returns (NIFTYR), Hang Seng returns (HSR), DAX returns (DR), Crude Oil Price (COP), CBOE VIX (CV) and India VIX (IV) as the independent variables.

The authors explained the adoption of the independent variables as follows; the NIFTYR represented daily returns from the Indian stock market, DJIAR and DR represented returns from the western part of the world, and HSR represented returns from the eastern part of the world. Moreover, the authors included CV and IV measures of Implied Volatility to control the relative uncertainty in the Indian market vs the US market. The authors mentioned that COP was included to represent the current account in the payments balance since it was the single largest import item of India. As a conclusion, both the current account and capital account variables have been included, along with measures of volatility.

For models performance evaluation, Mean Squared Error (MSE) and Correlation Coefficient (R) have been used, also for statistical significance, Jarque-Bera test has been conducted. From the obtained results, it was observed that the actual exchange rate and the predicted exchange rate are very close in the model training, validation, and testing. Furthermore, the authors observed a linear trend between the actual and the predicted exchange rate. This linearity justified the proposed model efficiency.

The obtained predictive model statistics; MSE and R values showed a high R values and a small MSE values for training and testing dataset as well. This observation implied that MLFFNN architecture could be used in currency exchange rate prediction using independent variables e.g., FX4, DJIAR, NIFTYR, HSR, DR, CV, COP and IV.

The authors calculated MSE and Theil Inequality Coefficient using actual and obtained forecast values for quantitative assessment of the forecasting accuracy. The obtained results showed that both MSE and Theil Inequality Coefficient were significantly low. Furthermore, the conducted t-Test statistic proved that ANN-based models performed better than time-series GARCH models in terms of MSE values.

In [22] the author proposed an alternative forecasting technique to the traditional hybrid ARIMA-ANNs models for financial time-series forecasting. The proposed model incorporated the Artificial Neural Networks (ANNs) and the AutoRegressive Integrated Moving Average (ARIMA) for financial time-series forecasting. The authors discussed that the most popular hybrid models were the hybrid techniques that decomposed the time-series into its linear and non-linear components. Moreover, the authors stated the main limitation in the traditional hybrid models that they have some assumptions that may degraded their performance if the opposite situation occurred, moreover, they maybe inadequate in some situations.

Despite the popularity of using hybrid models, the authors believed that they were not always perform well since the model selection process remained an important step. The authors stated that the proposed model did not require any assumptions in the modeling process. Therefore, in the proposed model, it can be guaranteed that the performance of the proposed model will not be worse than either of its components individually, in contrast to the traditional hybrid ARIMA-ANNs model.

The proposed model divided into two stages. The first stage aimed to perform linear modeling; therefore, ARIMA model was used to model the linear component. The residuals from the first stage were the non-linear relationships that linear model did not able to model them, and also the linear relationships that linear model did not able to model them completely. The second stage aimed to perform non-linear modeling. So, a multilayer perceptron was used to model the linear and non-linear relationships existed in the residuals from the first stage and the original data.

The authors adopted 3 datasets; Indian Rupee versus United States dollar exchange rate dataset, it was obtained from FX database for the period from January 6, 1994 to July 10, 2003, for a total of 497 observations. The second dataset was British pound and United States dollar dataset contained the weekly observations from 1980 to 1993, having 731 data points in the time-series, and finally the Euro and United States dollar dataset contained the daily observations from March 2005 to March 2006, giving 365 data points in the time-series. All the adopted datasets were divided into in-sample and out-of-sample as training and testing datasets.

In the in-sample performance evaluation i.e., training phase, the proposed model was evaluated against the neural network, linear autoregressive, and the random walk models as baseline models. The adopted datasets were the weekly Indian rupee versus the United States dollar (INR/USD), the weekly British pound versus the United States dollar (BP/USD), and daily Euro against the United States dollar (Euro/USD) exchange rates respectively. The obtained results showed that the proposed model outperformed the neural network, the linear autoregressive, and the random walk models in RMSE as well as MAE metrics.

The out-of-sample performance evaluation of the proposed model was evaluated against Zhang's hybrid ARIMA- ANNs, neural network, linear autoregressive, and the random walk models as baseline models. The aforementioned exchange rates datasets were used respectively. The obtained results were also outperformed the baseline models in both RMSE and MAE metrics in INR/USD, BP/USD, and Euro/USD exchange rates cases. Finally, the obtained empirical results in both weekly and daily exchange rate forecasting confirmed the effectiveness of the enhanced hybrid model in improving the forecasting accuracy performed by the traditional hybrid ARIMA-ANNs models. Therefore, this model can be used as an alternative model for exchange rate forecasting, particularly when higher forecasting accuracy was needed.

In the work presented in [38], the authors discussed the Gross Domestic Product (GDP) as one of the most important indicators of economic growth, welfare, and health. The authors aimed in this study to investigate the possibility of adopting ANN with feed-forward back-propagation learning techniques in GDP prediction based on non-economic data. In achieving this objective, different architectures of neural network models have been adopted. For optimum ANN model, the authors tested different ANN models with more than one hidden layer and more neurons. Some of the parameters were kept constant while the hidden layer and neuron numbers were randomly changed by trial and error in the developed models.

4.4 Gross Domestic Product

The Gross Domestic Product (GDP) is considered as the main index in measuring the economic development of a country and region. Therefore, GDP future expectations could be the primary indicators for investments, wages, em- ployment, profits, and even stock market activities. The importance of GDP prediction stemmed from many reasons related to GDP as an economic indicator. GDP is considered to be a main pillar for the economic development strategy, planning, and a variety of macroeconomic policies. GDP can reflect a country's development level, a country's health, and standard of living. So it is urgently needed to predict GDP in a scientific method and forecast GDP precisely [41].

In the work presented in [38], the authors discussed the Gross Domestic Product (GDP) as one of the most important indicators of economic growth, welfare, and health. The authors aimed in this study to investigate the possibility of adopting ANN with feed-forward back-propagation learning techniques in GDP prediction based on non-economic data. In achieving this objective, different architectures of neural network models have been adopted. For optimum ANN model, the authors tested different ANN models with more than one hidden layer and more neurons. Some of the parameters were kept constant while the hidden layer and neuron numbers were randomly changed by trial and error in the developed models.

The following performance metrics were used for ANN training evaluation including Value of correlation coefficient (R), Root Mean Square Error (RMSE), Coefficient of Determination (R2), Logarithmic Transformation Variable (e). Many experiments have been performed on the developed models, and according to the obtained results, it was observed that among the developed ANN models, the feed-forward back-propagation technique provided the best optimal ANN model. Therefore, ANN can be used as GDP estimation model based on non-economic parameters and the authors proved this observation with quite good and satisfactory results.

In [19], the authors adopted ANN in forecasting Turkey GDP. The authors explained that GDP consists of a composite of dependent and independent macroeconomic variables. Thus, they adopted the following dependent and independent variables; Gross National Product (GDP), Resident Household Consumption (RHC), Time (T), Government final consumption expenditure (GFCE), Gross fixed capital formation (GFCF), Stock Exchanges (SE), Goods and Services Expenditures (GSE), and Import of Goods and Services (IGS). In their study, data have been drawn from the Turkish Statistical Institute website, 52 data pieces have been used for each variable covering 13 years from 1998 to 2010 in quarterly basis. The adopted data was splitted into 20% for testing and 80% for training, this randomly created 4 different groups.

For performance evaluation metrics; RMSE (Root mean square), MSE (Mean Square Error), and MAPE (Mean absolute percentage error) were used as they are commonly used in prediction evaluation. The authors tested several ANN models with different training and learning functions. The obtained results concluded that using the ANN model inforecasting GDP has improved the forecasting performance of macroeconomic indicators.

In [27] the author explored the positive relationship between the country's economic growth and the stock market development. They adopted ANN as a predictive tool versus the statistical method of multiple regression analysis. The authors illustrated Nigeria's economic growth represented by GDP as a function of key stock market indicators including Market Capitalization (MC), All-Share Value Index (ASVI), Number of Deals (ND), Total Value of Shares Traded (TVST), and Inflation Rate (IR). They aimed in their work to examine the ability of ANN in the prediction of GDP and compare the prediction accuracy of ANN against the traditional prediction technique of multiple linear regression analysis.

The authors adopted quarterly data with a sample period from 1990:Q1 to 2009:Q4. This was to ensure enough data points for the analysis. The data were obtained from the Central Bank of Nigeria and Nigeria Stock Exchange (NSE) official reports and publications. The perfo mance evaluation has been carried out in two parts; the first one was to evaluate the correlation between GDP and the independent stock market indicators. And the second part was to evaluate the prediction capabilities of the two models (Regression model, ANN model) using evaluation metrics e.g., Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Normalized Mean Square Error.

In [41] the authors aimed to enhance the prediction accuracy Anhui province GDP using an improved Back Propagation (BP) neural network. The improved BP model was proposed to overcome the shortcoming of the traditional BP neural network e.g., the local minimum and slow convergence speed, etc. The improved BP neural network was proposed using the momentum factor, steepness factor, adaptive learning rate, and optimized genetic algorithm that overcame the aforementioned shortcomings in the sense that, the momentum factor improved the training speed and avoided the local minimum problem. Also, the the convergence speed have been improved using the steepness factor and adaptive learning rate as well. The proposed model was compared against the traditional BP model and other models, such as ARMA and SVR model. The obtained prediction results showed the proposed model superiority over the alternatives on both RMSE and MAPE. It also showed that the proposed model has the good predictive ability in forecasting Anhui province GDP.

In [39] the author demonstrated the prediction of GDP development in Eurozone countries until the year 2025. The authors applied neural networks looking for the GDP growth time-series in the period 1960 to 2015, then based on the obtained results, they estimated the GDP growth of Eurozone countries until the year 2025. Radial Basic Function neural network (RBF) and Multiple Perceptron Neural network (MLP) with different structures were selected in the prediction process. The selected neural structures exhibited satisfactory numerical characteristics and were equivalent to expert evaluations of GDP development.

The authors aimed to achieve the best selection of ANN and GDP development prediction of Eurozone countries. Based on the conducted analysis, the RBF 1-10-1 network was determined to be the best since it exhibited satisfactory numerical characteristics, i.e., minimal residues, also it came substantially close to the possible GDP development that was achieved by expert analysis. From the obtained results, it can be stated that the RBF models appeared to be the most useful tool for predicting GDP.

In [8], the authors proved that Japan GDP growth can be calculated using "‘Hybrid ANN"’ rather than multiple regression models. The author demonstrated that a hybrid ANN model outperformed both filtered multiple regression models and simple multiple regression model. The authors adopted 12 independent variables for their hybrid modeling and observed that not all of the 12 independent variables were significantly impacted the model. Thus, non-significant independent variables have been removed from the model. As a result, some of the factors that affected Japan's GDP growth have been defined and have proven the hybrid ANN model efficacy over multiple regression models.

The authors in [13] aimed to forecast Albania's GDP. They designed an ANN model equipped with the Genetic Algorithm (GA) as a learning algorithm instead of the traditional gradient descent, called the "‘neuro-genetic"’ model. They adopted 10 factors that affected Albania's GDP forecasting. The authors adopted GA to train the weights of different ANN architectures, then compared the output of these models and find the best ANN architecture that achieved GDP forecasting with high accuracy.

The accuracy of GDP forecasting using ANN model depends on the variables selection that were included as input to the network. These variables were collected from three categories; economic variables, financial variables, and variables from surveys. The neuro-genetic forecasting GDP growth accuracy was evaluated against real GDP growth using Mean Forecasting Error (MFE), Mean Absolute Error (MAE), Tracking Signal (TS), and Mean Square Error (MSE). The obtained results showed that the forecasting model tended to slightly overforecast, with an average absolute error of 0:195.

4.5 Inflation Rate

The Consumer Price Index (CPI), i.e., the inflation rate reflects the increased cost of living. The CPI is calculated by measuring the costs of essential services and goods, including vehicles, professional services, medical care, clothing, shelter, transportation, and electronics. Then, inflation is determined by the average increased cost of the total basket of goods over a period of time.

In [10], the authors presented a new approach that forecasts the inflation rate precisely considering the financial markets non-linear nature and complex behavior. The authors introduced a hybrid model that attempted to forecast the inflation rate in the presence of subtractive clustering technique and a fuzzy inference neural network. The authors aimed from this integration was to overcome the individual methodologies shortcomings. The authors started to select macroeconomic factors to predict the CPI historical data from the US markets. This selection has been carried out in three stages; the first stage involved performing a literature survey on macroeconomic variables, as a result a list of the candidate macroeconomic and financial variables have been generated. After that, the financial expert started to choose the most widely used and significant variables. At the second stage, rules identification was performed by applying the subtractive clustering algorithm. In the final stage, the generated rules in the second stage were fed to the Fuzzy Inference Neural Network. The authors aimed at these three stages to forecast the CPI prices change in coming periods.

In [32], the author demonstrated the adoption of ARIMA model in forecasting the Kingdom of Bahrain inflation rates since it is one of the most widely used methods in forecasting time-series data. The authors explained their steps in defining the ARIMA model and its usage. The first step towards model selection was to differentiate the time-series data to achieve model stability. Once this process was completed, they examined the correlation to specify the AR and MA components orders. It is worth mentioning that, choosing the AR and MA components orders were achieved based on personal judgment since no clear cut rules were defined in deciding the appropriate orders of AR and MA components.

Thus, experience played a vital role in this step. The next step was to estimate the tentative model followed by achieving diagnostic check. The diagnostic testing was usually done by generating a set of residuals and testing these residuals whether they satisfied the white noise process characteristics or not. In the case they are not satisfying, respecification the tentative model is urgently required and the process repeated again; this time from the second stage. The process might proceed until an appropriate model was identified. After following these steps, they considered only the AIC as the criteria for choosing the best forecasting model for Bahrain's inflation rate, and so, the ARIMA (0; 1; 1) model was accurately selected.

The used data for evaluating the prediction model was the annual inflation rates in Bahrain in the period from 1966 to 2017 and was collected from the World Bank. The authors in this research decided to forecast inflation rate in the Kingdom of Bahrain for the upcoming period from 2018 to 2027 and the defined model with accurate fitting results was selected.

The authors presented the ARIMA (0; 1; 1) as the selected model. The achieved diagnostic check indicated that Bahrain inflation series was I (1). In performing the stability test on the selected model, the authors confirmed that the chosen ARIMA (0; 1; 1) model was stable and suitable for predicting inflation in Bahrain over the period under study since the corresponding inverse roots of the characteristic polynomial lied in the unit circle. Furthermore, they performed some statistical measurements, indicating that the inflation series was non-symmetric and positively skewed indicating the normal distribution characteristic in the inflation series.

The forecasting results obtained in the period from 2018 to 2027 showed that Kingdom of Bahrain inflation rate was expected to be around 1:5% in the next 10 years (approximately 1:5% by 2020). This proved the existence of price stability in the Kingdom of Bahrain and this was predicted over the next decade. Finally, the authors confirmed that ARIMA (0; 1; 1) model was the stable and the most suitable model to forecast Kingdom of Bahrain's inflation rate in the coming ten years.

5 USING ECONOMIC INDICATORS IN ECONOMIC GROWTH PREDICTION

In this section, multiple research adopted economic indicators as predictors to country economic growth. Some research used a combination of multiple indicators. Other researches predicted new economic variables that impacted the country's economic growth.

In [2] the authors demonstrated the prediction of the Indonesian economic growth using macroeconomic variables that considered as a good indication to the country economical state. They proposed time-series forecasting model based on ANN to predict economic growth using economic indicators' historical data such as GDP constraint price, government total expenditures, total investment, export, and import. The authors performed many experiments that tested multiple ANN configuration in order to select the best ANN architecture. They evaluated the tested configurations accuracy using MAPE metric. Moreover, MSE metric was used to measure the error in the training process represented by the average error between the actual outputs and the desired targets. As a result, the best ANN archi- tecture configuration was 5-11-1 ¹2N +1º, the selected architecture achieved a good fit model with error in training equal 0:001537, and 95:81% forecasting accuracy represented by the average error between the actual outputs and the desired targets. As a result, the best ANN architecture configuration was 5-11-1 (2N +1), the selected architecture achieved a good fit model with error in training equal 0:001537, and 95:81% forecasting accuracy.

In [14] the author demonstrated the importance of forecasting energy consumption especially electricity demand. They explained that, recently an extremely increase in the electricity demand has been noticed since the world became more populated and as more electrical appliances dominated in the people's daily lives. Thus, different forecasting tools have been applied to predict future electricity demand. In this work, the authors adopted Multiple Layer Regression (MLR) in modeling Turkey's annual gross electricity demand. They also adopted ANN models using multiple descriptor variables such as population, inflation percentage, GDP, unemployment percentage, average summer temperature, and average winter temperature.

It was observed that, population and GDP among the other variables were the major factors that affected the electricity demand, while average summer temperature and inflation percentage had minor effect. Moreover, the authors discovered that other factors like unemployment percentage and the average winter temperatures were insignificant in determining the electricity demand from 1975 to 2013. So, they excluded the inefficient data between 2007 and 2013 from the dataset, and adopted the time-series ANN models to predict the significant descriptor variables in these years. The adopted ANN models were trained by the data from 1975 to 2006. Then, the authors constructed the MLR and the ANN model to simulate the adopted variables predicted values. The authors validated the proposed models by forecasting the electricity demand between 2007 and 2013.

The obtained results from the aforementioned experiments showed that the ANN model prediction accuracy outperformed the official predictions (published by the Ministry of Energy and Natural Resources of Turkey). However, the MLR model prediction accuracy was unacceptable. This proved the successful validation that have been achieved on the applied ANN modeling approach.

The authors applied a similar electricity demand forecasting procedure in the period from 2014 to 2028 using the statistically significant descriptors' values. They simulated ANN model to forecast the electricity demand for the future years using the adopted descriptors' predicted values. The obtained results showed that in 2028 the electricity demand will be doubled reaching over 460 TWh. To conclude, the authors in this work discovered the significant influence of the statistically descriptor variables on the electricity demand. Thus, the proposed models can be implemented in other countries for accurate predictions in the future.

In the work presented in [34], the authors examined the relation between economic growth and inflation in Nigeria within the period from 1961 to 2016. In addition, the study estimated the inflation threshold as well as inflation rate forecasting in the same period. The study employed Granger causality test, Autoregressive Distributed Lag (ARDL), ARIMA, and a multivariate time-series Vector AutoRegressive (VAR) models. The obtained results from Granger causality test showed that there is no causality relationship between economic growth granger and inflation in both directions during the study period. Furthermore, the authors in their study attempted to adopt VAR and ARIMA methodologies inforecasting the inflation rate. The obtained results showed that VAR achieved a high degree of accuracy in forecasting the inflation rate in Nigeria. The study concluded that achieving of 14% inflation threshold would improve the Nigerian economy and put it on a stable growth path. Using an accurate inflation level forecasting would help policymakers in maintaining their economic effective policies.

6 CONCLUSION

The main objective of this research was to assist decision makers in their economic strategic planning by providing additional economic indicators to assess their countries economic state and to measure the impact of their effective policies and decisions on different economic activities. The paper summarized popular economic indicators and explained different techniques used in predicting popular economic indicators as well as using these indicators in predicting the economic growth or predicting other economic variables that affect the country's citizenry living. The importance of this research stemmed from predicting and preventing the occurrence of an economic crisis that could take place again in the near future by efficient forecasting of the economic conditions in the country.

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