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A Review of Two Decades of Deep Learning Hybrids for Financial Time Series Prediction

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ABSTRACT: Financial time series is non-stationary, chaotic and noisy. Its prediction is a complex problem. Deep learning, a subset of machine learning, in conjunction with related techniques, is being utilized to predict financial time series. This paper presents a comprehensive review of such deep learning based hybrid forecasting models during 1999-2019. It is observed that there are 34 different deep learning based financial time series prediction hybrids proposed during these two decades. This comprehensive review can be beneficial to financial forecasters to have an idea of existing deep learning hybrids to be applied and to budding researchers to study existing deep learning based hybrids and propose novel hybrids.

Keywords: CNN, Deep learning, Financial time series, Hybrid, LSTM, MLP, Prediction.

Abbreviations: ANN, artificial neural network; AR, auto regression; ARMA, auto-regressive moving averages; ARIMA, auto-regressive integrated moving averages; BPNN, back-propagation neural network; CEEDMAN, complete ensemble empirical mode decomposition with adaptive noise; CNN, convolutional neural network; DBN, deep belief network; DENFIS, dynamic evolving neural-fuzzy inference system; EKF, extended kalman filter; EMD, empirical mode decomposition; ES, exponential smoothing; FOREX, foreign exchange; GA, genetic algorithm; GAN, generative adversarial network; GARCH, generalized autoregressive conditional heteroscedasticity; GLAR, generalized linear auto-regression; GMDH, group method of data handling; GP, genetic programming; GRNN, general regression neural network; LSTM, long short-term memory; MARS, multivariate adaptive regression splines; MGA, meiosis genetic algorithm; MLANN, multi-layer ANN; MLP, multi-layer perceptron; NSGA-II, non-dominated sorting genetic algorithm-II; PR, polynomial regression; PSO, particle swarm optimization; RNN, recurrent neural network; SAE, stacked autoencoder; SVR, support vector regression; VAR, Vector Auto-regression; WN, wilcoxon norm; WNN, Wavelet Neural Network; WT, wavelet transform;

I. INTRODUCTION

Financial time series is a set of chronologically recorded values of financial variable (s). For example, intra-day stock price and daily exchange rates are financial time series. Financial time series are non-stationary and chaotic [1]. A time series is said to be chaotic if it is non-linear, deterministic and sensitive to initial conditions [2]. It is also noisy and its statistical properties are different at different times. It works as a random-walk process, contributing the prediction impossible [3, 4]. So, it reveals that the financial time series prediction is a complex and challenging task.

The construction of a right financial time series prediction model that captures patterns is always the challenging task. As financial time series prediction is a complex task, applying deep learning approaches to achieve better prediction accuracy is a fascinating task [5, 6]. Deep learning, a subset of machine learning, allows ANNs to learn representations of data with multiple levels of abstraction (hierarchical learning) [7, 8]. It is applied to diverse areas of finance including such as stock market prediction, portfolio optimization, financial information processing and trade execution strategies [9]. However, this field still remains relatively unexplored.

Deep learning neural networks can construct non-linear and complex function that maps inputs to output.

The most popular deep learning neural networks used for time series prediction are described as follows:

Multi-layer Perceptron (MLP). A simple MLP model [10] has a single hidden layer of nodes, and an output layer used to make a prediction. In the case of financial time series prediction, MLPs take observations at previous steps as input features and predict one or more observations at future time steps from those observations.

Convolutional Neural Network (CNN). CNN [11] is a neural network that is not only suitable for modeling two-dimensional image data, but also for modeling one-dimensional time series or text data [12]. When operating on one- dimensional financial time series data, the CNN reads across a sequence of lag observations using convolutional layers and learns to extract features that are relevant using pooling and dense layers for making a prediction.

Long Short-Term Memory (LSTM). The LSTM [13] is a type of RNN that will read each time step of financial time series one step at a time. It has an internal memory allowing it to accumulate internal state as it reads across the steps of a given input sequence. At the end of the sequence, each node in a layer of hidden LSTM units will output a single value. This vector of values summarizes what the LSTM learned or extracted from the input sequence.

A hybrid forecasting model (in short, Hybrid) combines two or more stand-alone forecasting models into a combined model in the hope to improve prediction accuracy and overcoming the deficiencies of stand-alone models. Several researchers demonstrated that hybrid or ensemble models do yield better results compared to stand-alone models in the context of time series prediction [14-16]. The current review focuses on various deep learning hybrids available for financial time series prediction.

The rest of the paper is organized is as follows. Section II presents the earlier reviews found in the literature. Later, Section III comprehensively describes the deep learning hybrids found in literature. Finally, Section IV concludes the paper and Section V presents future directions for budding researchers.

II. EARLIER REVIEWS

In the past, there were good amount of reviews of financial time series prediction using ANNs. These are presented in Table 1.

Recently, in 2018, Pradeepkumar and Ravi [22] reviewed various Soft Computing hybrids for FOREX rate prediction. Their work is exclusively for FOREX rate prediction and it does not involve hybrids of deep learning neural networks such as CNN and LSTM. Within this scope, the proposed review:

1. Describes various deep learning neural networks such as MLP, CNN and LSTM-based hybrids applied for financial time series prediction comprehensively and
2. Guides the budding researchers in deep learning for future contributions within the scope of proposed theme.

So, this comprehensive review can be beneficial to financial forecasters to have an idea of existing deep learning hybrids to be applied and to budding researchers to study existing deep learning based hybrids and propose novel hybrids.

Table 1: Earlier Reviews.

Year	Author(s)	Description
2004	Huang *et al.*, [17]	A survey of FOREX rate prediction using ANNs
2007	Yu *et al.*, [18]	A survey of financial time series prediction including 45 journal articles from 1971 to 2004 in detail involving ANN.
2008	Mochon *et al.*, [19]	A short introduction of several application areas including FOREX rate prediction
2010	Li and Ma [20]	The application of ANNs in forecasting various financial market prices
2010	Bahrammirzaee [21]	A comparative survey of ANNs, expert system and hybrid intelligent systems in finance
2016	Cavalcante *et al.*, [5]	An overview of the studies applying computational intelligence techniques for solving financial market problems

III. DEEP LEARNING HYBRIDS

Since there is a lot of growing interest in deep learning, we present here a comprehensive review of all deep learning hybrids for financial time series prediction. We found 34 research papers with the proposed theme (Table 2) from various sources such as Google Scholar, Science direct, Springer Link, IEEE Explore Digital Library, Taylor & Francis, ACM Digital Library, and Wiley Online Library.

Table 2: Deep learning hybrids found in literature.

Year	Deep Learning Hybrid
1999	ANN+GA [35]*
2001	ANN ensemble [36]*
2002	GA+MLP+EKF [37]*; GANN [38]*
2005	ANN+ARIMA [39]*, GLAR+ANN [40], GP+ANN [41]
2006	ANN+SVR [42]*; ES+BPNN [43]
2007	Bootstrapped ANNs[44]
2009	SOMLP [45]; PSOMLP[46];
2009	GA+ANN[47]*;ARIMA+ANN+ Fuzzy Regression [48]*
2010	GA/PSO-based BPN [49]*; ANN+MGA [50]
2011	GA+GA, GA+MLP, GA+PSO[51]*; PSOBPN[52]
2012	MLANN+WN[53];
2012	Ensemble of BPNN, WNN, MARS, SVR, DENFIS, GMDH, and GP [54]*
2014	Chaos + MLP+PSO/PR, PSO+MLP/PR [55]
2015	ARMA+ES+RNN [56]*
2016	ANN-ARIMA [57]
2017	WT+SAE+LSTM[6]*; DA-RNN [58]
2017	Chaos+MLP+MOPSO, Chaos+MLP+NSGA-II[59]*
2018	GEW-LSTM [60]*; ModAugNet [61]*
2018	CNN-TA [62]*; GARCH-LSTM [60]*
2019	EMD-LSTM,CEEDMAN-LSTM [63]*; DBN-AR [64]*
2019	GAN+MLP+LSTM [9]; MFNN [65]*

From literature, it is clearly observed that the financial time series can be predicted using statistical approaches (e.g, [23-25]) and stand-alone deep learning approaches including MLP, LSTM and CNN (e.g., [26-34], [73-74]).

From Table 2, it is also clearly observed that there is good number of research publications in the area of deep learning hybrids for financial time series prediction.

We can also observe that:

1. From 1999 to 2019, there are 34 different types of deep learning hybrids for financial time series prediction proposed.
2. Out of 34 publications, 22 belong to journals and 12 belong to conference proceedings.
3. There are three types of deep learning hybrids found: 1) MLP-based hybrids, 2) LSTM-based hybrids and 3) CNN-based hybrids. Majority of hybrids are MLP-based hybrids. Very less number of hybrids involving LSTM or CNN is proposed.

These deep learning hybrids, in chronological order, are described as follows:

Shazley and Shazley [35] proposed ANN+GA to forecast exchange rate. In this hybrid, GA is used to obtain weights of ANN. The authors concluded that the hybrid could predict the direction of change and turning points. However, the GA parameters such as mutation style, population size, number of generations, and halting criteria should be tuned to get optimal weights of ANN.

Zhang and Berardi [36] proposed a serial ensemble model of ANNs that could predict time series including exchange rates very well. Although the ensemble methods show considerable advantages over the traditional Keep-The-Best (KTB) approach, they do not have significant improvement compared to the widely used random walk model.

Andreou *et al.*, [37] proposed GA+MLP+EKF wherein GA obtained optimal structure of MLP and a localized version of the EKF is used for training. The proposed hybrid could yield better one-step-ahead and multi-step-ahead predictions. A demerit of the algorithm is a small sensitivity in periods characterized by highly frequent and abrupt fluctuations.

Nag and Mitra [38] proposed genetically optimized neural network (GANN) to predict FOREX rates. The parameters of GANN are obtained using GA. The GA helped the proposed model to outperform conditional heteroscedastic models and fixed-geometry neural network (FGNN) models. However, the authors reported that Max Absolute Error (MAE) values are more for GANN and these can be minimized.

Zhang [39] proposed a hybrid of ARIMA and ANN to forecast time series including financial time series. The authors concluded that proposed hybrid outperformed the combination of several ANNs. Furthermore, they also stated that fitting ARIMA first to the data could solve overfitting problem.

Yu *et al.* [40] proposed GLAR+ANN to forecast FOREX rates. In this hybrid, GLAR model is first constructed. Later, GLAR's nonlinear components are computed. Next, ANN is used to model nonlinear components and finally, the forecast results are combined. The authors concluded that proposed hybrid could yield accurate predictions. They also recommended to improve prediction quality further.

Alvarez-Diaz and Alvarez [41] employed GP and ANN separately to forecast exchange rates, and the results are then genetically fused. The authors concluded that fusing GP and ANN could not improve forecasting results. They gave an interesting remark of their failure- "due to the great complexity present in the financial market, an accurate forecast analysis would require an extremely high number of observations".

Ince and Trafils [42] presented a two-stage forecasting model for FOREX rate prediction. In the first stage, inputs are selected using both ARIMA and co-integration analysis. Later, ANN and SVR in tandem are applied. They revealed that the SVR could outperform the ANN for two input selection methods. The authors suggested the use of VAR to determine inputs for MLP and the use of ARIMA input selection technique gives the best results if SVR method is employed for training.

Lai *et al.*, [43] implemented ES+BPNN to predict financial time series. ES captures linear patterns and BPNN captures nonlinear patterns. The forecasts from ES and BPNN are synergized via the linear programming technique to produce better forecasts than the stand-alone BPNN and ES.

He and Shen [44] predicted exchange rate using a novel ensemble in which a bootstrap mechanism is used to train multiple ANNs. After training, the test data is presented to ANNs. Finally, an aggregator function is employed to ensemble the results from these ANNs. It is observed that the proposed ensemble could improve exchange rate forecasts. However, the authors reported the simulated results proposed ensemble.

Mahdi *et al.*, [45] proposed Self-organized MLP (SOMLP), an adaptive neural network inspired by the immune system. The predictions obtained from SOMLP demonstrated that all ANNs with stationary data as input generated profit and all ANNs with non-stationary data as input failed to generate any profit.

Chang *et al.*, [46] proposed a hybrid namely PSOBPN in which PSO for selecting the optimal number of input neurons of BPNN. The authors concluded that proposed hybrid could achieve better forecast ability. However, this study employed PSO-based linear model. They suggested the use of non-linear PSO model and further adoption of other evolutionary methods for comparative study.

Sheikhan and Movaghar [47] proposed GA+ANN to predict exchange rates in which GA is used to optimize structure, parameters, learning rate and momentum rate of ANN. It is observed that the GA+ANN could predict better than other time series forecasting models.

Khashei *et al.*, [48] proposed a novel method to forecast time series using ARIMA, ANNs and Fuzzy regression model to forecast point estimates of financial time series. Fuzzy logic in ARIMA model is applied to overcome the data limitation by obviating the need of large amounts of historical data. The proposed model is more flexible for forecasting even there is less data available.

Chang and Lee [49] had come up with GA-based BPNN and PSO-based BPNN to forecast exchange rates. In this work, the whole data divided into six periods of sliding windows. Later, GA/PSO helped in selecting the superior variables. Finally, the exchange rate was forecast by BPNN with the selected variables. The authors used GA/PSO based linear model to select optimal variables. The authors suggested to extend the work by the use of GA/PSO based non-linear model and other evolutionary algorithms.

Nayakovit *et al.*, [50] proposed ANN+MGA, in which, MGA is used to obtain optimal parameters of ANN. The authors concluded that ANN+MGA outperformed traditional time series forecasting models. The proposed hybrid yielded accurate predictions based on accuracy of information in the past. If the information is not accurate, the proposed model may fail.

Chang [51] proposed GA+GA, GA+PSO, and GA+MLP in which optimal variable weights for macroeconomic factors are selected using GA. They concluded that GA+GA model is could perform better than the other two. The authors recommended further adoption of nonlinear model in GA and application of the proposed models to other currencies for long-term prediction.

Chang and Hsieh [52] optimally forecasted exchange rates by constructing PSOBPN, in which, PSO helped in selecting the optimal number of neurons in BPNN. Later, BPNN is used to obtain predictions. The authors concluded that PSOBPN yielded better predictions and suggested the use of nonlinear PSO model for future research.

Mohapatra *et al.*, [53] proposed a novel hybrid namely MLANN+ rank-based WN. The authors concluded that the proposed hybrid could perform better in the presence of outliers too.

Ravi *et al.*, [54] proposed an application of six nonlinear ensemble architectures involving BPNN, WNN, MARS, SVR, DENFIS, GMDH and GP. Their results indicated that both GMDH and GP based ensembles could perform well in the case of exchange rate prediction. But, they did not consider the optimal lagged variables in the prediction model scientifically. Instead, they tried different lag values.

Pradeepkumar and Ravi [55] had come up with two intelligent chaos-based hybrids namely ANN(MLP/ GRNN/GMDH)+PSO/PR and PSO+ANN/PR. The authors concluded that the hybrids outperformed stand-alone models. However, the work can also be extended using Multi-objective optimization.

Rather *et al.*, [56] proposed a hybrid of ARMA, ES and RNN, for prediction of stock returns. In this proposed hybrid, GA is used to obtain weights of RNN. Predictions obtained from ARMA, ES and RNN are merged. It is clearly observed that the hybrid outperformed the stand-alone models. However, it did not guarantee excellent predictions on all datasets. The authors also suggested future implementation of hybrid involving extreme learning machines and PSO. They also recommended to minimize computation time of RNN. And also, the proposed model can be extended to apply to different areas such as engineering sciences, exchange rate risk etc.

Wang *et al.*, [57] proposed a hybrid namely ANN-ARIMA. In their work, nine descriptors were also used to train ANN. The authors concluded that ANN-ARIMA could perform better than the global modeling techniques in terms of profit returns. The authors suggested a research possibility of examining the impact of external variables, such as political events, on the exchange rate mechanism.

Bao *et al.*, [6] presented a novel 3-stage deep learning framework combining WT, SAEs and LSTM. In the proposed framework, WT is used decompose stock price series so that noise is eliminated. Later, SAEs generated deep high-level denoising features. Finally, LSTM forecasted next day's closing stock price using these features selected. The authors concluded that the proposed model outperformed other similar models in both predictive accuracy and profitability performance. The proposed system needs a more advanced hyper-parameters selection scheme to further optimize the results. In addition, deep learning methods are time-consuming, and more attention needs to be paid to GPU-based and heterogeneous computing-based deep learning methods.

Quin *et al.*, [58] proposed a dual-stage attention-based recurrent neural network (DA-RNN) to predict time series including NASDAQ 100 Stock dataset. In this model, first, relevant driving series is extracted by an input attention mechanism. Later, relevant encoder hidden states are selected is temporal attention mechanism. The authors concluded that the DA-RNN performed well compared with other models. The authors highlighted that proposed DA-RNN not only can be used for time series prediction, but also has the potential to serve as a general feature learning tool in computer vision tasks. In the future, it can employed to perform ranking and binary coding.

Ravi *et al.*, [59] proposed two three-stage chaos-based hybrids for financial time series prediction namely Chaos + MLP+Multi-objective PSO (MOPSO) and Chaos+MLP+NSGA-II. The authors concluded that the proposed hybrids out performed stand-alone models including MLP. The hybrids can also be extended by adopting different multi-objective evolutionary algorithms.

Kim and Young [60] proposed a new hybrid LSTM model, GARCH-LSTM to forecast stock price volatility. The proposed hybrid combined LSTM with various GARCH-type models or more than two econometric models. The authors discovered that proposed hybrid outperformed other bench-mark models. The authors concluded that hybrid combined excellent sequential pattern learning with improved prediction performance in stock market volatility. It can be extended to various fields as an integrated model combining time-series and neural network models.

Baek and Kim [61] proposed ModAugNet framework to forecast financial time series. In this model, LSTM is used for two purposes including the prevention of overfitting and prediction. The results confirmed the ModAugNet framework could return good forecasting accuracy. This framework can be extended by incorporating different types of information, such as investors' sentiment, news events, and macroeconomic factors in stock market index time series. They also suggested the use of technical indicators in making profitable models.

Sezer and Ozbayoglu [62] proposed a novel algorithmic trading model namely CNN-TA. In CNN-TA, the CNN is used to convert financial time series into 2-D images by utilizing 15 different technical indicators with different parameters selected. Later, the model labeled each image as Buy, Sell or Hold based on ups and downs of time series. The authors concluded that the trained model provided better results for stocks and Exchange-Traded Fund (ETFs). The authors recommended to use more ETFs and stocks in order to create more data for the deep learning models. The work can be extended to come up with more profitable trading models.

Cao *et al.*, [63] proposed two hybrid forecasting models namely EMD-LSTM and CEEDMAN-LSTM. Both EMD and CEEDMAN are used to reduce the impact of noise in financial time series by decomposing original series. After then the denoised series are input to LSTM to obtain predictions. The authors concluded that the proposed hybrids could yield accurate one-step-ahead forecast. For improving accuracy and robustness of model, the authors suggested to use more input data like the trading volume and the highest price, and the different time-scale series along with closing price. The work can be used to predict weather and traffic time series.

Xu *et al.*, [64] proposed DBN-AR hybrid to predict non-linear exchange rates. In this model, a state-dependent auto-regressive (SD-AR) model is proposed to characterize the nonlinear time series. For obtaining coefficients of the SD-AR model, a set of DBNs is used. It is shown that the DBN-AR model is superior to some existing models. The authors recommended to study the structure optimization of the DBN-AR model and to further improve the prediction accuracy of the model. The model DBN-AR can be extended to DBN-ARX model for modeling non-linear input/output system.

Zhang *et al.*, [9] had come up with a novel architecture of GAN with the MLP as the discriminator and the LSTM as the generator for forecasting the closing price of stocks. The authors concluded that proposed model outperformed the stand-alone machine learning and deep learning models. The work can be extended by incorporating more valuable and influential financial factors from stock markets so that proposed model can learn the data distributions more accurately to obtain a higher precision of trend or price prediction in stock market.

Long *et al.*, [65] proposed multi-filters neural network (MFNN) to extract features from financial time series samples and to predict price movement. Both CNN and RNN are integrated to build the multi-filters structure, so that the information from different feature spaces and market views can be obtained. It is observed that MFNN performed well in terms of the accuracy, profitability, and stability. The authors want to explore how the way of integration affects the quality of trading signals in terms of the risk, profitability, and stability.

IV. CONCLUSION

This paper reviewed various deep learning hybrids for financial time series prediction from 1999-2019. There were 34 different kinds of hybrids were proposed. Majority of publications are found in journals and majority of publications are of hybrids involving MLP. We observed that there are more MLP-based deep learning hybrids, whereas other deep learning neural networks are very less applied in hybrids. It is clearly observed that almost all hybrids outperformed stand-alone models.

This comprehensive review presented each hybrid model along with corresponding strengths, weaknesses and future recommendations. Some interesting and critical observations are worth to be noted from this review:

1. The works [35], [38]. [47], [49], and [51] implemented GA trained neural networks. The works [46] and [52] implemented PSO-trained neural networks. Thus, it can be observed that evolutionary algorithms can be used to obtain optimal weights of neural networks. These can also be used to obtain optimal structure of neural network.
2. The limitation of [54] is well addressed by [55] and [59] in order to yield accurate predictions.

Thus, this comprehensive review and critical observations can help financial forecasters to have an idea of existing hybrids for financial time series prediction.

V. FUTURE DIRECTIONS

Almost all the authors reported future recommendations and extensions. In addition, the budding researchers can be directed to the following:

1. It is worth to propose hybrids involving evolutionary computation and deep learning neural networks such as LSTM or CNN for financial time series prediction which were developed for predicting other time series [66].
2. It is worth applying fuzzy logic with deep learning hybrids.
3. It is also worth to propose hybrids involving deep learning networks CNN, LSTM or other neural networks and Chaos theory.
4. Machine learning techniques such as SVM can also be combined with deep learning techniques to propose new hybrids. Other machine learning techniques as in [67-72] can also be worth explored.

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