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Review Article

Stock Market Prediction using Novel Deep Learning Approaches: A Review

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Abstract - *Stock market prediction has been an intriguing subject for academic researchers and financial experts for a long time. Stock data is highly volatile, which makes stock price prediction a difficult challenge. Financial experts use a combination of various fundamental and technical stock analysis techniques to understand market trends and make decisions. Countless studies have presented numerous stock prediction frameworks. But the researchers are still on the quest of achieving better accuracy to maximize profits. Recent advancements in deep learning have enabled researchers to develop various stock prediction techniques which outperform previous methodologies. This review study is aimed at analyzing 15 novel deep learning-based stock prediction techniques from 2020-2021. These studies are selected from journals of notable publishers. The review includes a discussion of datasets, models, evaluation metrics, and results obtained by these techniques. Researchers have employed a combination of techniques ranging from word embedding algorithms, candlestick charts analysis, deep neural networks, deep reinforcement learning, Long Short Term Memory (LSTM), and Convolutional Neural Network (CNN) to perform stock market prediction. CNN and LSTM based predictive models have shown great results. All novel approaches achieved better results compared to previous state-of-the-art techniques. It can be concluded that stock market prediction is very complex due to its volatile and chaotic nature. This survey highlights the open issues of stock market prediction and aims to serve as a guideline for future research directions. As the technology progresses, we'll continue to observe better deep learning approaches for stock market forecasting.*

Keywords - *Stock Prediction, Technical Market Analysis, Deep Learning, Reinforcement Learning, LSTM.*

I. INTRODUCTION

Individuals, investors, and countries all rely on financial markets to gain economic success and stability. But due to high volatility in the stock market, the risk of financial loss increases manifold. To curb these financial losses, both market investors and academic researchers have proposed numerous stock market prediction techniques that can support the financial decision-making process and ultimately reduce the chances of massive financial losses. On the one hand, we have an Efficient Market Hypothesis (EMH) which states that one cannot predict the outcome of the stock market as the stock values are determined by all the currently available information and to forecast stock prices, new real-time news, or information is necessary.

With the advancement in artificial intelligence, which feeds on data, we have state-of-the-art prediction systems for almost all domains. As the stock market is data-intensive, researchers have formulated numerous deep learning stock price prediction techniques over the years. We have automated stock traders, automated stock portfolio optimizers based on Modern Portfolio Theory (MPT), which can reallocate funds to maximize stock profits and curtails financial losses. Now, researchers not only rely on the historical stock data but also consider market sentiment while proposing robust solutions. Social media websites like Twitter and other news-related platforms are scraped to obtain the required financial news to analyze the impact of news on stock prices. Investors make financial projections based on all available information which can include changing political situations and government policies. Researchers use different feature selection and extraction techniques based on the historical stock time-series datasets. The datasets usually contain the stock closing price, volume, opening price, highest price, and lowest price for a certain number of trading days. With all this information available, the researchers have proposed hybrid deep learning models that are capable of learning highly chaotic non-linear stock data.

In the past, various studies have been conducted which present a survey of the numerous stock prediction techniques. These surveys include basic or fundamental stock analysis techniques which only rely on the company's stock information, financial statements, or market environment to determine whether the stock price is overvalued or undervalued. And technical stock analysis techniques that consider trends, formations, and market philosophy based on the historical stock data, before reaching a decision. In this regard, the Dow Theory for price development serves as a guideline for investors to make Buy, Sell and Hold decision-based on the current stock price and its historical trends. These surveys also cover automated stock trading and prediction techniques based on machine learning and deep learning. Nti, Adekoya, and Weyori [1] summarized 122 techniques and concluded that ANN and SVM-based machine learning techniques are commonly used for predicting stock market data. However, further work is required to improve the accuracy of these models, which can be done by using hybrid ensemble machine learning models. Usmani and Shamsi [2] reviewed 99 papers and concluded that various CNN and LSTM based techniques are effective in stock prediction with more focus on financial news categorization to understand the impact of news on the stock prices. This survey also highlights various pre-processing and feature extraction techniques. İcan and Çelik [3] condensed 25 ANN-based papers and compared their techniques and results. This survey concluded that ANN observes better results when it is combined with other statistical techniques to predict the stock market. Gandhmal and Kumar [4] summarized 50 papers that discussed various techniques ranging from ANN, SVM, Fuzzy classifiers, Bayesian model, and other machine learning techniques. This survey found ANN and Fuzzy classifiers as the most used techniques in stock market prediction. Building on the previous surveys, we are going to target the latest advances in stock market forecasting and discuss novel deep learning approaches that have displayed promising results.

Table 1. Important notations are used in this paper

Abbreviation	Description
Adaboost	Adaptive Boosting
ANN	Artificial Neural Network
ARFIMA	Autoregressive Fractional Integrated Moving Average
ARIMA	Autoregressive Integrated Moving Average
BI	Binomial Tree
BIST	Borsa Istanbul Stock Exchange
BR	Bayesian regularization
BS	Black-Scholes
CNN	Convolutional Neural Network
CT2TFDNN	Chaotic Type-2 Transient-Fuzzy Deep Neurooscillatory Network with Retrograde Signaling
DDQN	Double Deep Q-network
DNN	Deep Neural Network
DMLP	Deep Multilayer Perceptron
DRL	Deep Reinforcement Learning
FCM	Fuzzy c-means Clustering
FDM	Finite Differential Method
FPA	Flower Pollination Algorithm
GA	Genetic Algorithm
GRNN	Generalized Regression Neural Network
IM	Levenberg–Marquardt
KNN	K-Nearest Neighbors
KOSPI	Korea Composite Stock Price Index
LSTM	Long Short Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MC	Monte-Carlo method
MSE	Mean Squared Error
MDD	Maximum Drawdown
NARX	Nonlinear Autoregressive Artificial Neural Networks
PMMRL	Parallel Multi-Module Deep Reinforcement Learning
PSO	Particle Swarm Optimization
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
ROMAD	Return Over Maximum Drawdown
SCG	Scaled Conjugate Gradient
SVC	Support Vector Classifier
SVM	Support Vector Machine
XGBoost	eXtreme Gradient Boosting
YOLO	You Only Look Once

Table 1 presents a summary of major notations used in this paper for the reader's convenience. The purpose of the work presented in this study is summarized as:

(1) To highlight the most recent advancement in stock market prediction and analysis.
(2) To show the technological trends in stock market prediction, which can serve as a guideline for future researchers.
(3) To highlight the flaws in the current stock market prediction ecosystem.

The remaining paper is organized into 3 sections. Section 2 states the research methodology adopted to select relevant research materials required for this review. Section 3 summarizes the details of all the selected state-of-the-art deep learning approaches proposed by the various researchers. This includes different preprocessing techniques, selected datasets, model design or architecture, and evaluation criteria. It presents a summary of the effectiveness of the novel deep learning approaches in stock market forecasting. Section 4 concludes this review paper by providing a summary of all the sections and further outlining the future research directions.

II. RESEARCH REVIEW METHODOLOGY

This section discusses the process adopted to filter out the research content relevant to this review. Fifteen papers related to deep learning-driven stock market prediction were randomly selected from IEEE, Elsevier, and Springer due to their high impact factor with selection preference given to journals. Only those papers were selected which presented a state-of-the-art deep learning-based solution for the stock market published from 2020 to 2021. Table 2 shows a breakdown of the research paper count based on the publisher.

Table 2. Summary of the paper count

Publisher Name	Paper Count
IEEE Explore	7
Elsevier	4
Springer	4
Total	15

III. LITERATURE REVIEW

This section discusses the previous research on analyzing the stock market using novel deep learning techniques. It summarizes the approaches used by the researchers along with their model evaluation criteria and results. Table 3 presents a summary of these researches, which includes the data source, proposed techniques, evaluation metrics, and their values.

Table 3. Summary of novel deep learning approaches for stock market forecasting

Paper Reference	Data Source	(1) Proposed Models (2) Evaluation Metrics	Best Results
[5]	Textual Data from Twitter, Mynet Finans, Bigpara & KAP	(1) Word2Vec+CNN, GloVe+CNN, FastText+CNN, Word2Vec+RNN, GloVe+RNN, FastText+ RNN, Word2Vec+LSTM, GloVe+LSTM, FastText+LSTM (2) Accuracy	Word2Vec+LSTM = 80.61% FastText+LSTM = 86.39% Word2Vec+RNN = 77.82% FastText +RNN = 79.74%
[6]	Historical data (2009-2018) of Pakistan Stock Exchange (PSX)	(1) ARFIMA-LSTM (2) RMSE, MAE, MAPE	RMSE = 0.0539 MAE = 0.02694 MAPE = 0.002%
[7]	Historical Data of London, National, New York, Bombay, Nasdaq, and Toronto Stock Exchanges	(1) RNN-LSTM with PSO and FPA (2) Error rate, Precision, Recall, F1-score	Average metrics values using FPA: Error rate = 0.14 Precision = 0.87 Recall = 0.86 F1-score = 0.86 Average metrics values using PSO: Error rate = 0.15 Precision = 0.85 Recall = 0.85 F1-score = 0.85
[8]	550 2D candlestick charts created from the historical stock data (2000-2018) of Borsa Istanbul (BIST)	(1) YOLO DarkNet-53 (2) IoU for bounding boxes, the Prediction accuracy for the "Buy-Sell" label	IoU true positive threshold value = 0.5 Prediction Accuracy = 83%
[9]	Historical data from Shanghai & Shenzhen securities index and S&P 500 companies index.	(1) Online clustering-based DRL (2) Profit, Accuracy	Profit = 14507.9 Accuracy = 0.551
[10]	Historical data (2000-2019) of 30 companies of Dow Jones Industrial Average index.	(1) Adaptive Sentiment-Aware Deep Deterministic Policy Gradients (2) Sharpe Ratio, Annualized Return (%), Annualized Standard Deviation Error, Final Portfolio Value	Sharpe Ratio = 2.07 Annualized Return = 22.05 Annualized Standard Deviation Error = 0.096 Portfolio Value = $25,051
[11]	Historical data of 8 indices of American and Chinese stock markets. NASDAQ data is also	(1) Double Deep Q-Network (2) Accuracy	Accuracy (average accuracy of 8 stock indices) = 0.5936

Paper Reference	Data Source	(1) Proposed Models (2) Evaluation Metrics	Best Results
	used.		
[12]	Historical data (2005-2020) from Shanghai and Shenzhen Stock Exchanges available on JointQuant	(1) Parallel Multi-Module Deep Reinforcement Learning (PMMRL) (2) Cumulative Return Ratio (%), Sharpe Ratio, Sortino Ratio, Calmar Ratio, Maximum Drawdown (MDD) (%), Longest DD days	Best metric values for different stocks: Cumulative Return Ratio = 533.42 Sharpe Ratio = 1.86 Sortino Ratio = 3.38 Calmar Ratio = 2.47 MDD = -10.40 Longest DD days = 111
[13]	Historical data of S&P 500, JP Morgan and Microsoft single stock indexes.	(1) RL-ensemble (2) Long Precision, MDD, Return, RoMAD	Proposed technique metrics values: Long precision = 0.50 MDD = 221.74 Return = 1265.50 RoMAD = 5.70
[14]	Historical data of 9 major cryptocurrencies from AvaTrade.com, 84 foreign currencies, 19 commodities, & 17 financial indices from forex.com.	(1) CT2TFDNN (2) Target RMSE, Average System Training Time (Av. STT)	RMSE = $1x10^{-7}$ Av. STT = 983.19
[15]	Historical data (2000-2016) of KOSPI from Bloomberg.	(1) GA-CNN (2) Accuracy	Accuracy = 73.74%
[16]	Historical data (2009-2019) of 4 stock market groups (petroleum, diversified financials, basic metals , and non-metallic minerals) from www.tsetmc.com	(1) Decision Tree, Random Forest, Adaboost, XGBoost, SVC, Naïve Bayes, KNN, Logistic Regression, ANN, RNN, LSTM (2) Accuracy, F1-score & ROC-AUC curve	RNN on binary data: Accuracy = 0.8875 F1-score = 0.8925 ROC = 0.885 LSTM on binary data: Accuracy = 0.885 F1-score = 0.89 ROC = 0.88
[17]	Historical data (2007-2015) of China Securities 100 Index	(1) DMLP+MSAD, DMLP+EW, LSTM+MSAD, LSTM+EW, CNN+MSAD, CNN+EW, SVR+MSAD, SVR+MV (2) Stock return predictive performance: MAE, MSE, H_R, H_{R+}, H_{R-} Portfolio optimization model: ER, SD, IR, TOR, MD, TUR	For DMLP (2015): MAE = 0.2617 MSE = 0.1336 H_R = 49.32% H_{R+} = 49.46% H_{R-} = 47.54% DMLP+MSAD (R_p=0.04): ER = 87.49% SD = 0.9452 IR = 0.9256 TOR = 338.41% MD = 59.74% TUR = 82.24%
[18]	Historical data (July 2018- December 2018) of S&P 500 call options from DeltaNeutral, EuroStoxx50 call options, and Hang Seng Index put options from IVolatility.	(1) DeepOption (2) RMSE, MAE, MAPE	Best metric values for the 3 options: RMSE = 11.0 MAE = 7.0 MAPE = 9.8
[19]	Historical data of 6 Egyptian Stock Exchange indices from Egypt for Information Dissemination (EGID)	(1) NARX with BR, IM, and SCG (2) MSE, Pearson correlation R	Best MSE = 0.42055 Best R value = 0.99

A. Hybrid CNN & LSTM Techniques

Kilimci and Duvar [5] examined the direction highest transaction volume banking stocks in Istanbul Stock Exchange (BIST 100) using a combination of deep learning and word embedding algorithms. To make a robust prediction model by capturing market sentiment, they utilized social media and financial platforms like Twitter, Public Disclosure Platform (KAP), Mynet Finans, and Bigpara to obtain user financial reviews, comments, Turkish financial analysis, and announcements. The first phase examines the labeled preprocessed datasets collected from these platforms using three-word embedding algorithms, namely Word2Vec, GloVe, and FastText, to create 100-dimensional word vectors which are utilized in the second phase as input to three deep learning models: CNN, RNN & LSTM to predict the direction of stocks. A total of nine hybrid models are trained, where each word embedding output is fed to each deep learning model. The researchers concluded that using a combination of word embedding and deep learning outperforms the accuracy results of individual techniques.

Bukhari et al. [6] introduced a novel ARFIMA based LSTM hybrid model which minimizes the stock forecasting risks caused due to fast fluctuations present in the stock data of the Pakistan Stock Exchange (PSX). The training pipeline starts with data cleaning and transformation, where seasonality and trend are removed. Then, the ARFIMA sequence is prepared by estimating the AR and MA parameters using Box-Jenkin's methodology. The ARFIMA output is passed to the LSTM model as input to detect patterns in the data after removing any residual noise. This hybrid model is evaluated using RMSE, MAE, and MAPE metrics. Individual ARFIMA, ARIMA, and GRNN models are also trained for comparison. The researchers concluded that the hybrid ARFIMA-LSTM model achieved the lowest evaluation errors.

Kumar and Haider [7] proposed a hybrid RNN-LSTM model with two optimization techniques: PSO and FPA for stock market forecasting on six stock exchange datasets. The technique is divided into three layers. The data preparation layer performs data extraction, feature selection, and feature engineering on 14 technical indicators. See Table 4 for a list of major indicators. The second layer contains the RNN-LSTM model where PSO and FPA are applied to automatically optimize the hyper-parameters like time lag, number of hidden layers, batch size, epochs, and number of hidden neurons. The third layer contains the optimized model, which is used for model evaluation. The proposed model is evaluated based on error rate, precision, recall, and f1-score. The model is compared with previous state-of-the-art approaches, and it outperforms them by reducing the error rate by 35% and increasing the remaining metrics values by 6%.

Birogul, Temür, and Kose [8] introduced a state-of-the-art YOLO model for real-time object detection on 2D candlestick charts of stocks available on BIST from 2000-2018 to make “Buy-Sell” decisions. Instead of analyzing the numerical data, this research relies on examining 550 labeled (“Buy” and “Sell” signals) 2D candlestick chart images created from that data. A candlestick chart displays the high, low, open, and close prices of the stocks. A sample candlestick chart is presented in Figure 1. It represents the trends and formations in stock data. YOLO is a CNN-based model which accurately detects the “Buy-Sell” signal labels in the charts. To reduce the training time, YOLO utilizes pre-trained weights of the DarkNet-53 backbone model. Intersection over Union (IoU) metric was used to evaluate the predicted bounding boxes of the "Buy-Sell" labels marked on the chart. The trained model was tested on 1-year candlestick charts after 2018. The model was able to predict "Buy-Sell" signals on the charts with more than 80% accuracy. At some places, the model failed to predict any label. The authors concluded that the investors could use this model to strengthen the "Buy-Sell" decision for any stock along with other techniques.

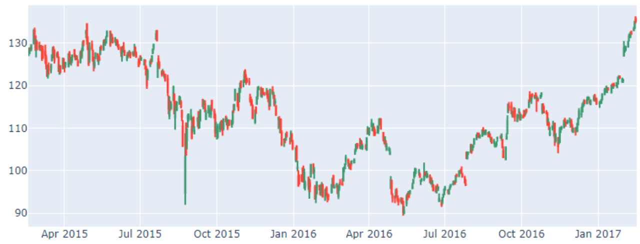

Fig. 1 Candlestick chart of AAPL stock from Apr 2015 to Jan 2017.

B. Hybrid Reinforcement Learning Techniques

Fengqian and Chao [9] proposed a new deep reinforcement learning (DRL) based method to select the learning features of stock market data using K-line candlesticks generalization. Candlestick charts are also known as K-line. Several experiments are conducted to check the robustness of the proposed model. The data used in these experiments comes from Shanghai and Shenzhen securities indexes. In this research, stock data is denoised by K-line features calculation. K-means, FCM, and online clustering are applied to this denoised data. The cluster centers are passed as input data to the DRL method, which maximizes the reward function by using the q-learning technique. DRL with an online clustering approach maximizes the stock profits. The proposed DRL model is also compared with RNN, LSTM, and FNN models. The data used in these experiments are taken from the S&P 300 index from the period of 2000-2016. The results favored the proposed approach to obtain high profit and a high winning rate for stock. The authors concluded that with DRL-based prediction models, investors could make better-informed decisions on real-time stock data.

Koratamaddi, Wadhwani, Gupta, and Sanjeevi [10] examined the stocks of 30 Dow Jones listed companies using a novel deep reinforcement learning model. The authors implemented an automated stock trader who predicts stock prices based on historical data of stock prices and the market sentiment about the stocks to maximize the returns of the stock portfolio. The proposed approach is called Adaptive Sentiment-Aware Deep Deterministic Policy Gradients, which incorporates market sentiment by analyzing Google News and Twitter data related to the 30 Dow Jones companies. Google News sentiment score and Twitter sentiment score is calculated for each company's stock which was combined with Dow Jones stock closing price data and passed to a Q-value-based deep reinforcement learning model. The authors concluded that their sentiment-aware stock trader achieved higher stock value when compared with other portfolio prediction models.

Shi, Li, Zhu, Guo, and Cambria [11] proposed a novel reinforcement learning-based double deep Q-network (DDQN) model which employs CNN layers to extracts relationships among different stock trading dates to predict stock price fluctuations on randomly selected stocks for different American and Chinese stock indices. Two reward functions: accrual basis and cash basis, are proposed for DRL training and testing. Training and testing are performed on randomly selected stocks and stock indices from all over the world. The proposed approach rewards the buying, selling, and holding actions of the stocks. DDQN outperforms its SVM and LSTM based counterparts in most stocks based on accuracy and returns. It also solves the stock prediction overestimation problem by efficiently extracting features and finding hidden dependencies in those features. The authors also concluded that the accrual basis reward function is better than the cash basis function in terms of accuracy.

Ma, Zhang, Liu, Ji, and Gao [12] introduced a novel learning framework known as Parallel Multi-Module Deep Reinforcement Learning (PMMRL) that uses DDQN to derive the optimal policy in combination with LSTM layers to predict the long-term trends in the China stock market. The proposed algorithms execute two approaches in parallel. The first module learns the current state of the market using fully connected neural network layers, and the second module learns the historical trends in the stock data using LSTM. Input data contains different stock prices and several indicators. See Table 4 for a list of major indicators. The proposed approach is compared with several baseline methods and evaluated on several performance metrics. See Table 3 for a list of performance metrics. The proposed model outperforms baseline models for most metrics. The research analyzes individual stocks to perform a detailed analysis. The authors concluded that the proposed algorithm could be used for stock trading, but more work needs to be done for portfolio management.

Carta, Corrigan, Ferreira, Podda, and Recupero [13] analyzed S&P 500, JP Morgan, and Microsoft stock data by introducing a three-layered novel reinforcement learning (RL) and multi-ensemble stock trader. The first layer pre-processes the time series data and converts it into images where 1000s of CNNs are applied on these images to extract meta-features which are used as input to the next layer. The second layer applies the Double Q-learning technique to perform stacking. The third layer combines all outputs of the previous layer to make a trading decision. Several evaluation metrics are employed to check the robustness of the proposed model. The RL-ensemble approach maximizes the stock return by 28.78% when compared with other baseline trading approaches. The proposed approach also outperforms other state-of-the-art techniques like CNN-Tar and LS-STM (Support Tensor Machine).

Table 4. Some major financial trading indicators

Notation	Indicator Name
AC	Accelerator Oscillator
AD	Accu. and Distribution
ADX	Average Directional Movement Index
ADXWilder	Average Directional Movement Index by Welles Wilder
Alligator	Alligator
AMA	Adaptive Moving Average
AO	Awesome Oscillator
ATR	Average True Range
BearsPower	Bears Power
Bands	Bollinger Bands
BullsPower	Bulls Power
CCI	Commodity Channel Index
Chaikin	Chaikin Oscillator
Custom	Custom indicator
DEMA	Double Exponential MA
DeMarker	DeMarker
DX	Directional Movement Index
EMA	Exponential Moving Average
EMV	Ease of Movement
Envelopes	Envelopes
FI	Force Index
Fractals	Fractals
FrAMA	Fractal Adaptive MA
GO	Gator Oscillator
Ichimoku	Ichimoku Kinko Hyo
IMI	Intro-day Momentum Index
BWMFI	Market Facilitation Index
Momentum	Momentum
MFI	Money Flow Index
MA	Moving Average
OsMA	Oscillator of Moving Average
MACD	Moving Average Convergence Divergence
OBV	On Balance Volume
SAR	Parabolic Stop & Rev Sys.
ROC	Rate of Change
RSI	Relative Strength Index
RVI	Relative Vigor Index
SMA	Simple Moving Average
StdDev	Standard Deviation
Stochastic	Stochastic Oscillator
TEMA	Triple Exp. MA
TriX	Triple Exp. MA Oscillator
WPR	Williams' Percent Range
VIDyA	Variable Index Dynamic Av.
Volumes	Trading Volumes

C. Hybrid Genetic Algorithm Techniques

Lee [14] analyzed 129 worldwide financial products and proposed a state-of-the-art Chaotic Type-2 Transient-Fuzzy Deep Neurooscillatory Network with Retrograde Signaling (CT2TFDNN) deep learning approach that resolves the overtraining and deadlock issues of the neural network to forecast highly unpredictable financial products. The CT2TFDNN consists of four parts: Chaotic neural oscillators, which represents the basic structure of the neural networks in this technique; a Chaotic Type-2 Transient-Fuzzification technique which models 39 input trading signals, Genetic Algorithm (GA) is used for selecting 10 most important financial trading signals from the list of 39, and Chaotic Transient-Fuzzy Deep Neuro-oscillatory Networks with Retrograde Signaling technique is used for financial predictions. By selecting only 10 input signals using GA, it eliminates the overtraining and deadlock problems of massive financial datasets. CT2TFDNN is compared with 5 prediction models with RMSE as the evaluation metric. The author concluded that the proposed techniques show promising results where it outperforms 2 predictions models in performance comparison and performs at par with the rest.

Chung and Shin [15] proposed a GA-based CNN approach to automatically optimize the CNN model hyper-parameters. Seven financial indicators are calculated from the 17-years of KOSPI historical data, which are used as seven input channels for CNN. GA population includes chromosomes with coded information about the number of convolutional layer kernels, size of the kernels, and pooling window size. The fitness is calculated for each chromosome of the population based on the accuracy of stock market movement. Crossover and mutation are also applied to produce future generations. GA converges to an optimal solution of hyper-parameters. Figure 2 presents the complete GA process. The novel approach is compared with ANN and CNN models and found to be more accurate in predicting the stock market. The authors concluded that GA-based CNN is effective in predicting stock market data, and this approach for hyper-parameter optimization can be further extended to include more hyper-parameters in the search space, which may further increase the accuracy of the model.

D. Other Novel Techniques

Nabipour, Nayyeri, Jabani, Shahab, and Mosavi [16] suggested a new method for reducing the risk of predicting stock market trends using different machine learning and deep learning approaches by experimenting with two preprocessing techniques for the input data, i.e., continuous data and binary data. The input data consists of 10 technical stock market indicators like Momentum (MOM), Relative strength index (RSI), Commodity channel index (CCI), etc. Table 4 presents some of the commonly used stock market indicators. Each technical indicator is calculated on Tehran's historical stock market data from 2009-2019, belonging to 4 market groups, i.e., non-metallic minerals, diversified financials, petroleum, and basic metals. They compared the performance of 9 machine learning models: Decision Tree, Random Forest, Adaboost, XGBoost, SVC, Naïve Bayes, KNN, Logistic Regression, and Artificial Neural Network (ANN) and two deep learning models: RNN and LSTM. The experiments showed that RNN and LSTM models with preprocessed binary data presented the best performance when compared with continuous data models. The authors concluded that converting input values to binary data can achieve better deep learning model performance, which outperforms machine learning models.

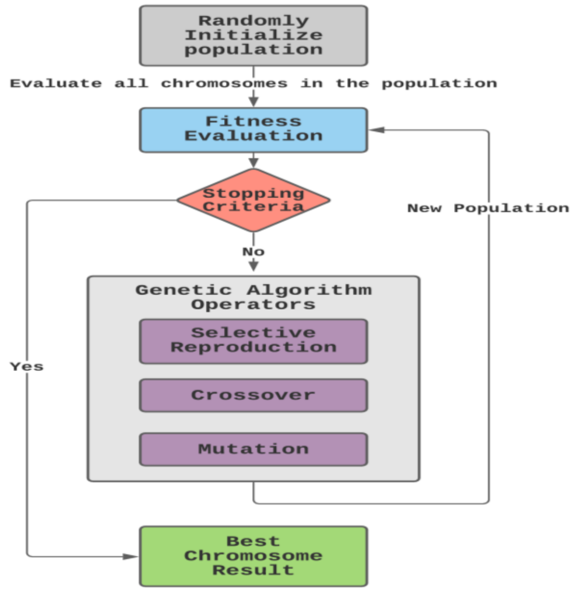

Fig. 2 Genetic Algorithm process flowchart.

Ma, Han, and Wang [17] presented prediction-based stock market portfolio optimization models for the China Securities 100 Index using a combination of DNN like deep multilayer perceptron (DMLP), LSTM, and CNN. They examined 9 years of historical data of China stock market from 2007-2015. First, DNNs predict the stock return for each stock, then prediction-based portfolio models are prepared using semi-absolute deviation (MSAD) and equal weighting (EW) techniques to compare which models maximize the portfolio profits and minimize the risks. In all experiments, the mean absolute error (MAE) and mean squared error (MSE) of DMLP outperform their counterparts to achieve better stock return prediction. For portfolio optimization, three desired return (Rp) values are selected to conduct experiments i.e. 0.001, 0.02, 0.04. DMLP+MSAD portfolio model maximizes the profits for the three Rp values by minimizing the predictive errors.

Jang, Yoon, Kim, Gu, and Kim [18] proposed a novel approach called DeepOption, which works by fusing 4 parametric option pricing methods: BS, BI, MC, FDM to improve the pricing performance in a three-stage training process. In the first and second stages, transfer learning is applied to fine-tune the simulated training data (distilled data) using real-world option pricing data. The distilled data is generated by fusing the four parametric methods. In the third stage, the value of delta is estimated for delta-hedging using the fine-tuned distilled option data. Option pricing data is hard to obtain because of high liquidity and class imbalance problem. These option classes can be in-the-money (ITM), at-the-money (ATM), and out-of-the-money (OTM) in terms of moneyness. The proposed framework solves the class imbalance problem. Several experiments are conducted, and results are compared between individual parametric models, their combinations, and the fusion of all 4 models. The results show that DeepOption, with the fusion of 4 parametric models, achieves the best results for predicting the options price.

Houssein, Dirar, Hussain, and Mohamed [19] presented an RNN based Nonlinear Autoregressive neural network with an Exogenous (NARX) input model for predicting the closing price of stock indices available on the Egyptian Stock Exchange in combination with three training algorithms: BR, IM, or SCG. The three neural network training algorithms aim to minimize network error by optimizing the weights and biases. The model is evaluated using MSE and R metrics. The authors concluded that the proposed NARX model achieved better prediction performance when compared with similar models. Experiments showed that the NARX model with BR training algorithm produced better stock predictions for up to 3 days ahead. Whereas IM achieved better accuracy in price prediction for 7-days ahead. Overall, the three training algorithms achieved more than 95% accuracy in all experiments.

IV. CONCLUSION

Due to the chaotic nature of the stock market, no single approach can guarantee financial success. This is why investors rely on numerous market indicators and techniques to maximize their profits and minimize losses. Deep learning is used frequently to tackle the complex stock market prediction problem. With each passing year, researchers are improving prediction techniques by building hybrid deep learning models. This paper presents a survey of 15 deep learning techniques which are published recently. The main contribution of this paper is highlighting and summarizing the complex hybrid deep learning approaches which can guide future researchers in the right direction.

The survey concludes that techniques like CNN, LSTM, and deep reinforcement learning are all quite effective in stock market forecasting when utilized in an optimized manner. To achieve maximum results using deep learning, the researcher must use a combination of different pre-processing techniques, hybrid models, and optimized hyper-parameters. A drawback of the complexity of the stock market is that no single model fits all requirements.

In most techniques mentioned above, the researchers usually work on a subset of stock market data. Different stock market indexes and financial instruments are randomly chosen to provide a representation of the complete stock market. The results are never completely robust. This is due to massive amounts of historical stock datasets, and the difficulty researchers might face in acquiring them. In the future, researchers can work on building a comprehensive stock trader agent which can effectively cover the complete stock market of a country or at least cover the stocks of all companies in a stock market index. Researchers can experiment with big data techniques to handle large datasets which truly represent the stock market.

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