Evaluating the Performance of Machine Learning Algorithms in Financial Market Forecasting: A Comprehensive Survey

Lukas Ryll*
Centre for Alternative Finance
University of Cambridge
Cambridge, UK
lr487@cam.ac.uk

Sebastian Seidens
Allianz Endowed Chair of Finance
WHU - Otto Beisheim School of Management
Vallendar, Germany
sebastian.seidens@whu.edu

***Abstract*—With increasing competition and pace in the financial markets, robust forecasting methods are becoming more and more valuable to investors. While machine learning algorithms offer a proven way of modeling non-linearities in time series, their advantages against common stochastic models in the domain of financial market prediction are largely based on limited empirical results. The same holds true for determining advantages of certain machine learning architectures against others.**
This study surveys more than 150 related articles on applying machine learning to financial market forecasting. Based on a comprehensive literature review, we build a table across seven main parameters describing the experiments conducted in these studies. Through listing and classifying different algorithms, we also introduce a simple, standardized syntax for textually representing machine learning algorithms. Based on performance metrics gathered from papers included in the survey, we further conduct rank analyses to assess the comparative performance of different algorithm classes.
Our analysis shows that machine learning algorithms tend to outperform most traditional stochastic methods in financial market forecasting. We further find evidence that, on average, recurrent neural networks outperform feed forward neural networks as well as support vector machines which implies the existence of exploitable temporal dependencies in financial time series across multiple asset classes and geographies.

***Index Terms*—Machine learning, Time series forecasting, Financial engineering, Artificial Neural Network, Financial technology, Financial Markets, Literature review, Rank analysis**

I. Introduction

Since the early beginnings of capital markets, investors have tried to gain a competitive advantage over other market participants, and being able to accurately predict time series undoubtedly represents a constant topic of interest for market participants. Given the growth in available data sources and the increasing interconnectedness of investors, fast and efficient decision making is becoming more important than ever. Machine learning algorithms offer capabilities in approximating non-linear functions, dealing with noisy, non-stationary data, and discovering latent patterns in datasets.
With advances in machine learning throughout the last decades, most notably tackling issues arising from gradient flow which made recurrent networks impractical [40], [67], as well as significant progress in efficient computing using tensor operations on GPUs, machine learning algorithms pose a highly attractive option for financial time series forecasting. Yet, despite the fast-growing importance of machine learning in the financial industry, the degree of academic consolidation and standardization in this field is still comparably sparse. Notwithstanding an increasing number of papers being released within this area of research over the course of the late 20th- and early 21st century, the literature currently fails to provide a compelling analysis of the different algorithms and their respective findings.
Therefore, our study conducts a comprehensive, systematic review of existing works on trading algorithms to close this gap in contemporary research. Apart from providing an overview over the evolution of research in the application of machine learning in financial markets, this paper also suggests and confirms robust hypotheses about the performance of certain classes of algorithms based on rank analyses. For a comparison between different machine learning models through direct application, one would have to compile vast amounts of data from different exchanges and implement a large variety of different trading strategies. By gathering a large number of samples from different experimental methodologies, our study avoids capturing biases from authors using different financial interfaces and datasets and, thus, converges towards representing true differences between the actual algorithm classes.

In regard to the rank analyses, our main research hypothesis states that machine learning algorithms offer superior predictive performance to stochastic models due to their ability to capture recurring non-linear patterns in time series. As most modern supervised machine learning algorithms are trained using cross-validation, the resulting forecasts remain smooth, i.e., generalizable enough to avoid overfitting on the training data set, while still taking into account non-linearities. We further expect recurrent machine learning algorithms to systematically outperform purely feed-forward models in time

*Corresponding author

series forecasting given their potential to model temporal dynamics, i.e., long-term dependencies within time series.

The remainder of this paper is organized as follows. Section II provides a brief introduction to machine learning in financial market prediction while section III reviews existing literature on surveys and meta-studies in this field. Section IV outlines the research methodology and provides summary statistics of the dataset. Section V presents the findings of our analysis across measures, markets and time. Lastly, section VI concludes and presents some challenges for future research, followed by the table of studies.

II. Machine learning in financial time series prediction

While the term *Machine Learning* remains ill-defined to some degree in contemporary literature, it can be broadly referred to as a process where a system interacts with its environment in such way that the structure of the system changes, and that this interaction process itself changes as a consequence to structural alterations. This is an abridged modification of a definition coined by [119] which was applied to the concept of neural networks by [66]. Within this high-level theorem, there are three main learning paradigms which each having different application areas in financial time series prediction.

Supervised learning is used for prediction tasks where a dataset with inputs and labeled targets is available. This may, for instance, entail using technical market indicators to predict whether the next day's stock price will go up (1) or down (0) (binary classification). Apart from classification, supervised learning algorithms may also perform regression tasks, i.e. predicting a continuous value instead of a class label. Taking the stock price example from above, this would translate to predicting the actual stock price or return instead of labeling winners and losers.

Based on the results from forecasting or classification, there are several choices of financial interface, including building portfolios in a multi-asset classification/forecasting task [155], systematic timing strategies [157] or simpler buy-and-hold strategies for single asset experiments (which can be found in the majority of all studies which we include in our survey).

Unsupervised learning algorithms are usually designed for tasks that precede supervised learning, for instance, clustering or dimensionality reduction. An unsupervised learning algorithm may, for example, cluster stocks according to the similarity of their input features. The resulting cluster can then be further used for supervised classification [70].

Reinforcement learning is radically different from the two aforementioned paradigms in that it is based on an action-response model. Reinforcement learning algorithms learn certain action policies which maximize expected rewards. Thus, they are highly applicable to environments where actions and rewards are clearly defined, such as board games. The reinforcement learning process is commonly based on a value function which expresses the expected reward for an action undertaken at the current state of the system. In stock market forecasting, finding a suitable value function represents a major challenge, which is why other approaches, such as direct reinforcement using differential metric optimization objectives, have been proposed [122].

The application of machine learning algorithms to financial time series has been covered by a large range of authors throughout the last two decades. Stemming from the simplest multi-layer perceptrons, state-of-the-art deep learning algorithms have evolved to capture time dynamics through recurrent neural architectures, and, specifically, gated neuron designs which allow for capturing long-term dependencies in time series (e.g., Long Short-Term Memory (LSTM) [67]).

Yet, while machine learning techniques are well suited for a variety of approximation tasks, they represent so-called 'black-box' models, meaning that their output behavior cannot be fully explained. In an on-line learning context, this property implies a lack of decision transparency which is essential for interpreting individual model outputs. This characteristic is especially vital in the case of abnormal market movements as the forecasting error may increase sharply for outlier events. Therefore, standardization and transparency in financial machine learning research are pivotal in illustrating varying behaviors across asset- and algorithm classes.

III. Literature

As aforementioned, while existing research covers a variety of different algorithms, inputs, and concepts, there are few examples of studies which attempt to systematically review and compare existing works. [7] present a list of soft computing methods (including machine learning, evolutionary computing, and fuzzy logic) used in various research papers on trading algorithms. Their study largely serves as a passive reference due to its limited scope of analysis. While they conclude that soft computing algorithms represent a feasible stock forecasting method, they also note that "[...] difficulties arise when defining the structure of the model (the hidden layers the neurons etc.). For the time being, the structure of the model is a matter of trial and error procedures.".

A highly comprehensive perspective is provided by [19] who present a brief overview of applications of computational intelligence to financial data in studies from 2009-2015. Apart from the survey, the paper establishes a standardized framework for constructing these algorithms. [9] presents similar results, concluding that artificial intelligence algorithms generally possess a higher accuracy than comparable statistical methods. Nevertheless, his study denies evidence of outperformance on an absolute scale. Our study addresses this doubt with a ranking analysis and finds significant evidence of the outperformance of machine learning against traditional stochastic models.

Practical-methodical studies on machine learning trading algorithms occasionally provide comparative data within their specific scope of parameters (for instance, in the case of [79], this is given by text mining algorithms with news sentiment inputs).

IV. Research Methodology

A. Meta-Analysis

We conduct our investigation using meta-analysis techniques. [58] define meta-analysis as the statistical analysis of a large collection of results from individual studies for the purpose of integrating the findings. A similar definition was proposed by [145] who state that meta-analysis is a set of quantitative techniques for evaluating and combining empirical results from different studies. Originally designed for application in health sciences, marketing or education [43], this technique is increasingly applied in economics and finance where meta-analysis is commonly referred to as meta-regression analysis [75], [153], [154]. Due to the heterogeneity of the subgroups within our sample (i.e., individual experiments conducted by studies), a parametric approach which makes hypotheses based on the comparison of subgroup parameters is unfeasible. The same is true for trying to find factors which influence performance: The lack of standardized testing metrics, standard testing datasets as well as study-specific information on optimization algorithms and weight initialization makes it impossible to form a meaningful meta-regression analysis. These aspects are further detailed in the next subsection.
Instead, we pursue an approach which evaluates algorithm classes based on their relative rank in subgroup experiments. While this methodology still lacks exhaustive explanatory power on an aggregate level, a pairwise rank analysis based on the same scoring system uncovers meaningful performance differences between algorithm classes.

B. Meta Statistics

Our data collection procedure encompassed an initial, unfiltered collection of 260 papers. The papers were originally sourced from Google Scholar and SciVerse Science Direct. For each of these sources, we selected the first 50 most relevant papers listed under the key terms "Artificial Intelligence + Financial forecasting", "Machine learning + trading" and "Market prediction + artificial intelligence". Subsequently, we gathered relevant references from these results, added them to the collection and removed duplicates, a procedure which was completed in August 2018. Thereafter, we filtered out scientific papers which did not comply with our self-imposed guidelines:

1) The paper/report demonstrates an application of a machine learning algorithm to forecasting or supporting trading decisions given a time series based on the prices of a publicly traded asset
2) The paper/report provides adequate numerical performance results
3) The paper/report has been published in a peer-reviewed journal or at a peer-reviewed conference

This procedure left us with a total of 170 papers to include in our analysis. From these papers, we extract a total of 2085 performance values from 225 individual experiments (one experiment for every distinct asset with more than one algorithm tested) which we use for the subsequent rank analyses.

C. Dataset

1) Assets: The studies presented in our dataset encompass an aggregate total of 11 distinct asset classes (stock, index, FX, ETF, mutual fund, commodity, future, option, crypto, bond, money market instrument). In the table of studies, the asset class is indicated in brackets after the specific asset used. If a study presents multiple assets, they are separated with a vertical bar. Furthermore, if the number of assets for a distinct group (e.g., 'stock') exceeds 3, they are not itemized by name.

2) Market geographies: This section analyses the market geographies for the asset classes used in the paper. For FX rates, we indicate the geographies pertinent to both currencies, respectively. For reasons of clarity, we do not itemize geographies exceeding three distinct countries.

TABLE I: Markets most frequently analyzed by geography and count

Country	Count
UNITED STATES	75
TAIWAN	19
INDIA	12
JAPAN	10
SOUTH KOREA	10
CHINA	9
BRAZIL	6
TURKEY	6
GERMANY	5
SINGAPORE	5

3) Periods: The Input Data represent the periods of data used in individual studies (includes training/testing datasets), with the timestep frequency indicated in brackets. When different periods were used for different assets, these experiments are contextually grouped using a vertical bar.

4) Input Proxies/Other Inputs: The 'Input Proxies/Other Inputs' field indicates the usage of features that are not inherent to the time series used by the paper in question. This includes any added information beyond the values of a time series (or transformations of the same). These inputs are represented according to the following taxonomy:

TABLE II: Taxonomy

Variable	Description
MARKET	Market data, i.e., data from other assets' t.s.
TECH	Technical indicators
FUND	Fundamental corporate finance metrics [128]
MACRO	Macroeconomic data
OTHER{SPECIFY}	Various

5) Algorithms compared: Our study presents a syntax for creating a high-level understanding of algorithm structures presented by studies on machine learning in financial market prediction. Given the lack of standardization in that field (especially concerning taxonomy), this notation makes a valuable contribution by depicting complex representations in concise terms.

TABLE III: SYNTAX

Syntax	Description
X-Y	Feed forward
X^Y	Ensemble
X{Y}	Attribute
X<-Y	Optimization or selection process
[X-Y]	Allows for syntax generalization and representation of complex relationships

6) Result metrics: The result metrics used in studies on financial forecasting using machine learning can roughly be divided into three main groups: Error-based, Return-based, and Accuracy-based. Within our sample, accuracy proved to be the most popular metric, closely followed by annual return and root mean squared error. These groups have different signaling functions related to algorithm- and financial interface performance, which we present and discuss in section IV.
The table of studies occasionally contains cells bearing an asterisk; this signals that the study included more metrics than shown within the table which we do not present for reasons of irrelevance or redundancy. Moreover, there are several samples with double asterisks. These signify extrapolation, i.e., integrating an element into our standardized taxonomy even though the study in question does not specifically name the element or is otherwise lacking in information necessary for a definite classification. For this reason, elements marked with two asterisks should be treated with caution as they are based on subjective assumptions given scarce information. It is important to note here that we solely base our rank analysis on performance metrics, excluding metrics such as computational feasibility.

D. Rank analysis

Even though the similarities in metrics used across the studies we reviewed appear to suggest a benchmark comparison between individual papers' results, we refrain from conducting a parametric analysis. Notwithstanding the existence of a sufficient amount of performance results for the same algorithm classes for each geography, we identified key differences between studies during our performance analysis which we believe would render a parametric analysis meaningless:

Experimental conditions

- Differences in performance evaluation and reporting
- Different architectures and different practices in varying architectures
- Testing environment and validation practices
- Length of training/testing sets
- Different asset classes and markets (without providing sufficient alpha return metrics)

Result evaluation

- Usage of different performance metrics (see section V)
- Different ways of annualizing returns
- Widely differing trading strategies

Instead, we seek to establish generalizing conclusions from non-parametric analyses on algorithms presented in individual studies. By using an average-over-all approach, we come up with a single rank score between 0 and 1 for a given algorithm type. Our ranking formula separates instances for each paper based on individual algorithms, assets, and performance metrics. Thus, if an algorithm is tested on two assets using three metrics, we receive two instances of three scores which are compiled and later averaged on all studies. For each algorithm class, this procedure can be expressed as follows:

$$s_{singular} = \frac{1}{N} \sum_{n=1}^{N} \frac{|R_n| - r_n}{|R_n| - 1} \tag{1}$$

Where N represents the total number of experiments, counting one experiment per metric, asset, and study. Moreover, r_n equals the ranking spot of an algorithm for an individual experiment where $|R_n|$ denotes the number of algorithms benchmarked in that experiment. In the case of multiple usages of an algorithm class within an individual experiment (e.g., 'ANN' and 'ANN{W}'), we compute an additional average of all ranking spots. Thus, the scoring system allows for multiple classes to attain the same rank score within the same experiment if they have more than one listing in it. This would, e.g., apply to ranks [3,6], [4,5]. Ranks were computed in ascending- or descending order depending on the performance metric used (i.e., ascending for error metrics and descending for accuracy as well as for the majority of return metrics). The results for the most frequently used algorithm classes can be found in Table IV. While these results can certainly be seen as indicative of the overall strength of an algorithm class per se, a direct comparison between classes is not always possible. One algorithm might receive a score which is overall higher than that of another although the two algorithms are never directly compared in an experiment. As a consequence, we ran a pairwise rank analysis visualized in Fig. 1 to be able to directly compare performance between algorithm classes, where

$$s^{(a,b)}_{pairwise} = \frac{|\{(y^{(a)}, y^{(b)}) \colon y \in Y, y^{(a)} > y^{(b)}\}|}{|\{(y^{(a)}, y^{(b)}) \colon y \in Y, y^{(a)} \neq y^{(b)}\}|} \tag{2}$$

$$Y = Y^{(a)} \frown Y^{(b)} \tag{3}$$

$$Y^{(i)} = \{\frac{|R^{(i)}_n| - r^{(i)}_n}{|R^{(i)}_n| - 1} \colon n \in N\} \tag{4}$$

The pairwise rank is computed by performing a simple percentage comparison of two algorithms' relative ranks for individual experiments, $Y^{(a)}$ and $Y^{(b)}$, given that the two algorithms are benchmarked against each other. Fig. 1 displays these pairwise rank scores leading by columns (i.e., the third cell in the first column can be interpreted as evidence that ANNs only perform better than SVMs in 34% of all surveyed experiments). 'No Data' fields indicate pairs which weren't tested together in any study or bear the same rank scores in all joint experiments For the purpose of assessing statistical significance, we also conduct a t-test against the null hypothesis that $mean(Y^{(a)}) = mean(Y^{(b)})$.

V. Results & Discussion

A. Rank analysis

The pairwise rank analysis (see Fig. 1) shows the percentage of times that an algorithm in the column title outperformed its row counterpart. Many of the fields remain empty due to missing data, pointing towards the tendency of studies to compare similar algorithms (e.g., different classes of ANNs), presumably due to the amount of effort involved in constructing fundamentally different model classes. Nevertheless, the pairwise perspective coins several interesting findings.

Importantly, given the methodology governing rank scoring and significance tests, observing the sample size in cases where the pairwise rank score is close to 50% is vital as this may still imply that two algorithm classes perform similarly even though there is no clear winner.

Evidently, the only trading strategy (Buy-and-hold) included in the matrix performs poorly against neural networks and largely does not outperform other algorithms in any scenario. While Buy-and-hold outperforms linear regression models in 32% of all cases, and random walk in 60% of all experiments, the differences in rank scores turn out not to be significant at the 5% significance level. The same holds true for the surprisingly good result against recurrent neural networks which is merely based on two experiments from one study.

As expected, random walk similarly gets outperformed by ANNs in the vast majority of all experiments. It also scores poorly against AR and GARCH models, and fares surprisingly well against linear regression models, albeit insignificantly so. Finding a clear winner among the traditional statistical models in direct comparison is an arduous task which can largely be explained by the fact that in our sample of studies, these models are most commonly used as a 'traditional' benchmark against various machine learning classes and are rarely tested against each other. Taken from all significant results of statistical models, GARCH models fare best against ANNs. ARIMA score even higher, and though the result is not significant, the large sample size (>25) does indicate that the overall performance of ARIMA vs. ANN tends to be more similar than that of GARCH vs. ANN which may suggest that the use of neural networks in returns/price forecasting adds comparatively less value than it does in volatility forecasting. Interestingly, GARCH models outscore SVMs and appear to fare moderately well against recurrent ANNs (albeit the result is not significant, stemming most likely from a small sample size). A similar pattern can be observed for the pairwise analysis of ANNs and Fuzzy Logic which are frequently used together, thus resulting in closer or equal rank scores per study. It is worthwhile to take a closer look at recurrent neural networks (ANN{R}) which significantly outperform other neural networks in our sample. While we do not explicitly list them in the pairwise ranking table due to the limited number of experiments, more recent techniques, such as Long Short-Term Memory ($s_{singular} = 0.843$) and Gated Recurrent Unit ($s_{singular} = 0.833$) appear to outclass simpler forms of recurrent neural networks which do not explicitly address the vanishing gradient problem, for instance, Elman Networks [50] ($s_{singular} = 0.580$) although the classes are never directly benchmarked against each other in our sample. Meanwhile, SVMs significantly outscore ANNs which cover similar objectives in classification. While it is difficult to pinpoint the advantages of each method, the significant outperformance of recurrent ANNs against SVMs and other NNs may indicate the relevance of classifiers being able to detect latent temporal patterns in data.

TABLE IV: Rank score results for different algorithm classes

Algorithm	Score
SVM	0.672
ANN{R}	0.643
ANN	0.579
FUZZ	0.528
GARCH	0.508
ARIMA	0.471
RW	0.333
LRM	0.298
AR	0.227
BH	0.167

B. Performance metrics for machine learning algorithms in finance

Relying on accuracy as a performance metric in benchmarking soft computing algorithms in financial applications is problematic. In the papers analyzed within the scope of this meta-analysis, accuracy is most often used in a directional sense. A correct forecast by an algorithm is determined by whether the forecasted variable actually moves in the same direction as the forecast. This definition creates a lack of clarity as some studies define more or less prediction states than others. While most authors limit themselves to forecasting 'Up' or 'Down' movements, others, e.g., [160] provide three desired output states, making it significantly harder to attain a similar success rate to examples with fewer states. Apart from confusing uninformed readers, this might also hinder direct analyses between different studies. Beyond definition issues, it also remains pivotal to be aware of the amount of information on the actual profitability of an algorithm that is carried by the accuracy metric. While accuracy might be a good approximation of an algorithm's general ability, it technically does not convey any information on profitability. Taking an extreme example, an algorithm with high accuracy might correctly forecast many comparably insignificant profit opportunities while missing a small number of large profit opportunities. Based on the studies reviewed in this large-scale meta-analysis,

Leading by columns	ANN	ANN{R}	SVM	FUZZ	GARCH	AR	ARIMA	LRM	RW	BH
ANN		87%**	64%**	38%	31%*	22%**	49%	12%**	21%**	9%**
ANN{R}	13%**		14%**	0%**	50%	40%	No Data	0%**	46%	50%
SVM	36%**	86%**		No Data	75%	0%**	25%	No Data	No Data	0%**
FUZZ	62%	100%**	No Data		No Data	No Data	0%**	0%**	50%	No Data
GARCH	69%*	50%	25%	No Data		No Data	No Data	No Data	0%**	No Data
AR	78%**	60%	100%**	No Data	No Data		No Data	No Data	17%*	No Data
ARIMA	51%	No Data	75%	100%**	No Data	No Data		67%	39%	No Data
LRM	88%**	100%**	No Data	100%**	No Data	No Data	33%		80%	32%
RW	79%**	54%	No Data	50%	100%**	83%*	61%	20%		60%
BH	91%**	50%	100%**	No Data	No Data	No Data	No Data	68%	40%	

FIG. 1: PAIRWISE RANK MATRIX
* FOR $p \leq 0.05$
** FOR $p \leq 0.01$

we instead advocate in favor of performance metrics which demonstrate the return capabilities of algorithms respective to their fields of forecasting or classification. Relative return metrics, in this context, take into account the magnitude of the trends that a system discovers. One of the most popular return metrics in the meta-analysis proves to be the demonstration of relative outperformance of a reference index (e.g., the S&P 500).

Going a step further, we propose a method based on [53], [71], [164] which takes an ideal classifier system that conducts a trading simulation subject to a pre-defined rule environment/trading strategy, and generates a maximum return indicator by taking optimal (i.e., return-maximizing actions) under all circumstances. The metric itself would then simply form a ratio of an experiment's performance and the ideal classifier. The rationale behind this metric is aligned with one of the main paradigms of stock forecasting using neural networks itself: Good forecasts are forecasts that generate returns. While metrics such as alpha do capture this logic to some extent, the ratio shown above allows for the definition of more sophisticated trading strategies than 'buy and hold'.

Yet, this metric alone does not exhaustively cover all information needed. For instance, consider that if a system shows low accuracy and high relative return, one could argue that this is the product of learning 'lucky' shared outliers present in both the training and testing set, which is also why our preference does not make the accuracy metric itself redundant. The same logic applies to error metrics: By being application-agnostic, they add valuable information about the viability of the tested methodology regardless of the type of testing data. Accuracy does not capture this; a set of forecasts may exhibit high directional accuracy and high errors at the same time if these forecasts systematically under- or overshoot the true value. This becomes problematic should the underlying system be tested on different data where directional accuracy is less consequential as a performance metric.

VI. CONCLUSION

In this study, we presented and analyzed a vast array of literature on machine learning applications for financial time series analysis. We collected over 150 relevant papers, forming a large sample containing experiments with different algorithms and asset classes. Following the aim of drawing robust conclusions on the comparative performance of different algorithm classes, we rejected a parametric approach due to the heterogeneity of our literature sample. Instead, we performed purely ranking-based analyses on the performance statistics collected from individual studies, consisting of an aggregate ranking score and a pairwise rank analysis. Our results show significant evidence for the systematic outperformance of machine learning algorithms vs. stochastic models, confirming our initial hypothesis that machine learning algorithms are able to capture meaningful non-linear dynamics in financial time series, and that these dynamics' existence is generalizable across different market geographies and asset class prices. We also demonstrate that recurrent machine learning algorithms tend to perform better at the task of financial market prediction than simple feed forward models, presumably due to their ability to take into account temporal dynamics.

Naturally, these findings have to be put into an appropriate context given the nature of prevailing research. First of all, there is no standardized dataset for machine learning algorithms in financial applications, as opposed to other popular application fields such as image recognition where the MNIST/CIFAR datasets have become a widely accepted standard. Without norms regarding input data, extrapolation based on the performance of an algorithm for one market or one specific asset is impossible, which is why we refrain from a parametric comparison between studies. The lack of standardized input may also exacerbate researcher's bias arising from the desire to achieve a market-beating performance. Given that many machine learning algorithms exhibit a significant black-box characteristic and are highly sensitive to small changes in parameters, they are prone to data manipulation. As a consequence, we identify a strong need for standardized training and testing procedures which will, as a side-effect, also bolster comparability.

Possible steps following this study include collecting a larger amount of studies which specifically test two or more groups of algorithms, i.e., feed forward NNs vs. recurrent NNs or ANNs vs. SVMs. This would be especially interesting for the purpose of comparing sub-classes, such as the ANN{R} variants shortly referred to in section V.

While the central aim of this meta-analysis is certainly an informative one, we also tried to discover and explain the relationship between the use of certain performance metrics and prevailing biases across studies as well as offering solutions to the same. Ideally, machine learning approaches should be tested on standardized datasets. Alternatively, they should be benchmarked against an ideal classifier to provide a relative perspective on performance. Furthermore, studies should include indications of the algorithm's performance (error metrics such as RMSE) while also relating its performance to a financial interface/trading system (via accuracy- and return metrics).

ACKNOWLEDGMENT

We would like to thank the reviewers from WHU-Otto Beisheim School of Management for their invaluable comments and thoughts. We further extend our expressions of gratitude to Derek Snow from the University of Auckland and all reviewers of the University of Cambridge for their meticulous efforts in correction and revision.

TABLE V: TABLE OF STUDIES

Authors, Year	**Assets**	**Market Geographies**	**Periods**	**Input Proxies/Other Inputs**	**Algorithms compared**	**Result metrics**
Abraham, Nath & Mahanti, 2001	NASDAQ-100 (index) | 6 (stock) ∈ NASDAQ-100	US	1999-2001		PCA-ANN-NFUZZ{EFNN}	RMSE, A
Adhikari & Agrawal, 2014	USD/INR (FX) | GBP/USD (FX) | S&P 500 (index) | IBM (stock)	US, IN, UK	2009-2011 (d) | 1980-1993 (w) | 2004-2007 (d) | 1965-2011 (m)		RW-ANNˆANN{R{EL}}, ANN, ANN{R{EL}}, RW	MAE, MSE, SMAPE
Andreou, Neocleous, Schizas & Toumpouris, 2000	CSE (index), 10 (stock) ∈ CSE	CY	1999	FUND, MACRO, OTHER{Int. Politics}, TECH	ANN	CC, MaxAE, A
Armano, Marchesi & Murru, 2005	COMIT | S&P 500 (index)	IT, US	9y (d)	TECH	NXCS, BH	AR%, std, SR, A{HR}, *
Atiya, Talaat & Shaheen, 1997	S&P 500 (stock)	US	1993-1994**	FUND	ANN, BH	AR
Bagheri, Peyhani & Akbari, 2014	EUR/USD | USD/JPY | GBP/USD | USD/CHF (FX)	Various	2011-2014 (d)	TECH	NFUZZ{ANFIS}, FUZZ{M}, FUZZ{TSK}, NFUZZ	A{HR}
Banik, Chanchary, Rouf & Khan, 2007	DSPI (index)	BGD	2003-2007 (d)		NFUZZ{ANFIS}, ANN, ARIMA	MAE, MAPE, RMSE, RMSPE, R2
Bildirici & Ersin, 2009	ISE 100 (index)	TR	1987-2008 (d)		GARCH, GARCH{E}, GARCH{T}, GARCH{GJR}, GARCH{SA}, GARCH{POW}, GARCH{N}, GARCH{AP}, GARCH{NP}, ANNˆGARCH, ANNˆGARCH{E}, ANNˆGARCH{T}, ANNˆGARCH{GJR}, ANNˆGARCH{SA}, ANNˆGARCH{POW}, ANNˆGARCH{N}, ANNˆGARCH{AP}, ANNˆGARCH{NP}	RMSE
Bildirici & Ersin, 2013	USD/bWTI (commodity)	US	1986-2012 (d)		GARCH, GARCH{AP}, GARCH{FI}, GARCH{FIAP}, LSTAR-LST-GARCH, LSTAR-LST-GARCH{AP}, LSTAR-LST-GARCH{FI}, LSTAR-LST-GARCH{FIAP}, ANN-GARCH, ANN-GARCH{AP}, ANN-GARCH{FI}, ANN-GARCH{FIAP}, LSTAR-LST-ANN-GARCH, LSTAR-LST-ANN-GARCH{AP}, LSTAR-LST-ANN-GARCH{FI}, LSTAR-LST-ANN-GARCH{FIAP},	RMSE, PC
Bildirici, Alp & Ersin, 2010	ISE 100 (index) | TRY/USD	TR, US	1987-2008 (m)	MARKET	TAR-VEC, TAR-VEC<Hansen & Seo, 2002>, ANN{TAR-VEC}, ANN{RBF{TAR-VEC}}, ANN{HE{TAR-VEC}}	RMSE
Bodyanskiy & Popov, 2006	DJIA (index)	US			GARCH, ANN{RMD}, ANN{QP}	NMSE, NMAE, A{HR}, A{WHR}
Cao & Tay, 2001	S&P 500 (index)	US	1993-1995 (d)	TECH	ANN, SVM	NMSE, MAE, DS, CP, CD

Cao & Tay, 2003	5 (future) ∈ CMM	US	1988-1999, *	TECH	SVM, ANN, ANN{RBF}, SVM{A}, ANN{WBP}	NMSE, MAE, DS
Cao, Leggio & Schniederjans, 2005	367 (stock) ∈ SHSE	CN	1999-2002 (d)	FUND	LRM{uni}, ANN{uni}, LRM{multi}, ANN{multi}	MAE, MAPE, MSE
Casas, 2001	x (stock) (bond) (MM)	US	1994-1999	MARKET, MACRO	ANN	AR
Chang & Liu, 2008	1 (stock) ∈ TSE | TSE (index)	TW	2002-2006 (d) | 2003-2005 (d)	TECH	FUZZ{TSK}, ANN, LRM{multi}	MAPE
Chang, Fan & Liu, 2009	9 (stock)	CN	2004-2006	TECH	PLR<-GA-ANN, ANN, PLR	AR, A{HR}
Chang, Liu, Lin, Fan & Ng, 2009	9 (stock)	TW	2004-2005 (d)	TECH	ANN{CBR}, CBR, ANN	AR
Chang, Wang & Zhou, 2012	1 (stock) ∈ TSE | TSE (index)	TW	2003-2006 (d) | 2005 (d)	TECH	ANN{PC}<-GA, FUZZ{TSK}, ANN, LRM	MAPE
Chavarnakul & Enke, 2008	S&P 500 (index)	US	1998-2003 (d)	TECH	ANN{GR}	MSE, SIGN
Chen & Leung, 2004	GBP/USD | CAD/USD | JPY/USD (FX)	Various	1980-2001 (m)	MACRO	ANN{GR}, MTF, GMM, BVAR, MTF-ANN{GR}, GMM-ANN{GR}, BVAR-ANN{GR}, RW	AR, RMSE, ThU
Chen, 1994	4** (stock)		1986-1992	TECH	AR, ANN, ANN{GR}, ANN{CS}	CC, RMSE
Chen, Abraham, J. Yang & B. Yang, 2005	NASDAQ-100 | NIFTY (index)	US, IN	1995-2002 | 1998-2001		ANN, FUZZ{T-S}, FUZZ{H-T-S}	RMSE, MAP, MAPE, CC
Chen, Dong & Zhao, 2005	NASDAQ-100 | NIFTY (index)	US, IN	1995-2002 | 1998-2001		ANN{LLWAV}, ANN{WAV}	CC, MAP, MAPE, RMSE
Chen, Leung & Daouk, 2003	TAIEX** (index)	TW	1982-1992	MACRO	ANN{P}, KF, RW, BH	AR, *
Chen, Ohkawa, Mabu, Shimada & Hirasawa, 2009	10 (stock) ∈ TSM	JP	2001-2004 (d)	TECH	GNP{CN}, GNP{RL}, GNP{Candlestick}, GA, BH	AR
Chen, Shih & Wu, 2006	Nikkei 225 | All Ordinaries | Hang Seng | Straits Times | TAIEX | KOSPI | (index)	Various	1971-2002 (d)	TECH	SVM, ANN, AR	MSE, NMSE, MAE, DS, WDS
Chen, Yang & Abraham, 2007	NASDAQ-100 | NIFTY (index)	US, IN	7y | 4y (d)		DT{FNT}, ENS[DT]{B}, ENS[DT]{G}, ENS[DT]{LWPR}	RMSE, MAP, MAPE, CC
Chenoweth & Obradovic, 1996	S&P 500 (index)	US	1985-1993 (d)	MACRO	ANN, ANNˆANN	AR, BETC
Chenoweth, Obradovic & Lee, 1996	S&P 500 (index)	US	1982-1993 (d)	MARKET, TECH	ANN, BH	AR, BETC
Chiang, Urban & Baldridge, 1996	101 (mutual fund)	US	1981-1986 (y)	MACRO	ANN, LRM, NLRM	MAPE, *
Chong, Han & Park, 2017	38 (stock) ∈ KOSPI	KR	2010-2014 (5-min)		AR, ANN, ANN{D}, AE-ANN{D}, PCA-ANN{D}, RBM-ANN{D}	NMSE, RMSE, MAE, MI
Chun & Park, 2005	KOSPI (index)	KR	2000-2004 (d)		ENS{CBR{DA}}, ENS{CBR{SE}}, RW	MAPE
Constantinou, Georgiades, Kazandjian & Kouretas, 2006	CSE (index)	CY	1996-2002 (d)		ANN, MarkS	RMSE

Dai, Wu & Lu, 2012	Nikkei 225 | Shanghai B-Share stock index (index)	JP, CN	2004-2009 (d)	MARKET	NLICA-ANN, LICA-ANN, PCA-ANN, ANN	RMSE, MAE, MAPE, RMSPE, DS
Das, Mishra & Rout, 2017	USD/INR | USD/EUR (FX)	US, IN, EU	2001-2016 (d)	TECH	ELM, ANN{FL}, ANN	MSE, MAPE, MAE, ThU, ARV
de A. Araujo, Nedjah, M. de Seixas, L.I. Oliveira & R. de L. Meira, 2018	5 (stock) ∈ BOVESPA	BR			ARIMA, ANN, ANN{RBF}, SVR{L}, SVR{POLY}, SVR{RBF}, IDL<-BP, IDL<-GA, IDL<-PSO, IDL<-BSA, IDL<-FFA, IDL<-CS	ARV, MAPE, MSE, POCID, ThU, EF
de C. T. Raposo & de O. Cruz, 2002	28 (stock) ∈ SPSE	BR	1986-1998	FUND	PCA-NFUZZ	A
de Faria, Marcelo Albuquerque, Gonzalez, Cavalcante & Marcio Albuquerque, 2009	Bovespa (index)	BR	1998-2008 (d)		ANN, AES	RMSE, A
de Oliveira, Nobre & Zarate, 2013	1 (stock) ∈ BM&FBOVESPA	BR	2000-2011 (m)	MARKET, MACRO, TECH	ANN	MAPE, RMSE, ThU, POCID
Dempster & Leemans, 2006	EUR/USD (FX)	EU, US	2000-2002 (1-min)		RL{R}	AR
Doeksen, Abraham, Thomas & Paprzycki, 2005	2 (stock)	US	1997-2003 (d)	MACRO, TECH	ANN, FUZZ{M}<-GA, FUZZ{TSK}<-GA	MSE, AR, A
Dunis, Laws & Sermpinis, 2011	EUR/USD (FX)	EU, US	1994-2001 (d)	MARKET, MACRO	ANN{PS}, ANN{HO}, ANN{R}, ANN, ANN{SCE}, ANN{GM}, MACDM, ARMA, LOGIT, NAIVE	SR, AR, MD, VOLA, *
Enke & Thawornwong, 2005	S&P 500 (index)	US	1976-1999 (m)	FUND, MACRO, MARKET	ANN, ANN{GR}, ANN{P}, LRM, BH	CC, RMSE, A, AR, std, SR, *
Fatima & Hussain, 2008	KSE100 (index)	PAK	2000-2002 (d)		ARIMA, GARCH, ANN, ARIMA-ANN, GARCH-ANN	FMSE
Fernandez & Gomez, 2007	5 (index)	Various	1992-1997 (w)	MARKET, TECH**	ANN{H}, GA, TS, SimA	MPE
Fernandez-Rodriguez, Gonzalez-Martel & Sosvilla-Rivero, 2000	IGBM (index)	ESP	1966-1997 (d)		ANN	A, alpha%, IPR, SR
Fischer & Krauss, 2018	S&P 500 (stock)	US	1990-2015 (d)		ANN{R{LSTM}}, RF, ANN, LRM	AR, SR, SortR, MD, *
Freitas, de Souza & de Almeida, 2009	52 (stock) ∈ Bovespa	BR	1999-2007 (w)		ANN{ARMR}	ME, RMSE, A, MAPE, AR
Ghazali, Hussain, Nawi & Mohamad, 2009	4 (FX)	Various	2000-2005 (d)	TECH	ANN, ANN{PS}, ANN{RP}, ANN{DRP}, RW, LRM, ARIMA	AR, VOLA, NMSE, A, RM, MAPE
Grudnitski & Osburn, 1993	S&P 500 (index) | (future) -> Gold	US	1982-1990 (m)	MACRO, MARKET, TECH	ANN	alpha, A

Guresen & Kayakutlu, 2008	XU100 (index)	TR	2003-2008 (d)		ANN, LTS, ANN{R}, ANN{DAN2}, GARCH-ANN, GARCH{E}-ANN, GARCH-LTS, GARCH{E}-LTS, GARCH-ANN{R}, GARCH{E}-ANN{R}, GARCH-ANN{DAN2}, GARCH{E}-ANN{DAN2}	MSE, MAE, MAPE
Guresen, Kayakutlu & Daim, 2011	NASDAQ (index)	US	2008-2009 (d)		ANN, ANN{DAN2}, GARCH-ANN, GARCH-ANN{DAN2}	MSE, MAE, MAPE
Hajizadeh, Seifi, Zarandi & Turksen, 2012	S&P 500 (index)	US	1998-2009 (d)	MARKET, MACRO, TECH	GARCH{E}-ANN, GARCH, GARCH{E}, GARCH{GJR}	RMSE, MAE, MAPE, MFE
Harvey, Travers & Costa, 2000	Emerging market indices & composites	Various	1997-1999 (w)	FUND, MARKET	ANN, BH	AR, DA, MM
Hassan, 2009	BAY | DAL | RYA | AAPL | IBM | DELL (stock)	US	2002-2004 (d, do, dh, dl)		HMM-FUZZ, ARIMA, ANN	MAPE
Hassan, Nath & Kirely, 2007	AAPL | IBM | DELL (stock)	US	2003-2005 (d, do, dh, dl)		HMM, [ANN-HMM]<-GA, [ANN-HMM]<-GA-WA, ARIMA	MAPE
Hsieh, Hsiao & Yeh, 2011	DJIA | FTSE | Nikkei 225 | TAIEX (index)	Various	1997-2003 & 2002-2008	TECH	ANN{R{W}}, ANN, ANN<-ABC, FUZZ<Chen>, FUZZ<Yu>, NFUZZ{ANFIS}	RMSE, MAE, MAPE, AR
Huang & Tsai, 2009	FITX (index)	TW	2000-2006 (d)	TECH	SOM-SVR, SVR	MSE, MAE, MAPE
Huang & Wu, 2008	7 (index)	Various	2003-2005	MARKET	GA-SVM, GARCH, ANN, SVM	RMSE
Huang, Nakamori & Wang, 2005	Nikkei 225 (index)	JP	1990-2002 (w)	MACRO, MARKET	RW, LDA, QDA, ANN{R{EL}}, SVM, RWˆLDAˆQDAˆANN{R{EL}}ˆSVM	A{HR}
Huang, Pasquier & Quek, 2009	HSI (index) | 1 (stock)	HK, SGP	1987-2006 (d), *	TECH	NFUZZ{EFNN}, NFUZZ{DENFIS}, NFUZZ{RSPOP}, NFUZZ{HiCEFS}, BH	AR
Huarng & Yu, 2008	TAIEX (index)	TW	1999-2004 (d)	MARKET	FUZZ{uni}<Chen, 1996>, LRM{uni}, ANN{uni}, ANN-FUZZ{uni}, ANN-FUZZ{subs}{uni}, LRM{bi}, ANN{bi}, ANN-FUZZ{bi}, ANN-FUZZ{subs}{bi}	RMSE
Hussain, Knowles, Lisboa & El-Deredy, 2008	EUR/USD | JPY/USD | GBP/USD (FX)	Various	1994-2001 (d)		ANN{PP}, ANN{FL}, ANN	AR, MD, MSE
J.-Z. Wang, J.-J. Wang, Zhang & Guo, 2011	SCI (index)	CN	1993-2009 (m)		ANN{WAV}, ANN	MAE, RMSE, MAPE
Kanas & Yannopoulos, 2001	FTAI | DJIA (index)	UK, US	1980-2000 (m)	FUND, TECH	ANN, LRM	RMSE
Kara, Boyacioglu & Baykan, 2011	ISE 100 (index)	TR	1997-2007 (d)	TECH	ANN, SVM, OLS, ANN<Diler, 2003>, ANN<Altay & Satman, 2005>	A
Khan, 2011	Nikkei 225 (index)	JP	1996-2009 (5-min)		HAR, SVM-HAR, HAR{J}, HAR{MSNR, J}, SVM-HAR{J}, SVM-HAR{MSNR, J}	RMSE, MAE, RMSPE, MAPE
Khemchandani, Jayadeva & Chandra, 2009	5 (stock) | S&P 500 (index)	US	2005-2007, * | 1989-1993 (d)		SVR{RLSF}, SVR	NMSE
Kim & Ahn, 2012	KOSPI (index)	KR	1989-1998 (d)	TECH	ANN<-GA, ANN	A
Kim & Chun, 1998	SGPI (index)	SGP	1985-1996 (d)	FUND, TECH	ANN{P}, ANN{R}, CBR, ANN	A{HR}
Kim & Han, 2000	KOSPI (index)	KR	1989-1998 (d)	TECH	GA-ANN<-GA, ANN, ANN<-GA	A{HR}

Kim & Shin, 2007	KOSPI 200 (index)	KR	1997-1999 (d)		ANN{ATD}<-GA, ANN{TD}<-GA, ANN{ATD}, ANN{TD}, ANN{R}	MSE
Kim, 2003	KOSPI (index)	KR	1989-1998 (d)	TECH	SVM, ANN, CBR	A{HR}
Kim, 2006	KOSPI (index)	KR	1991-1998 (d)	TECH	GA{CBR}-ANN, ANN	A{HR}
Kim, Han & Chandler, 1998	(future) -> KOSPI 200	KR	1996 (d)	TECH	ANNˆCBR, BH	A{HR}, AR
Kimoto, Asakawa, Yoda & Takeoka, 1990	TOPIX (index)	JP	1985-1989 (w)	MARKET, FUND**, MACRO, TECH**	ENS[ANN]	CC
Ko & Lin, 2008	21 (stock) ∈ Taiwan 50	TW	2000-2005		ANN{RA}	AR
Koulouriotis, Diakoulakis, Emiris & Zopounidis, 2005	ASE (index)	GRE	1996-1997 (w, *)	MARKET, TECH	LRM, ANN, ANN<-GA, ANN{RBF}, NFUZZ{ANFIS}, ANN{DC}	A, MSE
Krauss, Do & Huck, 2017	S&P 500 (stock)	US	1990-2015 (d)		ANN, DT{GB}, RF, [ANNˆDT{GB}ˆRF]{WA}	AR, ER, SR, MD, SortR, *
Kristjanpoller & Minutolo, 2015	Gold (commodity) | (future) -> Gold		1999-2014 (d)	MARKET	GARCH-ANN, GARCH	MAPE, MAE, MSD
Kristjanpoller & Minutolo, 2016	Oil (commodity) | (future) -> Oil	US	2002-2014 (d)	MARKET	GARCH-ANN, GARCH, ARFIMA	HMSE, HMAE, *
Kristjanpoller & Minutolo, 2018	USD/BTC (crypto)	US	2011-2017 (d)	TECH	ANN-GARCH{E}, GARCH{E}, *	MSE
Kristjanpoller, Fadic & Minutolo, 2014	Bovespa | IPSA | IPyC (index)	BR, CHI, MEX	2000-2011 (d)		GARCH, GARCH-ANN	MSE, RMSE, MAE, MAPE, MAPE reduction
Kryzanowski, Galler & Wright, 1993	120 (stock)	CAN**	1981-1991	FUND, MACRO	ANN{BM}	A, *
Kumar, Meghwani & Thakur, 2016	12 (index)	Various	2008-2013	TECH	SVM{PROX}, LC-SVM{PROX}, RC-SVM{PROX}, RR-SVM{PROX}, RF-SVM{PROX}, ANN, LC-ANN, RC-ANN, RR-ANN, RF-ANN	A
Kuo, 1998	x (stock) ∈ TAIEX	TW		TECH, MARKET	FUZZˆANN-ANN	MSE, AR, *
Kuo, L. C. Lee & C. F. Lee, 1996	TAIEX** (index)	TW	281d	MARKET, TECH	ANNˆFUZZ{Delphi}-ANN, ANN	MSE, AR, *
Kwon & Moon, 2007	36 (stock) ∈ NYSE/NASDAQ	US	1992-2004 (d, dh, dl)	TECH	ANN{R{EL}}<-GA, GA->CBE	Instance-based alpha
Lam, 2004	364 (stock) ∈ S&P 500	US	1985-1995	FUND, MACRO, TECH	ANN	AR
Lee & Chen, 2002	Nikkei 225 | MSCI Taiwan (index)	JP, TW	1998-1999 (5-min)	MARKET	ANN, RW, GARCH	RMSE, MAE, MAPE, RMSPE
Lee & Chiu, 2002	Nikkei 225 (index)	JP	1998-1999 (5-min)	MARKET	ANN, RW	RMSE, MAE, MAPE, RMSPE
Lee, 2009	NASDAQ (index)	US	2001-2007 (d)	MARKET	SVM, FSSFS-SVM, IG-SVM, SU-SVM, CFS-SVM, ANN, FSSFS-ANN, IG-ANN, SU-ANN, CFS-ANN	A
Lee, Cho & Baek, 2003	(future) -> KOSPI 200	KR	1999-2001	TECH	ANN{AA}	MAE
Leigh, Paz & Purvis, 2002	NYSE (index)	US	1980-1999 (d)		ANN{CBR}	A{HR}

Lendasse, de Bodt, Wertz & Verleysen, 2000	Bel 20 (index)	BEL	10y (d)	TECH, MARKET, MACRO	PCA-CCA-ANN{RBF}	A
Leu, Lee & Jou, 2009	NTD/USD (FX)	TW, US	2006-2007 (d)	MARKET	FUZZ{DB}, RW, ANN{RBF}	MSE, DS
Li & Kuo, 2008	TAIEX (index)	TW	1991-2002 (d)	TECH	SOM, SOM{DWT}	AbR, A{HR}, *
Li, Zhang, Wong & Qin (2009)	S&P 500 | FTSE100 | Nikkei 225 (index) | USD/EUR | USD/GBP | USD/JPY (FX)	Various	2000-2003 (d)		RW^AES^ARIMA^ANN-RBF, RW, AES, ARIMA	ER
Liao & Wang, 2010	SAI | SBI | HSI | DJIA | IXIC | S&P 500 (index)	CN, HK, US	1990-2008 (d)		ANN{STE}	ARE
Lin & Yeh, 2009	x (option) ∈ TAIFEX	TW	2003-2004	MARKET, TECH	ANN, Grey-ANN, GARCH-ANN	MAE, MAPE
Lu & Wu, 2011	Nikkei 225 | TAIEX (index)	JP, TW	2004-2008 (d)	MARKET	ANN{CMAC}, SVR, ANN	RMSE, MAE, MAPE, A, *
Lu, Que & Cao, 2016	Chinese energy index (index)	CN	2013-2016		GARCH{E}-ANN, GARCH{GJR}-ANN, GARCH{E}^ANN, GARCH{GJR}^ANN	RMSE
M.-Y. Chen, D.-R. Chen, Fan & Huang, 2013	TAIEX (index)	TW	2000-2010 (d)	MARKET	FUZZ{FTS{W}}, NFUZZ, NFUZZ{ANFIS}<Cheng, Wei & Chen, 2009>, NFUZZ{AR-ANFIS}, ANN{R{W}}, NFUZZ{ANFIS}, ANN	RMSE
M.-Y. Chen, Fan, Y.-L. Chen & Wei, 2013	Taiwan 50 (index) | 40 (stock) ∈ NYSE	TW, US	2006-2011 (d), *	FUND	ANN, ANN{RBF}, SVR, DOE-ANN, LRM, LMS	PC, RMSE
Majhi, G. Panda, Sahoo, A. Panda & Choubey, 2008	S&P 500 | DJIA (index)	US	1994-2006 (d)	TECH	ALC<-PSO, ANN	MAPE
Majhi, Panda & Sahoo, 2009	USD/INR | USD/GBP | USD/JPY (FX)	Various	1971-2005 (m), *	TECH	LMS, ANN{FL}, ANN{CFL}	MSE, APE
Majhi, Panda, Sahoo, Dash & Das, 2007	S&P 500 | DJIA (index)	US	1994-2006 (d)	TECH	ANN, ALC<-BFO	MAPE
Malliaris & Salchenberger, 1993	x (option)	US	1990 (dm, de)	MARKET, MACRO	ANN, NLM{Black Scholes}	MAE, MAPE, MSE
Mizuno, Kosaka, Yajima & Komoda, 1998	TOPIX (index)	JP	1982-1987 (w)	TECH	ANN	A
Monfared & Enke, 2014	NASDAQ (index)	US	1997-2011	MARKET	GARCH{GJR}, GARCH{GJR}-ANN, GARCH{GJR}-ANN{GR}, GARCH{GJR}-ANN{RBF}	MSE, MSE reduction
Motiwalla & Wahab, 2000	11 (index)	US	1990-1998 (m)	MARKET, MACRO	BH, ANN, LRM	AR, SR, std, A
Nayak, Misra & Behera, 2012	BSE S&P 100 | BSE S&P 500 (index)	IN	2005-2010	MARKET, MACRO	ANN, ANN<-GA, ANN{FL}<-GA	MAE
Ni & Yin, 2009	USD/GBP (FX)	US, UK	4000 days** (d)	TECH	SOM-SVR, SOM-ANN, GARCH, SOM{R}-SVR-GA	A

Oh & Kim, 2002	KOSPI 200 (index)	KR	1990-2000 (d)		BH, ANN, ANN{PWNL}	RMSE, MAE, MAPE, AR
Olson & Mossman, 2003	x (stock)	CAN	1976-1993	FUND	OLS, LOGIT, OLS-ANN, LOGIT-ANN	A{HR}, AR
Pai & Lin, 2005	10 (stock)	US	2002-2003 (d)		ARIMA, SVM, ARIMAˆSVM, ARIMA-SVM	MAE, MSE, MAPE, RMSE
Pan, Tilakaratne & Yearwood, 2005	AORD (index)	AUS	1990-2003	MARKET	ANN	RMSE, A, VR
Panda & Narasimhan, 2007	INR/USD (FX)	IN, US	1994-2003 (w)		ANN, AR, RW	RMSE, MAE, MAE, PC, DA, SIGN
Pantazopoulos, Tsoukalas, Bourbakis, Brun & Houstis, 1998	S&P 500 (index)	US	1928-1993 (d)	MARKET, TECH	NFUZZ, BH	RMSE, AR
Perez-Rodriguez, Torra & Andrada-Felix, 2005	Ibex 35 (index)	ESP	1989-2000 (d)		AR, ANN, ANN{R{EL}}, STAR{E}, LSTAR, ARˆANN	AR, SR, MAE, MAPE, RMSE, ThU, SIGN, DA
Petropoulos, Chatzis, Siakoulis & Vlachogiannakis, 2017	10 (FX)/USD	Various	2001-2015 (d)		[NBAYˆSVMˆANNˆRFˆBARTˆNˆBHˆSHˆAR]-GA, [NBAYˆSVMˆANNˆRFˆBARTˆNˆBHˆSHˆAR]-CLS, [NBAYˆSVMˆANNˆRFˆBARTˆNˆBHˆSHˆAR]-V{MAJ}, [NBAYˆSVMˆANNˆRFˆBARTˆNˆBHˆSHˆAR]-VAR	AR, SR, VOLA, MD, *
Qi, 1999	S&P 500 (index)	US	1954-1992	FUND, MACRO	LRM, ANN	AR, std, SR, A, RMSE, MAE, MAPE, CC
Quah, 2008	1630 (stock) ∈ DJIA	US	1995-2004 (d, *)	FUND	ANN, NFUZZ{ANFIS}, ANN{RBF{GGAP}}	A, AR
Quek, Yow, Cheng & Tan, 2009	23 (stock) ∈ NASDAQ, NYSE, *	US	1996-2005 (d)	TECH	NFUZZ{SO}	AR
R. Dash & P. K. Dash, 2016	BSE SENSEX | S&P 500 (index)	IN, US	2010-2014 (d)	TECH	ANN{FL}<-ELM, SVM, NBAY, kNN, DT	AR
Rast, 1999	DAX (index)	GER	1985-1987 & 1996-1998 (d)		ANN, NFUZZ	AR
Rather, 2011	6 (stock) ∈ NSE	IN	2007-2010 (w)		ANN{CBR}	ME, MSE, MAPE
Rather, 2014	3 (stock) ∈ BSE	IN	2013 (d)		AR-ANN{R{ARMR}}	MSE, MAE
Rather, Agarwal & Sastry, 2015	25 (stock) ∈ BSE	IN	2007-2010 (w) & 2013 (d)		[ANN{ARMR}ˆESˆARMA]<-GA, ANN{R}	MSE, MAE, CC
Refenes, Azema-Barac & Zapranis, 1993	143 (stock)	UK	1985-1991		ANN, LRM	RMSE
Rodriguez-Gonzalez, Garcia-Crespo, Colomo-Palacios, Guldris Iglesias & Gomez-Berbis, 2011	15 (stock) ∈ IBEX 35	ESP	16 years (d)	TECH	ANN{G}	A

Rout, P.K. Dash, R. Dash & Bisoi, 2017	BSE | S&P 500 (index)	IN, US	2004-2008 (d) | 2010-2012 (d)	TECH	ANN{FL{TR}}, ANN{FL{LAG}}, ANN{FL{CH}}, ANN{FL{LE}}, ANN{FL{CE}}, ANN{FL{RCE}}, ANN{RBF}, ANN{WAV}	RMSE, MAPE
S.-H. Hsu, Hsieh, Chih & K.-C. Hsu, 2009	Nikkei 225 | All Ordinaries | Hang Seng | Straits Times | TAIEX | KOSPI | Dow Jones (index)	Various	1997-2002 (d)	TECH	SOM-SVR, SVR	NMSE, MAE, DS, WDS
Sagar & Kiat, 1999	3 (stock) ∈ SES	SGP	1996-1997 (d)	OTHER{NEWS}	NLP-ANN{TD}	MAE
Sezer & Ozbayoglu, 2018	Dow 30 (stock) | 9 ETF (ETF)	US	2002-2017 (d)	TECH	ANNC, ANN{R{LSTM}}, ANN, BH, SMA	AR, std
Shen, Tan, Zhang, Zeng & Xu, 2018	S&P 500 (index)	US	1991-2017 (d)		ANN{R{GRU}}, ANN{R{GRU}}-SVM, ANN, SVM	A, AR
Shynkevich, McGinnity, Coleman, Belatreche & Li, 2017	50 (stock) ∈ S&P 500	US	2002-2012 (d)	TECH	SVM, ANN, kNN, BH	A, SR, WR
Siekmann, Kruse, Gebhardt, van Overbeek & Cooke, 2001	DAX (index)	GER	1994-1998		NFUZZ, LRM, NAIVE, BH	A{HR}, RMSE, AR, *
Soto & Melin, 2015	MSE (index)	MEX	2005-2009 (d)		NFUZZ{ANFIS{Type2}}, NFUZZ{ANFIS{Type1}}	RMSE
Steiner & Wittkemper, 1997	31 (stock) ∈ FSE	GER	1991-1994	MARKET, TECH**	BH, ANN{P}-ANN{GR}	alpha, AR, std
Tay & Cao, 2001	5 (future) ∈ CMM	US	1992-1999 (d)	TECH	ANN, SVM	NMSE, MAE, DS, WDS
Tenti, 1996	(future) -> DM	GER	1990-1994 (d)	TECH	ANN{R}	NMSE, ROE, ROC, A
Thawornwong & Enke, 2004	S&P 500 (index)	US	1976-1999 (m)	FUND, MACRO, MARKET	ANN, ANN{P}, LRM, BH, RW	A, AR, std, SR, *
Ticknor, 2013	AAPL | IBM (stock)	US	2003-2005 (d)	TECH	ANN{BR}, [ANN-HMM]<-GA-WA, ARIMA	MAPE
Tsaih, Hsu & Lai, 1998	(future) -> S&P 500	US	1983-1993 (d)	TECH	ANN{REAS}, BH	AR, A
Tseng, Cheng, Wang & Peng, 2008	x (option) ∈ TXO	TW	2005-2006 (d)	TECH, MARKET	GARCH{E}-ANN, Grey-GARCH{E}-ANN	RMSE, MAE, MAPE
Vanstone, Finnie & Tan, 2005	x (stock)	AUS	2002-2003	FUND	ANN, BH	AR, SR, MD, UI, *
Versace, Bhatt, Hinds & Shiffer, 2004	DIA (ETF)	US	2001-2003 (d)	MARKET, MACRO, TECH	GA->ANN	A
Wah & Qian, 2002	3 (stock)	US	1997-2002 (d)		ANN{R{FIR}}, CC, AR, ANN, IP	NMSE
Walczak, 1999	DBS50 | DJIA | Nikkei 225 (index)	SGP, US, JP	1994-1995 (d)	MARKET, TECH	ANN	A
Wang & Chan, 2006	3 (stock)	US	1990-1996 (d)	TECH	DT{BIAS}	AR, std, A
Wang, 2009	x (option) ∈ TXO	TW	2005-2006 (d)		Grey-GARCH{GJR}-ANN, GARCH{GJR}-ANN, GARCH-ANN	RMSE, MAE, MAPE

Wang, Xu & Zheng, 2018	SSE (index)	CN	2012-2015 (d)	OTHER{NEWS}, TECH	RSE-DBN, ANN, SVM, RF, ANN{R}, ANN{R{LSTM}}	F1, Precision, Recall Accuracy, AUC
Wen, Yang & Song, 2009	S&P 500 (index)	US	1000d		NFUZZ{ANFIS}, ANN, SVM, NFUZZ{ANFIS}ˆANNˆSVM, [NFUZZ{ANFIS}ˆANNˆSVM]-ANN	MSE
Wen, Yang, Song & Jia, 2010	422 (stock) ∈ S&P 500 | MSFT | IBM (stock)	US	11-12y** | 2004-2008 (d){OT} | 2004-2008 (d){OT}	TECH	SVM, BH	AR, SCC, MSE
Witkowska, 1995	3 (stock) ∈ PSE	PL	1993	MARKET	ANN	MSE
Wittkemper & Steiner, 1996	67 (stock)	GER	1967-1986 (d)	FUND, TECH	ANN{GR}, ANN{GR}<-GA	MSE
Wu, Fung & Flitman, 2001	S&P 500 (index)	US	1992-2000 (m)	MACRO	NFUZZ{FFNF}, ANN	A
Yeh, Lien & Tsai, 2011	TAIEX (index)	TW	1989-2004 (d)	TECH	ANN	AR
Yu, Wang & Lai, 2008	S&P 500 | FTSE100 | Nikkei 225 (index) | USD/EUR | USD/GBP | USD/JPY (FX)	Various	2000-2003 (d)		RW, AES, ARIMA, ANN	alpha
Yumlu, Gurgen & Okay, 2004	XU100 (index)	TR	1989-2003 (d)		ENS[ANN], ANN{R}, GARCH{GJR}	ThIC, CC, A{HR}, MSE
Yumlu, Gurgen & Okay, 2005	XU100 (index)	TR	1990-2002 (d)		ANN, ANN{R{EL}}, MOE, GARCH{E}	A{HR}, A{HR+}, A{HR-}, MSE, MAE,
Zhang & Berardi, 2001	GBP/USD (FX)	UK, US	1976-1994 (w)		ENS{SYS}[ANN], ENS{SER}[ANN]	MSE, MAE
Zhang & Pan, 2016	20 (stock) ∈ SZSE | 16 (stock) ∈ NASDAQ	CN, US	2010-2015	TECH	SVM{P}<-AdaBoost<-GA, SVM{P}, ANN	A, g-means
Zhang & Wan, 2007	USD/JPY | USD/GBP | USD/HKD (FX)	Various	1998-2001		NFUZZ{SFI}	MAPE
Zhang, 2003	GBP/USD (FX)	UK, US	1980-1993 (w)		ANNˆARIMA, ANN, ARIMA	MSE, MAE
Zhang, Akkaladevi, Vachtsevanos & Lin, 2002	6 (stock)	US	1981-1994		NFUZZ{GNN}, ANN	MAE**
Zhang, Jiang & Li, 2004	SCI (index)	CN	1995-2003 (d)		ANN, BH	R, A
Zhu, Wang, Xu & Li, 2008	NASDAQ | DJIA | STI (index)	US, SGP	1997-2005 | 1990-2005 | 1989-2005	MARKET, TECH	ANN	A, MSE

Algorithm Abbreviations

A	Adaptive parameters
AA	Auto-associative
ABC	Artificial Bee Colony Algorithm
AE	Autoencoder
AES	Adaptive Exponential Smoothing
ALC	Adaptive Linear Combiner
ANFIS	Adaptive Network-based Fuzzy Inference System
ANN	Artificial Neural Network
AP	Asymmetric Power
AR	Autoregressive
ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
ARMR	Autoregressive Moving Reference
ATD	Adaptive Time Delay
B	Basic
BART	Bayesian Autoregressive Tree
BFO	Bacterial Foraging Optimization
BH	Buy-and-hold
bi	Bivariate
BM	Boltzmann Machine
BR	Bayesian Regularized
BVAR	Bayesian Vector Autoregression
C	Convolutional
CBE	Context-Based Ensemble
CBR	Case-Based Reasoning
CC	Carbon Copy
CCA	Curvilinear Component Analysis
CE	Computationally Efficient
CFL	Cascaded Functional Link
CFS	Correlation-based Feature Selection
CH	Chebyshev polynomials
CLS	Constrained Least Squares
CMAC	Cerebellar Model Articulation Controller
CN	Control Nodes
CS	Class-Sensitive
D	Deep
DA	Dynamic Adaptive
DAN2	Dynamic Architecture for artificial neural Networks
DB	Distance-Based
DBN	Deep Belief Network
DC	Dynamic Cognitive
DENFIS	Dynamic Evolving Neural-Fuzzy Inference System
DOE	Design Of Experiment
DRP	Dynamic Ridge Polynomial
DT	Decision Tree
DWT	Discrete Wavelet Transform
E	Exponential
EFNN	Evolving Fuzzy Neural Network
EL	Elman
ELM	Extreme Learning Machine
ENS	Ensemble
ES	Exponential Smoothing
FFNF	Feed Forward Neuro Fuzzy
FI	Fractionally Integrated
FIAP	Fractionally Integrated Asymmetric Power
FIR	Finite-duration Impulse Response
FIS	Fuzzy Inference System
FL	Functional Link
FNT	Flexible Neural Tree
FSSFS	F-score and Supported Sequential Forward Search
FTS	Fuzzy Time Series
FUZZ	Fuzzy Logic
G	Generalized
GA	Genetic Algorithm
GARCH	General Autoregressive Conditional Heteroskedasticity
GB	Gradient-Boosted
GGAP	General Growing And Pruning
GJR	Glosten-Jagannathan-Runkle
GM	Gaussian Mixture
GMM	Generalized Method of Moments
GNN	Granular Neural Network
GNP	Genetic Network Programming
GR	General Regression
GRU	Gated Recurrent Unit
H	Hopfield
HAR	Heterogeneous Autoregressive
HE	Hybrid Elman
HMM	Hidden Markov Model
HO	Higher Order
HiCEFS	Hierarchical Co-Evolutionary Fuzzy System
IDL	Increasing-Decreasing-Linear
IG	Information Gain
IP	Ideal Predictor
J	Jumps
KF	Kalman Filter
L	Linear
LAG	Laguerre polynomials
LC	Linear Correlation
LDA	Linear Discriminant Analysis
LE	Legendre polynomials
LICA	Linear Independent Component Analysis
LLWAV	Local Linear Wavelet
LMS	Least Mean Squares
LOGIT	Logistic Regression
LRM	Linear Regression Model
LST	Logistic Smooth Transition
LSTAR	Logistic Smooth Transition Autoregressive
LSTM	Long Short-Term Memory
LTS	Lagged Time Series
LWPR	Local Weighted Polynomial Regression
M	Mamdani
MACDM	Moving Average Convergence Divergence Model
MAJ	Majority
MOE	Mixture of Experts
MSNR	Microstructure Noise Robust
MTF	Multivariate Transfer Function
MarkS	Markov Switching
N	Nonlinear
NBAY	Naive Bayes
NFUZZ	Neuro-Fuzzy
NLICA	Nonlinear Independent Component Analysis
NLM	Non-Linear Model
NLP	Natural Language Processing
NLRM	Non-Linear Regression Model
NP	Nonlinear Power

NXCS	Neural Extended Classifier System
OLS	Ordinary Least Squares
P	Probabilistic
PC	Partially Connected
PCA	Principal Components Analysis
PLR	Piecewise Linear Representation
POLY	Polynomial
POW	Power
PP	Polynomial Pipelined
PROX	Proximal
PS	Psi Sigma
PSO	Particle Swarm Optimization
PWNL	Piecewise Nonlinear
QDA	Quadratic Discriminant Analysis
QP	Quasiperiodic
R	Recurrent
RA	Resource Allocation
RBF	Radial Basis Function
RBM	Restricted Boltzmann Machine
RC	Rank Correlation
RCE	Recurrent Computationally Efficient
REAS	Reasoning
RF	Random Forest
RL	Reinforcement Learning
RLSF	Regularized Least Squares Fuzzy
RMD	Recurrent Mixture Density
RP	Ridge Polynomial
RR	Regression Relief
RSE	Random Subspace Ensemble
RSPOP	Rough Set-based Pseudo Outer-Product
RW	Random Walk
S	Static Ensemble
SA	Simple Asymmetric
SCE	Softmax Cross Entropy
SER	Serial
SFI	Statistical Fuzzy Interval
SH	Sell and Hold
SMA	Simple Moving Average
SO	Self-Organizing
SOM	Self-Organizing Map
STAR	Smooth Transition Autoregressive
STE	Stochastic Time Effective
SU	Symmetrical Uncertainty
SVM	Support Vector Machine
SVR	Support Vector Regression
SYS	Systematic
SimA	Simulated Annealing
T	Threshold
TAR	Threshold Autoregressive
TD	Time Delay
TR	Trigonometric Funcion
TS	Tabu Search
TSK	Takagi-Sugeno-Kang
Type1	Type 1 Fuzzy Logic
Type2	Type 2 Fuzzy Logic
V	Voting
VAR	Variance-based
VEC	Vector Error Correction
W	Weighted
WA	Weighted Average
WAV	Wavelet
WBP	Weighted Backpropagation
kNN	k-Nearest Neighbors
multi	Multivariate
subs	Substitutes
uni	Univariate

REFERENCES

[1] Abraham, A., Nath, B., & Mahanti, P. K. (2001, May). Hybrid intelligent systems for stock market analysis. In International Conference on Computational Science (pp. 337-345). Springer, Berlin, Heidelberg.

[2] Adhikari, R., & Agrawal, R. K. (2014). A combination of artificial neural network and random walk models for financial time series forecasting. Neural Computing and Applications, 24(6), 1441-1449.

[3] Andreou, A. S., Neocleous, C. C., Schizas, C. N., & Toumpouris, C. (2000). Testing the predictability of the Cyprus Stock Exchange: The case of an emerging market. In Neural Networks, 2000. IJCNN 2000, Proceedings of the IEEE-INNS-ENNS International Joint Conference on (Vol. 6, pp. 360-365). IEEE.

[4] Araujo, R. D. A., Nedjah, N., de Seixas, J. M., Oliveira, A. L., & Silvio, R. D. L. (2018). Evolutionary-morphological learning machines for high-frequency financial time series prediction. Swarm and Evolutionary Computation, 42, 1-15.

[5] Armano, G., Marchesi, M., & Murru, A. (2005). A hybrid genetic-neural architecture for stock indexes forecasting. Information Sciences, 170(1), 3-33.

[6] Atiya, A., Talaat, N., & Shaheen, S. (1997, June). An efficient stock market forecasting model using neural networks. In Neural Networks, 1997., International Conference on (Vol. 4, pp. 2112-2115). IEEE.

[7] Atsalakis, G. S., & Valvanis, K. P. (2009). Surveying stock market forecasting techniques - Part II: Soft computing methods. Expert Systems with Applications, 36, 5932-5941.

[8] Bagheri, A., Peyhani, H. M., & Akbari, M. (2014). Financial forecasting using ANFIS networks with quantum-behaved particle swarm optimization. Expert Systems with Applications, 41(14), 6235-6250.

[9] Bahrammirzaee, A. (2010). A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems. Neural Computing and Applications, 19(8), 1165-1195.

[10] Banik, S., Chanchary, F. H., Rouf, R. A., & Khan, K. (2007, December). Modeling chaotic behavior of Dhaka Stock Market Index values using the neuro-fuzzy model. In Computer and information technology, 2007. iccit 2007. 10th international conference on (pp. 1-6). IEEE.

[11] Bildirici, M., & Ersin, O. O. (2009). Improving forecasts of GARCH family models with the artificial neural networks: An application to the daily returns in Istanbul Stock Exchange. Expert Systems with Applications, 36(4), 7355-7362.

[12] Bildirici, M., & Ersin, O. O. (2013). Forecasting oil prices: Smooth transition and neural network augmented GARCH family models. Journal of Petroleum Science and Engineering, 109, 230-240.

[13] Bildirici, M., Alp, E. A., & Ersin, O. O. (2010). TAR-cointegration neural network model: An empirical analysis of exchange rates and stock returns. Expert Systems with Applications, 37(1), 2-11.

[14] Bodyanskiy, Y., & Popov, S. (2006). Neural network approach to forecasting of quasiperiodic financial time series. European Journal of Operational Research, 175(3), 1357-1366.

[15] Cao, L. J., & Tay, F. E. H. (2003). Support vector machine with adaptive parameters in financial time series forecasting. IEEE Transactions on neural networks, 14(6), 1506-1518.

[16] Cao, L., & Tay, F. E. (2001). Financial forecasting using support vector machines. Neural Computing & Applications, 10(2), 184-192.

[17] Cao, Q., Leggio, K. B., & Schniederjans, M. J. (2005). A comparison between Fama and French's model and artificial neural networks in predicting the Chinese stock market. Computers & Operations Research, 32(10), 2499-2512.

[18] Casas, C. A. (2001). Tactical asset allocation: an artificial neural network based model. In Neural Networks, 2001. Proceedings. IJCNN'01. International Joint Conference on (Vol. 3, pp. 1811-1816). IEEE.

[19] Cavalcante, R. C., Brasileiro, R. C., Souza, V. L., Nobrega, J. P., & Oliveira, A. L. (2016). Computational intelligence and financial markets: A survey and future directions. Expert Systems with Applications, 55, 194-211.

[20] Chang, P. C. (2012). A novel model by evolving partially connected neural network for stock price trend forecasting. Expert Systems with Applications, 39(1), 611-620.

[21] Chang, P. C., & Liu, C. H. (2008). A TSK type fuzzy rule based system for stock price prediction. Expert Systems with Applications, 34(1), 135-144.

[22] Chang, P. C., Fan, C. Y., & Liu, C. H. (2009). Integrating a piecewise linear representation method and a neural network model for stock trading points prediction. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 39(1), 80-92.

[23] Chang, P. C., Liu, C. H., Lin, J. L., Fan, C. Y., & Ng, C. S. (2009). A neural network with a case based dynamic window for stock trading prediction. Expert Systems with Applications, 36(3), 6889-6898.

[24] Chavarnakul, T., & Enke, D. (2008). Intelligent technical analysis based equivolume charting for stock trading using neural networks. Expert Systems with Applications, 34(2), 1004-1017.

[25] Chen, A. S., & Leung, M. T. (2004). Regression neural network for error correction in foreign exchange forecasting and trading. Computers & Operations Research, 31(7), 1049-1068.

[26] Chen, A. S., Leung, M. T., & Daouk, H. (2003). Application of neural networks to an emerging financial market: forecasting and trading the Taiwan Stock Index. Computers & Operations Research, 30(6), 901-923.

[27] Chen, C. H. (1994, June). Neural networks for financial market prediction. In Neural Networks, 1994. IEEE World Congress on Computational Intelligence., 1994 IEEE International Conference on (Vol. 2, pp. 1199-1202). IEEE.

[28] Chen, M. Y., Chen, D. R., Fan, M. H., & Huang, T. Y. (2013). International transmission of stock market movements: an adaptive neuro-fuzzy inference system for analysis of TAIEX forecasting. Neural Computing and Applications, 23(1), 369-378.

[29] Chen, M. Y., Fan, M. H., Chen, Y. L., & Wei, H. M. (2013). Design of experiments on neural network's parameters optimization for time series forecasting in stock markets. Neural Network World, 23(4), 369.

[30] Chen, W. H., Shih, J. Y., & Wu, S. (2006). Comparison of support-vector machines and back propagation neural networks in forecasting the six major Asian stock markets. International Journal of Electronic Finance, 1(1), 49-67.

[31] Chen, Y., Abraham, A., Yang, J., & Yang, B. (2005, August). Hybrid methods for stock index modeling. In International Conference on Fuzzy Systems and Knowledge Discovery (pp. 1067-1070). Springer, Berlin, Heidelberg.

[32] Chen, Y., Dong, X., & Zhao, Y. (2005, October). Stock index modeling using EDA based local linear wavelet neural network. In Neural Networks and Brain, 2005. ICNN&B'05. International Conference on (Vol. 3, pp. 1646-1650). IEEE.

[33] Chen, Y., Ohkawa, E., Mabu, S., Shimada, K., & Hirasawa, K. (2009). A portfolio optimization model using Genetic Network Programming with control nodes. Expert Systems with Applications, 36(7), 10735-10745.

[34] Chen, Y., Yang, B., & Abraham, A. (2007). Flexible neural trees ensemble for stock index modeling. Neurocomputing, 70(4-6), 697-703.

[35] Chenoweth, T., & Obradovi, Z. (1996). A multi-component nonlinear prediction system for the S&P 500 index. Neurocomputing, 10(3), 275-290.

[36] Chenoweth, T., Obradovic, Z., & Lee, S. S. (1996). Embedding technical analysis into neural network based trading systems. Applied Artificial Intelligence, 10(6), 523-542.

[37] Chiang, W. C., Urban, T. L., & Baldridge, G. W. (1996). A neural network approach to mutual fund net asset value forecasting. Omega, 24(2), 205-215.

[38] Chong, E., Han, C., & Park, F. C. (2017). Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. Expert Systems with Applications, 83, 187-205.

[39] Chun, S. H., & Park, Y. J. (2005). Dynamic adaptive ensemble case-based reasoning: application to stock market prediction. Expert Systems with Applications, 28(3), 435-443.

[40] Chung, J., Gulcehre, C., Cho, K., & Bengio, Y. (2014). Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555.

[41] Constantinou, E., Georgiades, R., Kazandjian, A., & Kouretas, G. P. (2006). Regime switching and artificial neural network forecasting of the Cyprus Stock Exchange daily returns. International Journal of Finance & Economics, 11(4), 371-383.

[42] Dai, W., Wu, J. Y., & Lu, C. J. (2012). Combining nonlinear independent component analysis and neural network for the prediction of Asian stock market indexes. Expert Systems with applications, 39(4), 4444-4452.

[43] Daniskova, K., & Fidrmuc, J. (2012). Meta-Analysis of the New Keynesian Phillips Curve (No. 314). IOS Working Papers.

[44] Das, S. R., Mishra, D., & Rout, M. (2017). A hybridized ELM-Jaya forecasting model for currency exchange prediction. Journal of King Saud University-Computer and Information Sciences.

[45] Dash, R., & Dash, P. K. (2016). A hybrid stock trading framework integrating technical analysis with machine learning techniques. The Journal of Finance and Data Science, 2(1), 42-57.

[46] De Faria, E. L., Albuquerque, M. P., Gonzalez, J. L., Cavalcante, J. T. P., & Albuquerque, M. P. (2009). Predicting the Brazilian stock market through neural networks and adaptive exponential smoothing methods. Expert Systems with Applications, 36(10), 12506-12509.

[47] Dempster, M. A., & Leemans, V. (2006). An automated FX trading system using adaptive reinforcement learning. Expert Systems with Applications, 30(3), 543-552.

[48] Doeksen, B., Abraham, A., Thomas, J., & Paprzycki, M. (2005, April). Real stock trading using soft computing models. In International Conference on Information Technology: Coding and Computing (ITCC'05)-Volume II (Vol. 2, pp. 162-167). IEEE.

[49] Dunis, C. L., Laws, J., & Sermpinis, G. (2011). Higher order and recurrent neural architectures for trading the EUR/USD exchange rate. Quantitative Finance, 11(4), 615-629.

[50] Elman, J. L. (1990). Finding structure in time. Cognitive science, 14(2), 179-211.

[51] Enke, D., & Thawornwong, S. (2005). The use of data mining and neural networks for forecasting stock market returns. Expert Systems with applications, 29(4), 927-940.

[52] Fatima, S., & Hussain, G. (2008). Statistical models of KSE100 index using hybrid financial systems. Neurocomputing, 71(13-15), 2742-2746.

[53] Fernandez-Rodrguez, F., Gonzalez-Martel, C., & Sosvilla-Rivero, S. (2000). On the profitability of technical trading rules based on artificial neural networks: Evidence from the Madrid stock market. Economics letters, 69(1), 89-94.

[54] Fernandez, A., & Gomez, S. (2007). Portfolio selection using neural networks. Computers & Operations Research, 34(4), 1177-1191.

[55] Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. European Journal of Operational Research, 270(2), 654-669.

[56] Freitas, F. D., De Souza, A. F., & de Almeida, A. R. (2009). Prediction-based portfolio optimization model using neural networks. Neurocomputing, 72(10-12), 2155-2170.

[57] Ghazali, R., Hussain, A. J., Nawi, N. M., & Mohamad, B. (2009). Non-stationary and stationary prediction of financial time series using dynamic ridge polynomial neural network. Neurocomputing, 72(10-12), 2359-2367.

[58] Glass, G. V. (1976). Primary, secondary, and meta-analysis of research. Educational researcher, 5(10), 3-8.

[59] Grudnitski, G., & Osburn, L. (1993). Forecasting S&P and gold futures prices: An application of neural networks. Journal of Futures Markets, 13(6), 631-643.

[60] Guresen, E., Kayakutlu, G., & Daim, T. U. (2011). Using artificial neural network models in stock market index prediction. Expert Systems with Applications, 38(8), 10389-10397.

[61] Guresen, E., & Kayakutlu, G. (2008, October). Forecasting stock exchange movements using artificial neural network models and hybrid models. In International Conference on Intelligent Information Processing (pp. 129-137). Springer, Boston, MA.

[62] Hajizadeh, E., Seifi, A., Zarandi, M. F., & Turksen, I. B. (2012). A hybrid modeling approach for forecasting the volatility of S&P 500 index return. Expert Systems with Applications, 39(1), 431-436.

[63] Harvey, C. R., Travers, K. E., & Costa, M. J. (2000). Forecasting emerging market returns using neural networks. Emerging Markets Quarterly, 4, 43-54.

[64] Hassan, M. R. (2009). A combination of hidden Markov model and fuzzy model for stock market forecasting. Neurocomputing, 72(16-18), 3439-3446.

[65] Hassan, M. R., Nath, B., & Kirley, M. (2007). A fusion model of HMM, ANN and GA for stock market forecasting. Expert Systems with Applications, 33(1), 171-180.

[66] Haykin, S. (1994). Neural networks: a comprehensive foundation. Prentice Hall PTR.

[67] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural computation, 9(8), 1735-1780.

[68] Hsieh, T. J., Hsiao, H. F., & Yeh, W. C. (2011). Forecasting stock markets using wavelet transforms and recurrent neural networks: An integrated system based on artificial bee colony algorithm. Applied soft computing, 11(2), 2510-2525.

[69] Hsu, S. H., Hsieh, J. P. A., Chih, T. C., & Hsu, K. C. (2009). A two-stage architecture for stock price forecasting by integrating self-organizing map and support vector regression. Expert Systems with Applications, 36(4), 7947-7951.

[70] Huang, C. L., & Tsai, C. Y. (2009). A hybrid SOM-SVR with a filter-based feature selection for stock market forecasting. Expert Systems with Applications, 36(2), 1529-1539.

[71] Huang, H., Pasquier, M., & Quek, C. (2009). Financial market trading system with a hierarchical coevolutionary fuzzy predictive model. IEEE Transactions on Evolutionary Computation, 13(1), 56-70.

[72] Huang, S. C., & Wu, T. K. (2008). Integrating GA-based time-scale feature extractions with SVMs for stock index forecasting. Expert Systems with Applications, 35(4), 2080-2088.

[73] Huang, W., Nakamori, Y., & Wang, S. Y. (2005). Forecasting stock market movement direction with support vector machine. Computers & Operations Research, 32(10), 2513-2522.

[74] Hussain, A. J., Knowles, A., Lisboa, P. J., & El-Deredy, W. (2008). Financial time series prediction using polynomial pipelined neural networks. Expert Systems with Applications, 35(3), 1186-1199.

[75] Jarrell, S. B., & Stanley, T. D. (1990). A meta-analysis of the union-nonunion wage gap. ILR Review, 44(1), 54-67.

[76] Kanas, A., & Yannopoulos, A. (2001). Comparing linear and nonlinear forecasts for stock returns. International Review of Economics & Finance, 10(4), 383-398.

[77] Kara, Y., Boyacioglu, M. A., & Baykan, O. K. (2011). Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul Stock Exchange. Expert Systems with Applications, 38(5), 5311-5319.

[78] Khan, M. A. I. (2011). Financial volatility forecasting by nonlinear support vector machine heterogeneous autoregressive model: evidence from Nikkei 225 stock index. International Journal of Economics and Finance, 3(4), 138.

[79] Khadjeh Nassirtoussi, A., Aghabozorgi, S., Wah, T. Y., Ngo, D. C. L. (2015). Text mining of news headlines for FOREX market prediction: A Multi-layer Dimension Reduction Algorithm with semantics and sentiment. Expert Systems with Applications, 42, 306-324.

[80] Khemchandani, R., & Chandra, S. (2009). Regularized least squares fuzzy support vector regression for financial time series forecasting. Expert Systems with Applications, 36(1), 132-138.

[81] Kim, H. J., & Shin, K. S. (2007). A hybrid approach based on neural networks and genetic algorithms for detecting temporal patterns in stock markets. Applied Soft Computing, 7(2), 569-576.

[82] Kim, K. J. (2003). Financial time series forecasting using support vector machines. Neurocomputing, 55(1-2), 307-319.

[83] Kim, K. J. (2006). Artificial neural networks with evolutionary instance selection for financial forecasting. Expert Systems with Applications, 30(3), 519-526.

[84] Kim, K. J., & Ahn, H. (2012). Simultaneous optimization of artificial neural networks for financial forecasting. Applied Intelligence, 36(4), 887-898.

[85] Kim, K. J., & Han, I. (2000). Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index. Expert Systems with Applications, 19(2), 125-132.

[86] Kim, K. J., Han, I., & Chandler, J. S. (1998). Extracting trading rules from the multiple classifiers and technical indicators in stock market. In The Korea Society of Management Information Systems' 98 International Conference on IS Paradigm reestablishment. The Korea Society of Management Information Systems.

[87] Kim, S. H., & Chun, S. H. (1998). Graded forecasting using an array of bipolar predictions: application of probabilistic neural networks to a stock market index. International Journal of Forecasting, 14(3), 323-337.

[88] Kimoto, T., Asakawa, K., Yoda, M., & Takeoka, M. (1990, June). Stock market prediction system with modular neural networks. In Neural Networks, 1990., 1990 IJCNN International Joint Conference on (pp. 1-6). IEEE.

[89] Ko, P. C., & Lin, P. C. (2008). Resource allocation neural network in portfolio selection. Expert Systems with Applications, 35(1-2), 330-337.

[90] Koulouriotis, D. E., Diakoulakis, I. E., Emiris, D. M., & Zopounidis, C. D. (2005). Development of dynamic cognitive networks as complex systems approximators: validation in financial time series. Applied Soft Computing, 5(2), 157-179.

[91] Krauss, C., Do, X. A., & Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500. European Journal of Operational Research, 259(2), 689-702.

[92] Kristjanpoller, W., & Minutolo, M. C. (2015). Gold price volatility: A forecasting approach using the Artificial Neural Network-GARCH model. Expert Systems with Applications, 42(20), 7245-7251.

[93] Kristjanpoller, W., & Minutolo, M. C. (2016). Forecasting volatility of oil price using an artificial neural network-GARCH model. Expert Systems with Applications, 65, 233-241.

[94] Kristjanpoller, W., & Minutolo, M. C. (2018). A hybrid volatility forecasting framework integrating GARCH, artificial neural network, technical analysis and principal components analysis. Expert Systems with Applications, 109, 1-11.

[95] Kristjanpoller, W., Fadic, A., & Minutolo, M. C. (2014). Volatility forecast using hybrid neural network models. Expert Systems with Applications, 41(5), 2437-2442.

[96] Kryzanowski, L., Galler, M., & Wright, D. W. (1993). Using artificial neural networks to pick stocks. Financial Analysts Journal, 21-27.

[97] Kumar, D., Meghwani, S. S., & Thakur, M. (2016). Proximal support vector machine based hybrid prediction models for trend forecasting in financial markets. Journal of Computational Science, 17, 1-13.

[98] Kuo, R. J. (1998). A decision support system for the stock market through integration of fuzzy neural networks and fuzzy Delphi. Applied Artificial Intelligence, 12(6), 501-520.

[99] Kuo, R. J., Lee, L. C., & Lee, C. F. (1996, October). Integration of artificial neural networks and fuzzy delphi for stock market forecasting. In Systems, Man, and Cybernetics, 1996., IEEE International Conference on(Vol. 2, pp. 1073-1078). IEEE.

[100] Kwon, Y. K., & Moon, B. R. (2007). A hybrid neurogenetic approach for stock forecasting. IEEE transactions on neural networks, 18(3), 851-864.

[101] Lam, M. (2004). Neural network techniques for financial performance prediction: integrating fundamental and technical analysis. Decision support systems, 37(4), 567-581.

[102] Lee, J., Cho, S., & Baek, J. (2003, March). Trend detection using auto-associative neural networks: Intraday KOSPI 200 futures. In Computational Intelligence for Financial Engineering, 2003. Proceedings. 2003 IEEE International Conference on (pp. 417-420). IEEE.

[103] Lee, M. C. (2009). Using support vector machine with a hybrid feature selection method to the stock trend prediction. Expert Systems with Applications, 36(8), 10896-10904.

[104] Lee, T. S., & Chen, N. J. (2002). Investigating the information content of non-cash-trading index futures using neural networks. Expert Systems with Applications, 22(3), 225-234.

[105] Lee, T. S., & Chiu, C. C. (2002). Neural network forecasting of an opening cash price index. International Journal of Systems Science, 33(3), 229-237.

[106] Leigh, W., Paz, M., & Purvis, R. (2002). An analysis of a hybrid neural network and pattern recognition technique for predicting short-term increases in the NYSE composite index. Omega, 30(2), 69-76.

[107] Lendasse, A., de Bodt, E., Wertz, V., & Verleysen, M. (2000). Non-linear financial time series forecasting-Application to the Bel 20 stock market index. European Journal of Economic and Social Systems, 14(1), 81-91.

[108] Leu, Y., Lee, C. P., & Jou, Y. Z. (2009). A distance-based fuzzy time series model for exchange rates forecasting. Expert Systems with Applications, 36(4), 8107-8114.

[109] Li, S. T., & Kuo, S. C. (2008). Knowledge discovery in financial investment for forecasting and trading strategy through wavelet-based SOM networks. Expert Systems with applications, 34(2), 935-951.

[110] Li, X., Zhang, Y., Wong, H. S., & Qin, Z. (2009). A hybrid intelligent algorithm for portfolio selection problem with fuzzy returns. Journal of Computational and Applied Mathematics, 233(2), 264-278.

[111] Liao, Z., & Wang, J. (2010). Forecasting model of global stock index by stochastic time effective neural network. Expert Systems with Applications, 37(1), 834-841.

[112] Lin, C. T., & Yeh, H. Y. (2009). Empirical of the Taiwan stock index option price forecasting model-applied artificial neural network. Applied Economics, 41(15), 1965-1972.

[113] Lu, C. J., & Wu, J. Y. (2011). An efficient CMAC neural network for stock index forecasting. Expert Systems with Applications, 38(12), 15194-15201.

[114] Lu, X., Que, D., & Cao, G. (2016). Volatility forecast based on the hybrid artificial neural network and GARCH-type models. Procedia Computer Science, 91, 1044-1049.

[115] Majhi, R., Panda, G., & Sahoo, G. (2009). Efficient prediction of exchange rates with low complexity artificial neural network models. Expert Systems with applications, 36(1), 181-189.

[116] Majhi, R., Panda, G., Sahoo, G., Dash, P. K., & Das, D. P. (2007, September). Stock market prediction of S&P 500 and DJIA using bacterial foraging optimization technique. In Evolutionary Computation, 2007. CEC 2007. IEEE Congress on (pp. 2569-2575). IEEE.

[117] Majhi, R., Panda, G., Sahoo, G., Panda, A., & Choubey, A. (2008, June). Prediction of S&P 500 and DJIA stock indices using particle swarm optimization technique. In 2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence) (pp. 1276-1282). IEEE.

[118] Malliaris, M., & Salchenberger, L. (1993, March). Beating the best: A neural network challenges the Black-Scholes formula. In Artificial Intelligence for Applications, 1993. Proceedings., Ninth Conference on (pp. 445-449). IEEE.

[119] Mendel, J. M., & McLaren, R. W. (1970). 8 Reinforcement-Learning Control and Pattern Recognition Systems. In Mathematics in Science and Engineering (Vol. 66, pp. 287-318). Elsevier.

[120] Mizuno, H., Kosaka, M., Yajima, H., & Komoda, N. (1998). Application of neural network to technical analysis of stock market prediction. Studies in Informatic and control, 7(3), 111-120.

[121] Monfared, S. A., & Enke, D. (2014). Volatility forecasting using a hybrid GJR-GARCH neural network model. Procedia Computer Science, 36, 246-253.

[122] Moody, J., & Saffell, M. (2001). Learning to trade via direct reinforcement. IEEE transactions on neural Networks, 12(4), 875-889.

[123] Motiwalla, L., & Wahab, M. (2000). Predictable variation and profitable trading of US equities: a trading simulation using neural networks. Computers & Operations Research, 27(11-12), 1111-1129.

[124] Nayak, S. C., Misra, B. B., & Behera, H. S. (2012, February). Index prediction with neuro-genetic hybrid network: A comparative analysis of performance. In Computing, Communication and Applications (ICCCA), 2012 International Conference on (pp. 1-6). IEEE.

[125] Ni, H., & Yin, H. (2009). Exchange rate prediction using hybrid neural networks and trading indicators. Neurocomputing, 72(13-15), 2815-2823.

[126] Oh, K. J., & Kim, K. J. (2002). Analyzing stock market tick data using piecewise nonlinear model. Expert Systems with Applications, 22(3), 249-255.

[127] Olson, D., & Mossman, C. (2003). Neural network forecasts of Canadian stock returns using accounting ratios. International Journal of Forecasting, 19(3), 453-465.

[128] Ou, J. A., & Penman, S. H. (1989). Financial statement analysis and the prediction of stock returns. Journal of accounting and economics, 11(4), 295-329.

[129] Pai, P. F., & Lin, C. S. (2005). A hybrid ARIMA and support vector machines model in stock price forecasting. Omega, 33(6), 497-505.

[130] Pan, H., Tilakaratne, C., & Yearwood, J. (2005). Predicting Australian stock market index using neural networks exploiting dynamical swings and intermarket influences. Journal of research and practice in information technology, 37(1), 43.

[131] Panda, C., & Narasimhan, V. (2007). Forecasting exchange rate better with artificial neural network. Journal of Policy Modeling, 29(2), 227-236.

[132] Pantazopoulos, K. N., Tsoukalas, L. H., Bourbakis, N. G., Brun, M. J., & Houstis, E. N. (1998). Financial prediction and trading strategies using neurofuzzy approaches. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 28(4), 520-531.

[133] Petropoulos, A., Chatzis, S. P., Siakoulis, V., & Vlachogiannakis, N. (2017). A stacked generalization system for automated FOREX portfolio trading. Expert Systems with Applications, 90, 290-302.

[134] Perez-Rodriguez, J. V., Torra, S., & Andrada-Felix, J. (2005). STAR and ANN models: forecasting performance on the Spanish Ibex-35 stock index. Journal of Empirical Finance, 12(3), 490-509.

[135] Qi, M. (1999). Nonlinear predictability of stock returns using financial and economic variables. Journal of Business & Economic Statistics, 17(4), 419-429.

[136] Quah, T. S. (2008). DJIA stock selection assisted by neural network. Expert Systems with Applications, 35(1-2), 50-58.

[137] Quek, C., Yow, K. C., Cheng, P. Y., & Tan, C. C. (2009). Investment portfolio balancing: application of a generic selforganizing fuzzy neural network (GenSoFNN). Intelligent Systems in Accounting, Finance & Management: International Journal, 16(12), 147-164.

[138] Raposo, R. D. C. T., & Cruz, A. D. O. (2002). Stock market prediction based on fundamentalist analysis with fuzzy-neural networks. In Proceedings of 3rd WSES International Conference on Fuzzy Sets.

[139] Rast, M. (1999, July). Forecasting with fuzzy neural networks: A case study in stock market crash situations. In Fuzzy Information Processing Society, 1999. NAFIPS. 18th International Conference of the North American (pp. 418-420). IEEE.

[140] Rather, A. M. (2011, December). A prediction based approach for stock returns using autoregressive neural networks. In Information and Communication Technologies (WICT), 2011 World Congress on (pp. 1271-1275). IEEE.

[141] Rather, A. M. (2014). A hybrid intelligent method of predicting stock returns. Advances in Artificial Neural Systems, 2014, 4.

[142] Rather, A. M., Agarwal, A., & Sastry, V. N. (2015). Recurrent neural network and a hybrid model for prediction of stock returns. Expert Systems with Applications, 42(6), 3234-3241.

[143] Refenes, A. N., Azema-Barac, M., & Zapranis, A. D. (1993). Stock ranking: Neural networks vs multiple linear regression. In Neural Networks, 1993., IEEE International Conference on (pp. 1419-1426). IEEE.

[144] Rodriguez-Gonzalez, A., Garcia-Crespo, A., Colomo-Palacios, R., Iglesias, F. G., & Gomez-Berbis, J. M. (2011). CAST: Using neural networks to improve trading systems based on technical analysis by means of the RSI financial indicator. Expert Systems with Applications, 38(9), 11489-11500.

[145] Rose, A. K., & Stanley, T. D. (2005). A metaanalysis of the effect of common currencies on international trade. Journal of economic surveys, 19(3), 347-365.

[146] Rout, A. K., Dash, P. K., Dash, R., & Bisoi, R. (2017). Forecasting financial time series using a low complexity recurrent neural network and evolutionary learning approach. Journal of King Saud University-Computer and Information Sciences, 29(4), 536-552.

[147] Sagar, V. K., & Kiat, L. C. (1999). A neural stock price predictor using qualitative and quantitative data. In Neural Information Processing, 1999. Proceedings. ICONIP'99. 6th International Conference on (Vol. 2, pp. 831-835). IEEE.

[148] Sezer, O. B., & Ozbayoglu, A. M. (2018). Algorithmic Financial Trading with Deep Convolutional Neural Networks: Time Series to Image Conversion Approach. Applied Soft Computing.

[149] Shen, G., Tan, Q., Zhang, H., Zeng, P., & Xu, J. (2018). Deep Learning with Gated Recurrent Unit Networks for Financial Sequence Predictions. Procedia computer science, 131, 895-903.

[150] Shynkevich, Y., McGinnity, T. M., Coleman, S. A., Belatreche, A., & Li, Y. (2017). Forecasting price movements using technical indicators: Investigating the impact of varying input window length. Neurocomputing, 264, 71-88.

[151] Siekmann, S., Kruse, R., Gebhardt, J., Van Overbeek, F., & Cooke, R. (2001). Information fusion in the context of stock index prediction. International journal of intelligent systems, 16(11), 1285-1298.

[152] Soto, J., & Melin, P. (2015). Optimization of the interval type-2 fuzzy integrators in ensembles of ANFIS models for time series prediction: case of the Mexican stock exchange. In Design of Intelligent Systems Based on Fuzzy Logic, Neural Networks and Nature-Inspired Optimization (pp. 27-45). Springer, Cham.

[153] Stanley, T. D., & Jarrell, S. B. (1989). Metaregression analysis: a quantitative method of literature surveys. Journal of economic surveys, 3, 161-170.

[154] Stanley, T. , Doucouliagos, H. , Giles, M., Heckemeyer, J. H., Johnston, R. J., Laroche, P., Nelson, J. P., Paldam, M., Poot, J., Pugh, G., Rosenberger, R. S., & Rost, K. (2013). Metaanalysis of economics research reporting guidelines. Journal of Economic Surveys, 27(2), 390-394.

[155] Steiner, M., & Wittkemper, H. G. (1997). Portfolio optimization with a neural network implementation of the coherent market hypothesis. European journal of operational research, 100(1), 27-40.

[156] Tay, F. E., & Cao, L. (2001). Application of support vector machines in financial time series forecasting. Omega, 29(4), 309-317.

[157] Tenti, P. (1996). Forecasting foreign exchange rates using recurrent neural networks. Applied Artificial Intelligence, 10(6), 567-582.

[158] Thawornwong, S., & Enke, D. (2004). The adaptive selection of financial and economic variables for use with artificial neural networks. Neurocomputing, 56, 205-232.

[159] Ticknor, J. L. (2013). A Bayesian regularized artificial neural network for stock market forecasting. Expert Systems with Applications, 40(14), 5501-5506.

[160] Tsaih, R., Hsu, Y., & Lai, C. C. (1998). Forecasting S&P 500 stock index futures with a hybrid AI system. Decision Support Systems, 23(2), 161-174.

[161] Tseng, C. H., Cheng, S. T., Wang, Y. H., & Peng, J. T. (2008). Artificial neural network model of the hybrid EGARCH volatility of the Taiwan stock index option prices. Physica A: Statistical Mechanics and its Applications, 387(13), 3192-3200.

[162] Vanstone, B. J., Finnie, G. R., & Tan, C. N. (2005). Evaluating the Application of Neural Networks and Fundamental Analysis in the Australian Stockmarket. In Computational Intelligence (pp. 62-63).

[163] Versace, M., Bhatt, R., Hinds, O., & Shiffer, M. (2004). Predicting the exchange traded fund DIA with a combination of genetic algorithms and neural networks. Expert Systems with applications, 27(3), 417-425.

[164] Wah, B. W., & Qian, M. (2002, July). Constrained formulations and algorithms for stock-price predictions using recurrent FIR neural networks. In AAAI/IAAI (pp. 211-216).

[165] Walczak, S. (1999). Gaining competitive advantage for trading in emerging capital markets with neural networks. Journal of Management Information Systems, 16(2), 177-192.

[166] Wang, J. L., & Chan, S. H. (2006). Stock market trading rule discovery using two-layer bias decision tree. Expert Systems with Applications, 30(4), 605-611.

[167] Wang, J. Z., Wang, J. J., Zhang, Z. G., & Guo, S. P. (2011). Forecasting stock indices with back propagation neural network. Expert Systems with Applications, 38(11), 14346-14355.

[168] Wang, Q., Xu, W., & Zheng, H. (2018). Combining the wisdom of crowds and technical analysis for financial market prediction using deep random subspace ensembles. Neurocomputing, 299, 51-61.

[169] Wang, Y. H. (2009). Nonlinear neural network forecasting model for stock index option price: Hybrid GJR-GARCH approach. Expert Systems with Applications, 36(1), 564-570.

[170] Wen, Q., Yang, Z., & Song, Y. (2009). Hybrid approaches for stock price prediction. Iccsa.

[171] Wen, Q., Yang, Z., Song, Y., & Jia, P. (2010). Automatic stock decision support system based on box theory and SVM algorithm. Expert Systems with Applications, 37(2), 1015-1022.

[172] Witkowska, D. (1995). Neural networks as a forecasting instrument for the polish stock exchange. International Advances in Economic Research, 1(3), 232-241.

[173] Wittkemper, H. G., & Steiner, M. (1996). Using neural networks to forecast the systematic risk of stocks. European Journal of Operational Research, 90(3), 577-588.

[174] Wu, X., Fung, M., & Flitman, A. (2001, May). Forecasting stock market performance using hybrid intelligent system. In International Conference on Computational Science(pp. 447-456). Springer, Berlin, Heidelberg.

[175] Yeh, I. C., Lien, C. H., & Tsai, Y. C. (2011). Evaluation approach to stock trading system using evolutionary computation. Expert Systems with Applications, 38(1), 794-803.

[176] Yu, L., Wang, S., & Lai, K. K. (2008). Neural network-based mean-variance-skewness model for portfolio selection. Computers & Operations Research, 35(1), 34-46.

[177] Yu, T. H. K., & Huarng, K. H. (2008). A bivariate fuzzy time series model to forecast the TAIEX. Expert Systems with Applications, 34(4), 2945-2952.

[178] Yumlu, M. S., Gurgen, F. S., & Okay, N. (2004). Turkish stock market analysis using mixture of experts. Proceedings of Engineering of Intelligent Systems (EIS), Madeira.

[179] Yumlu, S., Gurgen, F. S., & Okay, N. (2005). A comparison of global, recurrent and smoothed-piecewise neural models for Istanbul stock exchange (ISE) prediction. Pattern Recognition Letters, 26(13), 2093-2103.

[180] Zhang, D., Jiang, Q., & Li, X. (2004). Application of Neural Networks in Financial Data Mining. In International Conference on Computational Intelligence (pp. 392-395).

[181] Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing, 50, 159-175.

[182] Zhang, G. P., & Berardi, V. L. (2001). Time series forecasting with neural network ensembles: an application for exchange rate prediction. Journal of the Operational Research Society, 52(6), 652-664.

[183] Zhang, X. D., Li, A., & Pan, R. (2016). Stock trend prediction based on a new status box method and AdaBoost probabilistic support vector machine. Applied Soft Computing, 49, 385-398.

[184] Zhang, Y. Q., & Wan, X. (2007). Statistical fuzzy interval neural networks for currency exchange rate time series prediction. Applied Soft Computing, 7(4), 1149-1156.

[185] Zhang, Y. Q., Akkaladevi, S., Vachtsevanos, G., & Lin, T. Y. (2002). Granular neural web agents for stock prediction. Soft Computing, 6(5), 406-413.

[186] Zhu, X., Wang, H., Xu, L., & Li, H. (2008). Predicting stock index increments by neural networks: The role of trading volume under different horizons. Expert Systems with Applications, 34(4), 3043-3054.

[187] de Oliveira, F. A., Nobre, C. N., & Zarate, L. E. (2013). Applying Artificial Neural Networks to prediction of stock price and improvement of the directional prediction index-Case study of PETR4, Petrobras, Brazil. Expert Systems with Applications, 40(18), 7596-7606.