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Deep Learning for Financial Applications : A Survey

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Abstract

Computational intelligence in finance has been a very popular topic for both academia and financial industry in the last few decades. Numerous studies have been published resulting in various models. Meanwhile, within the Machine Learning (ML) field, Deep Learning (DL) started getting a lot of attention recently, mostly due to its outperformance over the classical models. Lots of different implementations of DL exist today, and the broad interest is continuing. Finance is one particular area where DL models started getting traction, however, the playfield is wide open, a lot of research opportunities still exist. In this paper, we tried to provide a state-of-the-art snapshot of the developed DL models for financial applications. We not only categorized the works according to their intended subfield in finance but also analyzed them based on their DL models. In addition, we also aimed at identifying possible future implementations and highlighted the pathway for the ongoing research within the field.

Keywords: deep learning, finance, computational intelligence, machine learning, financial applications, algorithmic trading, portfolio management, risk assesment, fraud detection

1. Introduction

Stock market forecasting, algorithmic trading, credit risk assessment, portfolio allocation, asset pricing and derivatives market are among the areas where ML researchers focused on developing models that can provide real-time working solutions for the financial industry. Hence, a lot of publications and implementations exist in the literature.

However, within the ML field, DL is an emerging area with a rising interest every year. As a result, an increasing number of DL models for finance started appearing in conferences and journals. Our focus in this paper is to present different implementations of the developed financial DL models in such a way that the researchers and practitioners that are interested in the topic can decide which path they should take.

In this paper, we tried to provide answers to the following research questions:

- What financial application areas are of interest to DL community?
- How mature is the existing research in each of these application areas?
- What are the areas that have promising potentials from an academic/industrial research perspective?

- Which DL models are preferred (and more successful) in different applications?
- How do DL models pare against traditional soft computing / ML techniques?
- What is the future direction for DL research in Finance?

Our focus was solely on DL implementations for financial applications. A substantial portion of the computational intelligence for finance research is devoted to financial time series forecasting. However, we preferred to concentrate on those studies in a separate survey paper [1] in order to be able to pinpoint other, less covered application areas. Meanwhile, we decided to include algorithmic trading studies with DL based trading strategies which may or may not have an embedded time series forecasting component.

For our search methodology, we surveyed and carefully reviewed the studies that came to our attention from the following sources: ScienceDirect, ACM Digital Library, Google Scholar, arXiv.org, ResearchGate, Google keyword search for DL and finance. The range of our survey spanned not only journals and conferences, but also Masters and PhD theses, book chapters, arXiv papers and noteworthy technical papers that came up in Google searches. Furthermore, we only chose the articles that were written in English.

Most of the papers in this survey used the term “deep learning" in their model description and they were published in the past 5 years. However, we also included some older papers that implemented deep learning models even though they were not called “deep learning" models at their time of publication. Some examples for such models include Recurrent Neural Network (RNN) and Jordan-Elman networks.

As will be introduced in the next section, a lot of ML surveys exist for different areas of finance, however, no study has concentrated on DL implementations. We genuinely believe our study will highlight the major advancements in the field and provide a roadway for the intended researchers that would like to develop DL models for different financial applications.

The rest of the paper is structured as follows. After this brief introduction, in Section 2, the existing surveys that are focused on ML and soft computing studies for financial applications are presented. In Section 3, we will provide the basic working DL models that are used in finance, i.e. Convolutional Neural Network (CNN), Long-Short Term Memory (LSTM), etc. Section 4 will focus on the implementation areas of the DL models in finance. Some of these include algorithmic trading, credit risk assessment, portfolio allocation, asset pricing, fraud detection and derivatives market. After briefly stating the problem definition in each subsection, DL implementations of each associated problem will be given.

In Section 5, these studies will be compared and some overall statistical results will be presented including histograms and heatmaps about the distribution of different subfields, models, features, datasets. These statistics will not only demonstrate the current state for the field but also will show which areas are mature, which areas still have opportunities and which areas are getting accelerated attention. Section 6 will have discussions about what has been done in the field so far and where the industry is going. The chapter will also include the achievements and expectations of both academia and the industry. Also, open areas and recommended research topics will be mentioned. Finally, in Section 7, we will summarize the findings and conclude.

2. Machine Learning in Finance

Finance has always been one of the most studied application areas for ML. So far, thousands of research papers were published in various fields within finance, and the overall interest does not seem to diminish anytime soon. Even though this survey paper is solely focused on DL implementations, we wanted to provide the audience with some insights about previous ML studies by citing the related surveys within the past 20 years.

There are a number of ML surveys and books with a general perspective such that their focus is not on any particular implementation area. Bahrammirzaee et al. [2] compared Artificial Neural Networks (ANNs), Expert Systems and Hybrid models for various financial applications. Zhang et al. [3] reviewed the data mining techniques including Genetic Algorithm (GA), rule-based systems, Neural Networks (NNs) preferred in different financial application areas. Similarly, Mochn et al. [4] also provided insights about financial implementations based on soft computing techniques like fuzzy logic, probabilistic reasoning and NNs. Even though Pulakkazhy et al. [5] focused particularly on data mining models in banking applications, they still had a span of several subtopics within the field. Meanwhile, Mullainathan et al. [6] studied the ML implementations from a high level and econometric point of view. Likewise, Gai et al. [7] reviewed the Fintech studies and implementations not only from an ML perspective but also from a different point of view such as security, data-oriented techniques, and application. The publications in [8, 9, 10, 11] constitute some of the books that cover the implementations of soft computing models in finance.

Meanwhile, there are some survey papers that are also not application area-specific but rather focused on particular ML techniques. One of those soft computing techniques is the family of Evolutionary Algorithms (EAs), i.e. GA, Particle Swarm Optimization (PSO), etc. commonly used in financial optimization implementations like Portfolio Selection. Chen et al. [12] wrote a book covering GAs and Genetic Programming (GP) in Computational Finance. Later, Castillo et al. [13], Ponsich et al. [14], Aguilar-Rivera et al. [15] extensively surveyed Multiobjective Evolutionary Algorithms (MOEAs) on portfolio optimization and other various financial applications.

Since ANNs were quite popular among researchers, a number of survey papers were just dedicated to them. Wong et al. [16] covered early implementations of ANNs in finance. Li et al. [17] reviewed implementations of ANNs for stock price forecasting and some other financial applications. Lately, Elmsili et al. [18] contained ANN applications in economics and management research in their survey.

In addition, LeBaron [19] covered the studies focused on agent-based computational finance. Meanwhile, Chalup et al. [20] wrote a book chapter on kernel methods in financial applications which includes models like Principal Component Analysis (PCA) and Support Vector Machine (SVM).

And then, there are application-specific survey papers that single out particular financial areas which are quite useful and informative for researchers that already know what they are looking for. These papers will be covered in the appropriate subsections of Section 4 during problem description. In the next section, brief working structures of the DL models used in the financial applications will be given.

3. Deep Learning

Deep Learning is a particular type of ML that consists of multiple ANN layers. It provides high-level abstraction for data modelling [21]. In the literature, different DL models exist: Deep Multilayer Perceptron (DMLP), CNN, RNN, LSTM, Restricted Boltzmann Machines (RBMs), Deep Belief Networks (DBNs), and Autoencoders (AEs).

3.1. Deep Multi Layer Perceptron

In the literature, DMLP was the first proposed ANN model of its kind. DMLP networks consist of input, output and hidden layers just like an ordinary Multilayer Perceptron (MLP); however, the number of layers in DMLP is more than MLP. Each neuron in every layer has $input(x)$, $weight(w)$ and $bias(b)$ terms. An output of a neuron in the neural network is illustrated in Equation 1. In addition, each neuron has a nonlinear activation function which produces the output of that neuron through accumulating weighted inputs from the neurons in the preceding layer. Sigmoid [22], hyperbolic tangent [23], Rectified Linear Unit (ReLU) [24], leaky ReLU [25], swish [26], and softmax[27] are among the most preferred nonlinear activation functions in the literature.

$$y_i = \sigma(\sum_i W_i x_i + b_i) \tag{1}$$

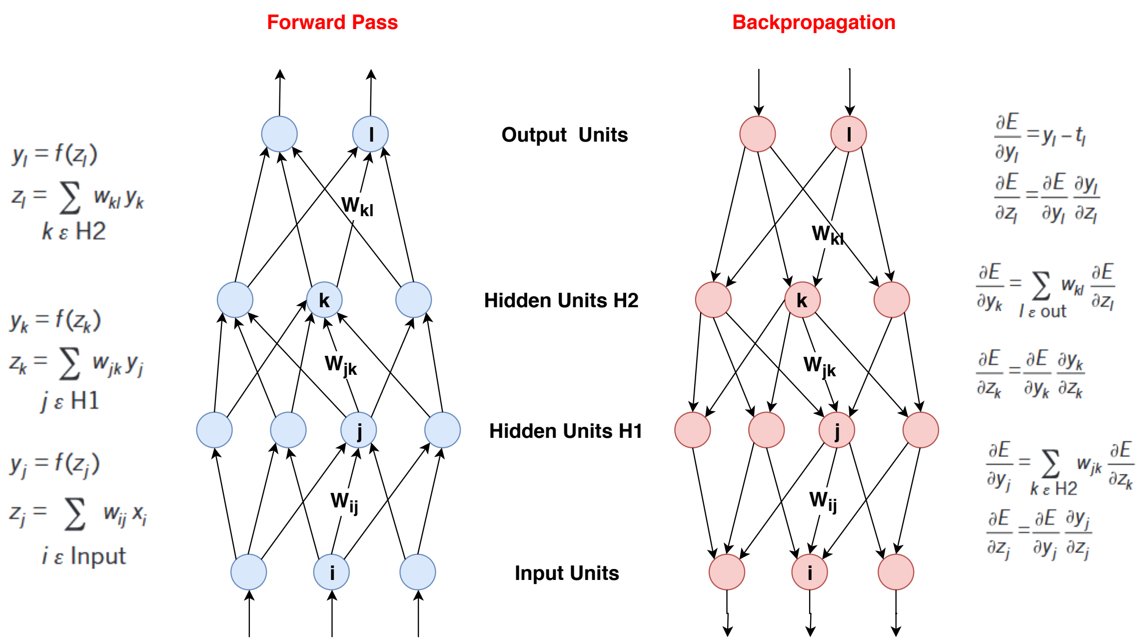

Figure 1: Deep Multi Layer Neural Network Forward Pass and Backpropagation [21]

With multi-layer deep ANNs, more efficient classification and regression performances are achieved when compared against shallow nets. DMLPs' learning process is implemented through backpropagation. The amount of the output error in the output layer neurons is also reflected back to the neurons in the previous layers. In DMLP, Stochastic Gradient Descent (SGD) method is (mostly) used for the optimization of learning (to update the weights of the connections between the layers). In Figure 1, a DMLP model, the layers, the neurons in layers, the weights between the neurons are shown.

3.2. Convolutional Neural Networks

CNN is a type of Deep Neural Network (DNN) that is mostly used for image classification and image recognition problems. In its methodology, the whole image is scanned with filters. In the literature, 1x1, 3x3 and 5x5 filter sizes are mostly used. In most of the CNN architectures, there are different types of layers: convolutional, pooling (average or maximum), fully connected layers. CNN consists of convolutional layers based on the convolutional operation. Figure 2 shows the generalized CNN architecture that has different layers: convolutional, subsampling (pooling) and fully connected layers.

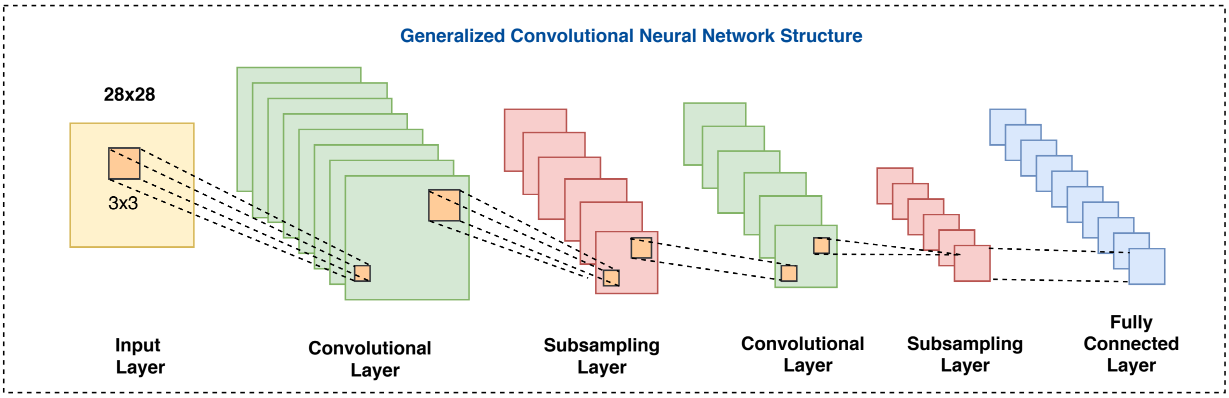

Figure 2: Generalized Convolutional Neural Network Architecture

3.3. Recurrent Neural Network

In the literature, RNN has been mostly used on sequential data such as time-series data, audio and speech data, language. It consists of RNN units that are structured consecutively. Unlike feed-forward networks, RNNs use internal memory to process the incoming inputs. RNNs are used in the analysis of time series data in various fields (handwriting recognition, speech recognition, etc).

There are different types of RNN structures: one to many, many to one, many to many. Generally, RNN processes the input sequence series one by one at a time, during its operation. Units in the hidden layer hold information about the history of the input in the "state vector" [21]. RNNs can be trained using the Backpropagation Through Time (BPTT) method. Using BPTT, the differentiation of the loss at any time t has reflected the weights of the network at the previous time step. Training of RNNs are more difficult than Feedforward Neural Networks (FFNNs) and the training period of RNNs takes longer.

In Figure 3, the information flow in the RNN's hidden layer is divided into discrete times. The status of the node S at different times of t is shown as s_t, the input value x at different times is x_t, and the output value o at different times is shown as o_t. The parameter values (U, W, V) are always used in the same step.

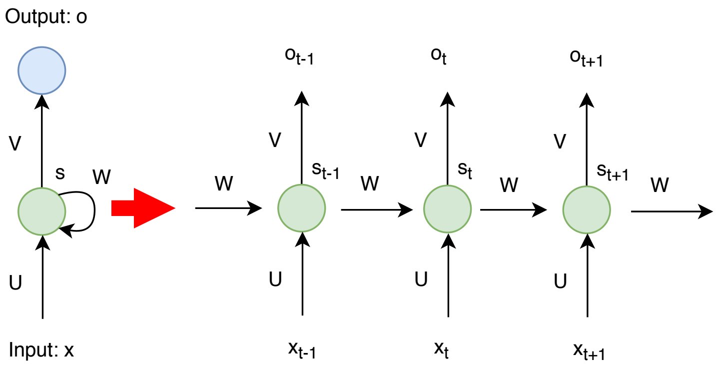

Figure 3: RNN cell through time[21]

3.4. Long Short Term Memory

LSTM network [28] is a different type of DL network specifically intended for sequential data analysis. The advantage of LSTM networks lies in the fact that both short term and long term values in the network can be remembered. Therefore, LSTM networks are mostly used for sequential data analysis (automatic speech recognition, language translation, handwritten character recognition, time-series data forecasting, etc.) by DL researchers.

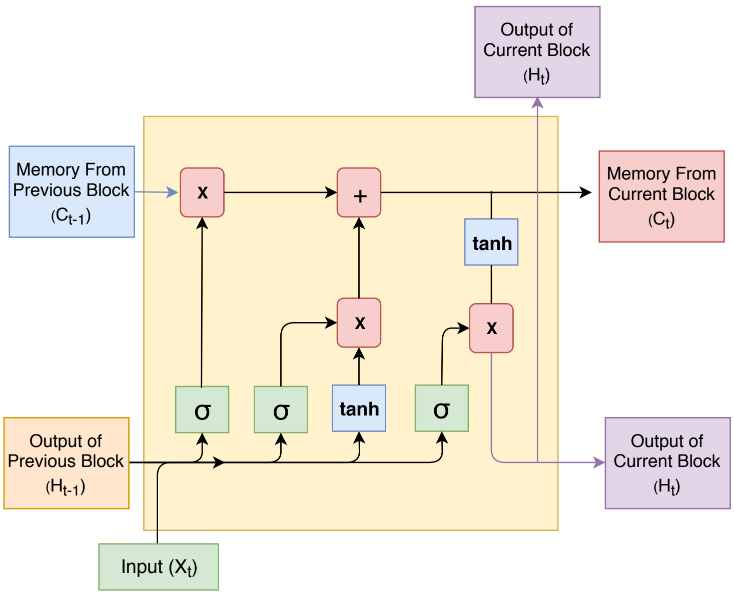

Figure 4: Basic LSTM Unit [28]

LSTM network [28] is a different type of DL network specifically intended for sequential data analysis. The advantage of LSTM networks lies in the fact that both short term and long term values in the network can be remembered. Therefore, LSTM networks are mostly used for sequential data analysis (automatic speech recognition, language translation, handwritten character recognition, time-series data forecasting, etc.) by DL researchers. LSTM networks consist of LSTM units. LSTM unit is composed of cells having input, output and forget gates. These three gates regulate the information flow. With these features, each cell remembers the desired values over arbitrary time intervals. LSTM cells combine to form layers of neural networks. Figure 4 illustrates the basic LSTM unit (σ_g: sigmoid function, *tanh*: hyperbolic tangent function, X: multiplication, $+$: addition).

3.5. Restricted Boltzmann Machines

RBM is a different type of ANN model that can learn the probability distribution of the input set [29]. RBMs are mostly used for dimensionality reduction, classification, and feature learning. RBM is a bipartite, undirected graphical model that consists of two layers; visible and hidden layer. The units in the layer are not connected to each other. Each cell is a computational point that processes the input. Each unit makes stochastic decisions about whether transmitting the input data or not. The inputs are multiplied by specific weights, certain threshold values (bias) are added to the input values, then the calculated values are passed through an activation function. In the reconstruction stage, the results in the outputs re-enter the network as the input, then they exit from the visible layer as the output. The values of the previous input and the values after the processes are compared to find the parameter which is used for optimization. During the training of RBM, this parameter (cost function) is reduced in each iteration. The learning is performed multiple times on the network [29]. RBM is a two-layer, bipartite, and undirected graphical model that consists of two layers; visible and hidden layers (see Figure 5). The layers are not connected among themselves. The disadvantage of RBM is its tricky training. “RBMs are tricky because although there are good estimators of the log-likelihood gradient, there are no known cheap ways of estimating the log-likelihood itself" [30].

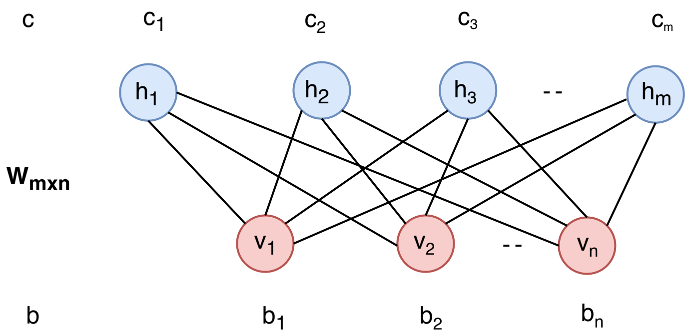

Figure 5: RBM Visible and Hidden Layers [29]

3.6. Deep Belief Networks

DBN is a type of ANN that consists of a stack of RBM layers. DBN is a probabilistic generative model that consists of latent variables. DBNs are used for finding independent and discriminative features in the input set using an unsupervised approach. DBN can learn to reconstruct the input set in a probabilistic way during the training process. Then the layers on the network begin to detect the discriminative features. After the learning step, supervised learning is carried out to perform for the classification [31]. Figure 6 illustrates the DBN structure.

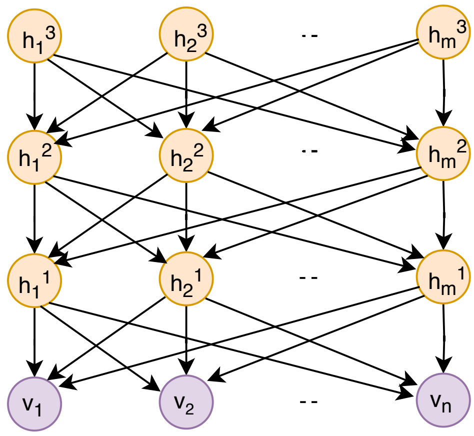

Figure 6: Deep Belief Network [29]

3.7. Autoencoders

AE networks are commonly used in DL models, wherein they remap the inputs (features) such that the inputs are more representative for the classification. In other words, AE networks perform an unsupervised feature learning process. A representation of a data set is learned by reducing the dimensionality with an AE. In the literature, AEs have been used for feature extraction and dimensionality reduction [27, 32]. The architecture of an AE has similarities with that of a FFNN. It consists of an input layer, output layer and one (or more) hidden layer that connects them together. The number of nodes in the input layer and the number of nodes in the output layer are equal to each other in AEs, and they have a symmetrical structure. AEs contain two components: encoder and decoder.

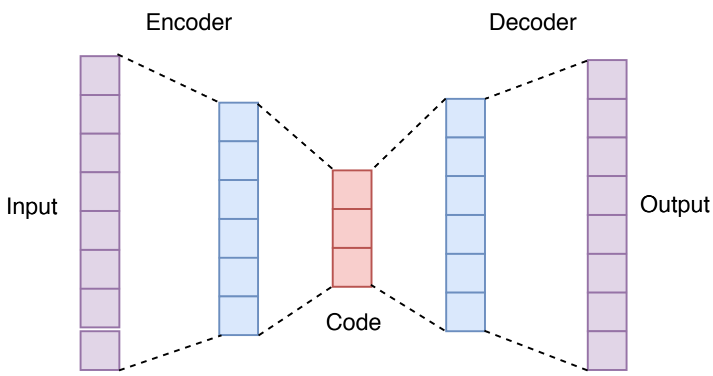

Figure 7: Basic Autoencoder Structure

The advantages of the usage of AE are dimensionality reduction and feature learning. However, reducing dimensions and feature extraction in AE cause some drawbacks. Focusing on minimizing the loss of the data relationship in the code of AE causes the loss of some significant data relationship. This may be a drawback of AE[33]. Figure 7 shows the basic AE structure.

3.8. Other Deep Structures

The DL models are not limited to the ones mentioned in the previous subsections. Some of the other well-known structures that exist in the literature are Deep Reinforcement Learning (DRL), Generative Adversarial Networks (GANs), Capsule Networks, Deep Gaussian Processes (DGPs). Meanwhile, we have not encountered any noteworthy academic or industrial publication on financial applications using these models so far, with the exception of DRL which started getting attention lately. However, that does not imply that these models do not fit well with the financial domain. On the contrary, they offer great potentials for researchers and practitioners participating in finance and deep learning community who are willing to go the extra mile to come up with novel solutions.

Since research for model developments in DL is ongoing, new structures keep on coming. However, the aforementioned models and their variations currently cover almost all of the published work. Next section will provide details about the implementation areas along with the preferred DL models.

4. Financial Applications

There are a lot of financial applications of soft computing in the literature. DL has been studied in most of them, although, some opportunities still exist in a number of fields.

Throughout this section, we categorized the implementation areas and presented them in separate subsections. Besides, in each subsection we tabulated the representative models, datasets, features of the relevant studies in order to provide as much information as possible in the limited space.

In addition, we tried to elaborate on the preferred model, data and feature choices for each financial application area separately in the subsections. Our focus was to identify the dominant models, features and data types that standout for each application area and very briefly explain the reasons behind those particular choices. To provide an overall snapshot view, we accumulated the corresponding model, feature and dataset associations coupled with the financial application areas within three separate heatmaps (Figures 10, 11 and 12) that are presented in Section 5.

Also, the readers should note that there were some overlaps between different implementation areas for some papers. There were two main reasons for that: In some papers, multiple problems were addressed separately, for e.g. text mining was studied for feature extraction, then algorithmic trading was implemented. For some other cases, the paper might fit directly into multiple implementation areas due to the survey structure, for e.g. cryptocurrency portfolio management. In such cases we included the papers in all of the relevant subsections creating some overlaps.

Some of the existing study areas can be grouped as follows:

4.1. Algorithmic Trading

Algorithmic trading (or Algo-trading) is defined as buy-sell decisions made solely by algorithmic models. These decisions can be based on some simple rules, mathematical models, optimized processes, or as in the case of machine/deep learning, highly complex function approximation techniques. With the introduction of electronic online trading platforms and frameworks, algorithmic trading took over the finance industry in the last two decades. As a result, Algo-trading models based on DL also started getting attention.

Most of the Algo-trading applications are coupled with price prediction models for market timing purposes. As a result, a majority of the price or trend forecasting models that trigger buy-sell signals based on their prediction are also considered as Algo-trading systems. However, there are also some studies that propose stand-alone Algo-trading models focused on the dynamics of the transaction itself by optimizing trading parameters such as bid-ask spread, analysis of limit order book, position-sizing, etc. High Frequency Trading (HFT) researchers are particularly interested in this area. Hence, DL models also started appearing in HFT studies.

Before diving into the DL implementations, it would be beneficial to briefly mention about the existing ML surveys on Algo-trading. Hu et al. [34] reviewed the implementations of various EAs on Algorithmic Trading Models. Since financial time series forecasting is highly coupled with algorithmic trading, there are a number of ML survey papers focused on Algo-trading models based on forecasting. The interested readers can refer to [1] for more information.

As far as the DL research is concerned, Tables 1, 2, and 3 present the past and current status of algo-trading studies based on DL models. The papers are distributed to these tables as follows: Table 1 has the particular algorithmic trading implementations that are embedded with time series forecasting models, whereas Table 2 is focused on classification based (Buy-sell Signal, or Trend Detection) algo-trading models. Finally, Table 3 presents stand-alone studies or other algorithmic trading models (pairs trading, arbitrage, etc.) that do not fit into the above categorization criteria.

Most of the Algo-trading studies were concentrated on the prediction of stock or index prices. Meanwhile, LSTM was the most preferred DL model in these implementations. In [35], market microstructures based trade indicators were used as the input into RNN with Graves LSTM to perform the price prediction for algorithmic stock trading. Bao et al. [36] used technical indicators as the input into Wavelet Transforms (WT), LSTM and Stacked Autoencoders (SAEs) for the forecasting of stock prices. In [37], CNN and LSTM model structures were implemented together (CNN was used for stock selection, LSTM was used for price prediction).

Using a different model, Zhang et. al. [38] proposed a novel State Frequency Memory (SFM) recurrent network for stock price prediction with multiple frequency trading patterns and achieved better prediction and trading performances. In an HFT trading system, Tran et al. [39] developed a DL model that implements price change forecasting through mid-price prediction using high-frequency limit order book data with tensor representation. In [40], the authors used Fuzzy Deep Direct Reinforcement Learning (FDDR) for stock price prediction and trading signal generation.

Table 1: Algo-trading Applications Embedded with Time Series Forecasting Models

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Environment
[35]	GarantiBank in BIST, Turkey	2016	OCHLV, Spread, Volatility, Turnover, etc.	PLR, Graves LSTM	MSE, RMSE, MAE, RSE, Correlation R-square	Spark
[36]	CSI300, Nifty50, HSI, Nikkei 225, S&P500, DJIA	2010-2016	OCHLV, Technical Indicators	WT, Stacked autoencoders, LSTM	MAPE, Correlation coefficient, THEIL-U	-
[37]	Chinese Stocks	2007-2017	OCHLV	CNN + LSTM	Annualized Return, Mxm Retracement	Python
[38]	50 stocks from NYSE	2007-2016	Price data	SFM	MSE	-
[39]	The LOB of 5 stocks of Finnish Stock Market	2010	FI-2010 dataset: bid/ask and volume	WMTR, MDA	Accuracy, Precision, Recall, F1-Score	-
[40]	300 stocks from SZSE, Commodity	2014-2015	Price data	FDDR, DMLP+RL	Profit, return, SR, profit-loss curves	Keras
[41]	S&P500 Index	1989-2005	Price data, Volume	LSTM	Return, STD, SR, Accuracy	Python, TensorFlow, Keras, R, H2O
[42]	Stock of National Bank of Greece (ETE).	2009-2014	FTSE100, DJIA, GDAX, NIKKEI225, EUR/USD, Gold	GASVR, LSTM	Return, volatility, SR, Accuracy	Tensorflow
[43]	Chinese stock-IF-IH-IC contract	2016-2017	Decisions for price change	MODRL+LSTM	Profit and loss, SR	-
[44]	Singapore Stock Market Index	2010-2017	OCHL of last 10 days of Index	DMLP	RMSE, MAPE, Profit, SR	-
[45]	GBP/USD	2017	Price data	Reinforcement Learning + LSTM + NES	SR, downside deviation ratio, total profit	Python, Keras, Tensorflow
[46]	Commodity, FX future, ETF	1991-2014	Price Data	DMLP	SR, capability ratio, return	C++, Python
[47]	USD/GBP, S&P500, FTSE100, oil, gold	2016	Price data	AE + CNN	SR, % volatility, avg return/trans, rate of return	H2O
[48]	Bitcoin, Dash, Ripple, Monero, Litecoin, Dogecoin, Nxt, Namecoin	2014-2017	MA, BOLL, the CRIX returns, Euribor interest rates, OCHLV	LSTM, RNN, DMLP	Accuracy, F1-measure	Python, Tensorflow
[49]	S&P500, KOSPI, HSI, and EuroStoxx50	1987-2017	200-days stock price	Deep Q-Learning, DMLP	Total profit, Correlation	-
[50]	Stocks in the S&P500	1990-2015	Price data	DMLP, GBT, RF	Mean return, MDD, Calmar ratio	H2O
[51]	Fundamental and Technical Data, Economic Data	-	Fundamental , technical and market information	CNN	-	-

For index prediction, the following studies are noteworthy. In [41], the price prediction of S&P500 index using LSTM was implemented. Mourelatos et al. [42] compared the performance of LSTM and GA with a SVR (GASVR) for Greek Stock Exchange Index prediction. Si et al. [43] implemented Chinese intraday futures market trading model with DRL and LSTM. Yong et al. [44] used DMLP method and Open,Close,High, Low (OCHL) of the time series index data to predict Singapore Stock Market index data.

Forex or cryptocurrency trading was implemented in some studies. In [45], agent inspired trading using deep (recurrent) reinforcement learning and LSTM was implemented and tested on the trading of GBP/USD. In [46], DMLP was implemented for the prediction of commodities and FX trading prices. Korczak et al. [47] implemented a forex trading (GBP/PLN) model using several different input parameters on a multi-agent-based trading environment. One of the agents used CNN for prediction and outperformed all other models.

On the cryptocurrency side, Spilak et al. [48] used several cryptocurrencies to construct a dynamic portfolio using LSTM, RNN, DMLP methods. In a versatile study, Jeong et al. [49] combined deep Q-learning and DMLP to implement price forecasting and they intended to solve three separate problems: Increasing profit in a market, prediction of the number of shares to trade, and preventing overfitting with insufficient financial data.

Table 2: Classification (Buy-sell Signal, or Trend Detection) Based Algo-trading Models

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Environment
[52]	Stocks in Dow30	1997-2017	RSI	DMLP with genetic algorithm	Annualized return	Spark MLlib, Java
[53]	SPY ETF, 10 stocks from S&P500	2014-2016	Price data	FFNN	Cumulative gain	MatConvNet, Matlab
[54]	Dow30 stocks	2012-2016	Close data and several technical indicators	LSTM	Accuracy	Python, Keras, Tensorflow, TALIB
[55]	High-frequency record of all orders	2014-2017	Price data, record of all orders, transactions	LSTM	Accuracy	-
[56]	Nasdaq Nordic (Kesko Oyj, Outokumpu Oyj, Sampo, Rautaruukki, Wartsila Oyj)	2010	Price and volume data in LOB	LSTM	Precision, Recall, F1-score, Cohen's k	-
[57]	17 ETFs	2000-2016	Price data, technical indicators	CNN	Accuracy, MSE, Profit, AUROC	Keras, Tensorflow
[58]	Stocks in Dow30 and 9 Top Volume ETFs	1997-2017	Price data, technical indicators	CNN with feature imaging	Recall, precision, F1-score, annualized return	Python, Keras, Tensorflow, Java
[59]	FTSE100	2000-2017	Price data	CAE	TR, SR, MDD, mean return	-
[60]	Nasdaq Nordic (Kesko Oyj, Outokumpu Oyj, Sampo, Rautaruukki, Wartsila Oyj)	2010	Price, Volume data, 10 orders of the LOB	CNN	Precision, Recall, F1-score, Cohen's k	Theano, Scikit learn, Python
[61]	Borsa Istanbul 100 Stocks	2011-2015	75 technical indicators and OCHLV	CNN	Accuracy	Keras
[62]	ETFs and Dow30	1997-2007	Price data	CNN with feature imaging	Annualized return	Keras, Tensorflow
[63]	8 experimental assets from bond/derivative market	-	Asset prices data	RL, DMLP, Genetic Algorithm	Learning and genetic algorithm error	-
[64]	10 stocks from S&P500	-	Stock Prices	TDNN, RNN, PNN	Missed opportunities, false alarms ratio	-
[65]	London Stock Exchange	2007-2008	Limit order book state, trades, buy/sell orders, order deletions	CNN	Accuracy, kappa	Caffe
[66]	Cryptocurrencies, Bitcoin	2014-2017	Price data	CNN, RNN, LSTM	Accumulative portfolio value, MDD, SR	-

In [52], technical analysis indicator's (Relative Strength Index (RSI)) buy & sell limits were optimized with GA which was used for buy-sell signals. After optimization, DMLP was also used for function approximation. In [53], the authors combined deep Fully Connected Neural Network (FNN) with a selective trade strategy unit to predict the next price. In [54], the crossover and Moving Average Convergence and Divergence (MACD) signals were used to predict the trend of the Dow 30 stocks' prices. Sirignano et al. [55] proposed a novel method that used limit order book flow and history information for the determination of the stock movements using LSTM model. Tsantekidis et al. [56] also used limit order book time series data and LSTM method for the trend prediction.

Several studies focused on utilizing CNN based models due to their success in image classification problems. However, in order to do that, the financial input data needed to be transformed into images which required some creative preprocessing. Gudelek et al. [57] converted time series of price data to 2-dimensional images using technical analysis and classified them with deep CNN. Similarly, Sezer et al. [58] also proposed a novel technique that converts financial time series data that consisted of technical analysis indicator outputs to 2-dimensional images and classified these images using CNN to determine the trading signals. In [59], candlestick chart graphs were converted into 2-dimensional images. Then, unsupervised convolutional AE was fed with the images to implement portfolio construction. Tsantekidis et al. [60] proposed a novel method that used the last 100 entries from the limit order book to create a 2-dimensional image for the stock price prediction using CNN method. In [61], an innovative method was proposed that uses CNN with correlated features combined together to predict the trend of the stocks prices. Finally, Sezer et al. [62] directly used bar chart images as inputs to CNN and predicted if the image class was Buy, Hold or Sell, hence a corresponding Algo-trading model was developed.

Serrano et al. [63] proposed a novel method called "GoldAI Sachs" Asset Banker Reinforcement Learning (RL) Algorithm for algorithmic trading. The proposed method used a random neural network, GP, and RL to generate the trading signals. Saad et al. [64] compared Timedelay Neural Network (TDNN), RNN and Probabilistic Neural Network (PNN) for trend detection using 10 stocks from S&P500. In [65], HFT microstructures forecasting with CNN method was performed. In [66], cryptocurrency portfolio management based on three different proposed models (basic RNN, LSTM and CNN) was implemented.

Tino et al. [67] used The Deutscher Aktienindex (DAX), London Financial Times Stock Exchange Index (FTSE)100, call and put options prices to predict the changes with Markov models and used the financial time series data to predict volatility changes with RNN. Meanwhile, Chen et al. [68] proposed a method that uses a filterbank CNN Algorithm on 15x15 volatility times series converted synthetic images. In the study, the financial domain knowledge and filterbank mechanism were combined to determine the trading signals. Bari et al. [69] used text mining to extract information from the tweets and financial news and used LSTM, RNN, Gated-Recurrent Unit (GRU) for the generation of the trading signals. Dixon et al. [70] used RNN for the sequence classification of the limit order book to predict a next event price-flip.

Chen et al. [71] used 1-dimensional CNN with an agent-based RL algorithm on the Taiwan stock index futures (TAIFEX) dataset. Wang et al. [72] proposed a Deep Co-investment Network Learning (DeepCNL) method that used convolutional and RNN layers. The investment pattern was determined using the extracted Rise-Fall trends. Day et al. [73] used financial sentiment analysis using text mining and DMLP for stock algorithmic trading. Sirignano et al. [74] proposed a "spatial neural network" model that used limit order book and spatial features for algorithmic trading. Their model estimates the best bid-ask prices using bid, ask prices in the limit order book. Gao et al. [75] used GRU, LSTM units, CNN, and DMLP to model Q values for the implementation of the DRL method.

Table 3: Stand-alone and/or Other Algorithmic Models

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Environment
[67]	DAX, FTSE100, call/put options	1991-1998	Price data	Markov model, RNN	Ewa-measure, iv, daily profits' mean and std	-
[68]	Taiwan Stock Index Futures, Mini Index Futures	2012-2014	Price data to image	Visualization method + CNN	Accumulated profits,accuracy	-
[69]	Energy-Sector/ Company-Centric Tweets in S&P500	2015-2016	Text and Price data	LSTM, RNN, GRU	Return, SR, precision, recall, accuracy	Python, Tweepy API
[70]	CME FIX message	2016	Limit order book, time-stamp, price data	RNN	Precision, recall, F1-measure	Python, TensorFlow, R
[71]	Taiwan stock index futures (TAIFEX)	2017	Price data	Agent based RL with CNN pre-trained	Accuracy	-
[72]	Stocks from S&P500	2010-2016	OCHLV	DCNL	PCC, DTW, VWL	Pytorch
[73]	News from NowNews, AppleDaily, LTN, MoneyDJ for 18 stocks	2013-2014	Text, Sentiment	DMLP	Return	Python, Tensorflow
[74]	489 stocks from S&P500 and NASDAQ-100	2014-2015	Limit Order Book	Spatial neural network	Cross entropy error	NVIDIA's cuDNN
[75]	Experimental dataset	-	Price data	DRL with CNN, LSTM, GRU, DMLP	Mean profit	Python

4.1.1. Model, Feature and Dataset selections for Algorithmic Trading

Since algorithmic trading relies on generating profitable financial transactions through identifying accurate entry-exit points from the price signal, it would make sense to use the models, features and datasets that highlight the temporal characteristics of the asset that is to be traded. So, one would assume, the models that are popular for time series forecasting would fit well into this description. This was precisely what we had encountered during our analyses. The majority (23) of the DL models used for algorithmic trading applications were RNN types, namely LSTM, RNN, and GRU. CNN and DMLP were also among the favored model choices, especially by the researchers focused on trend forecasting, which is basically a classification problem.

In a similar fashion, features that had temporal characteristics dominated the selected feature set for the algorithmic trading studies. Among those, price data, market characteristics, technical indicators, index, market microstructure data were the most notable ones.

The datasets that were preferred by the researchers were mostly the index/ETF data from US, European and Chinese markets. The price data of individual stocks, cryptocurrencies, commodities or forex were also quite common. In addition, there were also some cases where text data (news, tweets) were used as part of the algotrading systems.

Full distribution of models, features and datasets used by the algorithmic trading implementations are presented in Figures 10, 11 and 12.

4.2. Risk Assessment

Another study area that has been of interest to DL researchers is Risk Assessment which identifies the "riskiness" of any given asset, firm, person, product, bank, etc. Several different versions of this general problem exist, such as bankruptcy prediction, credit scoring, credit evaluation, loan/insurance underwriting, bond rating, loan application, consumer credit determination, corporate credit rating, mortgage choice decision, financial distress prediction, business failure prediction. Correctly identifying the risk status in such cases is crucial, since asset pricing is highly dependent on these risk assessment measures. The mortgage crisis based on improper risk assessment of Credit Default Swaps (CDS) between financial institutions caused the real-estate bubble to burst in 2008 and resulted in the Great Recession [76].

The majority of the risk assessment studies concentrate on credit scoring and bank distress classification. However, there are also a few papers covering mortgage default possibility, risky transaction detection or crisis forecasting. Meanwhile, there are some anomaly detection studies for risk assessment, most of which also fall under the "Fraud Detection" category which will be covered in the next subsection.

Table 4: Credit Scoring or Classification Studies

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[77]	The XR 14 CDS contracts	2016	Recovery rate, spreads, sector and region	DBN+RBM	AUROC, FN, FP, Accuracy	WEKA
[78]	German, Japanese credit datasets	-	Personal financial variables	SVM + DBN	Weighted-accuracy, TP, TN	-
[79]	Credit data from Kaggle	-	Personal financial variables	DMLP	Accuracy, TP, TN, G-mean	-
[80]	Australian, German credit data	-	Personal financial variables	GP + AE as Boosted DMLP	FP	Python, Scikit-learn
[81]	German, Australian credit dataset	-	Personal financial variables	DCNN, DMLP	Accuracy, False/Missed alarm	-
[82]	Consumer credit data from Chinese finance company	-	Relief algorithm chose the 50 most important features	CNN + Relief	AUROC, K-s statistic, Accuracy	Keras
[83]	Credit approval dataset by UCI Machine Learning repo	-	UCI credit approval dataset	Rectifier, Tanh, Maxout DL	-	AWS EC2, H2O, R

Before going into the details about specific DL implementations, it is worthwhile to mention the existing ML surveys on the topic. Kirkos et al. [84], Ravi et al. [85], Fethi et al. [86] reviewed the bank performance assessment studies based on Artificial Intelligence (AI) and ML models. Lahsasna et al. [87], Chen et al.[88] surveyed the credit scoring and credit risk assessment studies based on soft computing techniques whereas Marques et. al. [89] focused only on Evolutionary Computation (EC) Models for credit scoring implementations. Meanwhile, Kumar et al. [90], Verikas et al. [91] reviewed ML implementations of bankruptcy prediction studies. Similarly, Sun et al. [92] provided a comprehensive survey about research on financial distress and corporate failures. Apart from these reviews, for assessing overall risk, Lin et al. [93] surveyed the financial crisis prediction studies based on ML models.

Since risk assessment is vital for survival in today's financial world, a lot of researchers turned their attention to DL for higher accuracy. Tables 4 and 5 provide snapshot information about the different risk assessment studies implemented using various DL models.

For credit score classification (see Table 4), Luo et al. [77], used CDS data for Corporate Credit rating and corresponding credit classification (A,B or C). Among the tested models, DBN with RBM performed the best. This implementation was probably the first study to implement Credit rating with DBN. Similarly, in [78], a cascaded hybrid model of DBN, Backpropagation and SVM for credit classification was implemented and good performance results (the accuracy was above 80-90 %) were achieved. In [79], credit risk classification was achieved by using an ensemble of DMLP networks each using subspaces of the whole space by k-means (using minority class in each, but only a partial subspace of the majority class). The data imbalance problem was handled by using multiple subspaces for each classifier, where each of them had all the positive (minor) instances, but a subsample of negative (majority) instances, finally they used an ensemble of DMLPs combining each subspace model. In [80], credit scoring was performed using a SAE network and GP model to create credit assessment rules in order to generate good or bad credit cases. In another study, Neagoe et. al. [81] classified credit scores using various DMLP and deep CNN networks. In a different study [82], consumer credit scoring classification was implemented with a 2-D representation of the input consumer data through transforming the data into a 2-D pixel matrix. Then the resulting images were used as the training and test data for CNN. 2-D pixel matrix representation of the consumer data was adapted by using CNN for image classification. This was the first implementation of credit scoring using CNN. Niimi [83] used UCI credit approval dataset [1] to compare DL, SVM, Logistic Regression (LR), Random Forest (RF), eXtreme Gradient Boosting (XGBoost) and provided information about credit fraud and credit approval applications; then experimented with the credit approval problem with several models. Various models were compared for credit approval classification. Also, some introduction about credit fraud detection was provided.

Financial distress prediction for banks and corporates are studied extensively (see Table 5). In [94], a hybrid DBN with SVM was used for financial distress prediction to identify whether the firm was in trouble or not, whereas bank risk classification was studied in [95]. In [96], news semantics were extracted by the word sequence learning and associated events were labeled with the bank stress, then from the formed semantic vector representation, the bank stress was determined and classified against a threshold. Prediction and semantic meaning extraction were integrated in a neat way. In another study [97], text mining was again used for identifying the bank distress by extracting the data from financial news and then using a Deep Feed Forward Network (DFFN) on semantic sentence vectors extracted from word embeddings to classify if there was an event or not. Similarly, Cerchiello et al. [98] used text mining from the financial news to classify bank distress. Malik et al. [99] evaluated the bank stress by first predicting the bank's performance through an LSTM network, then Backpropagation network was used for finding the bank stress level.

[1] https://archive.ics.uci.edu/ml/datasets.html

Table 5: Financial Distress, Bankruptcy, Bank Risk, Mortgage Risk, Crisis Forecasting Studies

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[94]	966 french firms	-	Financial ratios	RBM+SVM	Precision, Recall	-
[95]	883 BHC from EDGAR	2006-2017	Tokens, weighted sentiment polarity, leverage and ROA	CNN, LSTM, SVM, RF	Accuracy, Precision, Recall, F1-score	Keras, Python, Scikit-learn
[96]	The event data set for large European banks, news articles from Reuters	2007-2014	Word, sentence	DMLP +NLP preprocess	Relative usefulness, F1-score	-
[97]	Event dataset on European banks, news from Reuters	2007-2014	Text, sentence	Sentence vector + DFFN	Usefulness, F1-score, AUROC	-
[98]	News from Reuters, fundamental data	2007-2014	Financial ratios and news text	doc2vec + NN	Relative usefulness	Doc2vec
[99]	Macro/Micro economic variables, Bank characteristics/performance variables from BHC	1976-2017	Macro economic variables and bank performances	CGAN, MVN, MV-t, LSTM, VAR, FE-QAR	RMSE, Log likelihood, Loan loss rate	-
[100]	Financial statements of French companies	2002-2006	Financial ratios	DBN	Recall, Precision, F1-score, FP, FN	-
[101]	Stock returns of American publicly-traded companies from CRSP	2001-2011	Price data	DBN	Accuracy	Python, Theano
[102]	Financial statements of several companies from Japanese stock market	2002-2016	Financial ratios	CNN	F1-score, AUROC	-
[103]	Mortgage dataset with local and national economic factors	1995-2014	Mortgage related features	DMLP	Negative average log-likelihood	AWS
[104]	Mortgage data from Norwegian financial service group, DNB	2012-2016	Personal financial variables	CNN	Accuracy, Sensitivity, Specificity, AUROC	-
[105]	Private brokerage company's real data of risky transactions	-	250 features: order details, etc.	CNN, LSTM	F1-Score	Keras, Tensorflow
[106]	Several datasets combined to create a new one	1996-2017	Index data, 10-year Bond yield, exchange rates,	Logit, CART, RF, SVM, NN, XGBoost, DMLP	AUROC, KS, G-mean, likelihood ratio, DP, BA, WBA	R

There are also a number of research papers that were focused on bankruptcy or corporate default prediction. Ribeiro et al. [100] implemented bankruptcy prediction with DBN. The results of DBN were compared with SVM and RBM. Yeh et al. [101] used the stock returns of default and solvent companies as inputs to RBM used as SAE, then the output of RBM was used as input to DBN to predict if the company was solvent or default. The results were compared with an SVM model and the DBN model outperformed SVM. Hosaka et al. [102] tried a different approach by converting the financial data to the image to use CNN for bankruptcy prediction.

The remaining implementations of risk assessment are as follows: Sirignano et al. [103] used the mortgage application data of 20 years for identifying the mortgage risk using various parameters. They also performed a lot of analyses relating different factors that affected the mortgage payment structure. The authors also analyzed the prepayment and delinquency behavior in their assessment. For another mortgage risk assessment application, Kvamme et al. [104] used CNN and RF models to predict whether a customer would default on its mortgage or not. In a different study, Abroyan et al. [105] used CNN and LSTM networks to classify if a transaction performed on the stock market (trade) was risky or not and high accuracy was achieved. Finally, Chatzis et al. [106] developed several ML and DL models for detecting events that caused the stock market to crash. DL models had good classification (detecting crisis or not) performance.

4.2.1. Model, Feature and Dataset selections for Risk Assessment

Risk assesment is mostly determined from company statements, financial reports, or analyst reports as well as micro/macroeconomic data. As a result, the models that successfully integrate spatial and temporal data would probably perform better, thus preferred by the researchers. DMLP, LSTM and CNN were among the most selected models. Since risk assessment can be considered as a classification problem, choosing DMLP and CNN were logical choices for such implementations. However through using LSTM, it might be easier to preserve the temporal nature of the problem. Meanwhile, there were also a few existing studies using other DL models; probably because risk assessment has a wide span of subtopics.

Meanwhile the most important features that were used for risk assessment models were based on text data extracted from company/personal financial statements. Even though not as often, there were also some other features like market microstructure data or price data that were also used.

The datasets for risk assessment were highly associated with the features. The most notable datasets were composed of credit data, consumer data and financial reports.

Full distribution of models, features and datasets used by the risk assessment implementations are presented in Figures 10, 11 and 12.

4.3. Fraud Detection

Financial fraud is one of the areas where the governments and authorities are desperately trying to find a permanent solution. Several different financial fraud cases exist such as credit card fraud, money laundering, consumer credit fraud, tax evasion, bank fraud, insurance claim fraud. This is one of the most extensively studied areas of finance for ML research and several survey papers were published accordingly. At different times, Kirkos et al. [107], Yue et al. [108], Wang et al. [109], Phua et al. [110], Ngai et al. [111], Sharma et al. [112], West et al. [113] all reviewed the accounting and financial fraud detection studies based on soft computing and data mining techniques. These type of studies mostly can be considered as anomaly detection and are generally classification problems. Table 6 presents different fraud detection studies based on DL models.

There are a number of studies focused on identifying credit card fraud. Heryadi et al. [114] developed several DL models for credit card fraud detection for Indonesian banks. They also analyzed the effects of the data imbalance between fraud and nonfraud data. In more recent studies, Roy et al. [115] used LSTM model for the credit card fraud detection, whereas in [116], the authors implemented DMLP networks to classify if a credit card transaction was fraudulent or not. Sohony et al. [117] used an ensemble of FFNN for the detection of card fraud. Jurgovsky et al. [118] used LSTM for detecting credit card fraud from credit card transaction sequences. They compared their results with RF.

Paula et al. [119] used deep AE to implement anomaly detection to identify the financial fraud and money laundering for Brazilian companies on export tax claims. In a similar study, Gomes et al. [120] proposed an anomaly detection model that identified the anomalies in parliamentary expenditure spending in Brazilian elections using also deep AE.

Table 6: Fraud Detection Studies

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[114]	Debit card transactions by a local Indonesia bank	2016-2017	Financial transaction amount on several time periods	CNN, Stacked-LSTM, CNN-LSTM	AUROC	-
[115]	Credit card transactions from retail banking	2017	Transaction variables and several derived features	LSTM, GRU	Accuracy	Keras
[116]	Card purchases' transactions	2014-2015	Probability of fraud per currency/origin country, other fraud related features	DMLP	AUROC	-
[117]	Transactions made with credit cards by European cardholders	2013	Personal financial variables to PCA	DMLP, RF	Recall, Precision, Accuracy	-
[118]	Credit-card transactions	2015	Transaction and bank features	LSTM	AUROC	Keras, Scikit-learn
[119]	Databases of foreign trade of the Secretariat of Federal Revenue of Brazil	2014	8 Features: Foreign Trade, Tax, Transactions, Employees, Invoices, etc	AE	MSE	H2O, R
[120]	Chamber of Deputies open data, Companies data from Secretariat of Federal Revenue of Brazil	2009-2017	21 features: Brazilian State expense, party name, Type of expense, etc.	Deep Autoencoders	MSE, RMSE	H2O, R
[121]	Real-world data for automobile insurance company labeled as fradulent	-	Car, insurance and accident related features	DMLP + LDA	TP, FP, Accuracy, Precision, F1-score	-
[122]	Transactions from a giant online payment platform	2006	Personal financial variables	GBDT+DMLP	AUROC	-
[123]	Financial transactions	-	Transaction data	LSTM	t-SNE	-
[124]	Empirical data from Greek firms	-	-	DQL	Revenue	Torch

Wang et al. [121] used text mining and DMLP models for the detection of automobile insurance fraud. Longfei et al. [122] developed DMLP models to detect online payment transaction fraud. Costa et al. [123] used character sequences in financial transactions and the responses from the other side to detect if the transaction was fraud or not with LSTM. Goumagias et al. [124] used deep Q-learning (RL) to predict the risk-averse firms' tax evasion behaviours. Finally, they provided suggestions for the states to maximize their tax revenues accordingly.

4.3.1. Model, Feature and Dataset selections for Fraud Detection

Fraud Detection, more or less, has similar domain characteristics when compared with Risk Assessment, hence the corresponding model, feature and dataset selections were also highly correlated. As a result, the underlying dynamics that are valid for Risk Assessment are also applicable to Fraud Detection. Maybe, the only notable difference we can mention was the preferrence of the consumer data as the most preferred dataset instead of the credit data for Fraud Detection.

Full distribution of models, features and datasets used by the fraud detection implementations are presented in Figures 10, 11 and 12.

4.4. Portfolio Management

Portfolio Management is the process of choosing various assets within the portfolio for a predetermined period. As seen in other financial applications, slightly different versions of this problem exist, even though the underlying motivation is the same. In general, Portfolio Management covers the following closely related areas: Portfolio Optimization, Portfolio Selection, Portfolio Allocation. Sometimes, these terms are used interchangeably. Li et al. [125] reviewed the online portfolio selection studies using various rule-based or ML models.

Portfolio Management is actually an optimization problem, identifying the best possible course-of-action for selecting the best-performing assets for a given period. As a result, there are a lot of EA models that were developed for this purpose. Metaxiotis et al. [126] surveyed the MOEAs implemented solely on the portfolio optimization problem. However, some DL researchers managed to configure it as a learning model and obtained superior performances. Since Robo-advisory for portfolio management is on the rise, these DL implementations have the potential to have a far greater impact on the financial industry in the near future. Table 7 presents the portfolio management DL models and summarizes their achievements.

There are a number of stock selection implementations. Takeuchi et al. [127] classified the stocks in two classes, low momentum and high momentum depending on their expected return. They used a deep RBM encoder-classifier network and achieved high returns. Similarly, in [128], stocks were evaluated against their benchmark index to classify if they would outperform or underperform using DMLP, then based on the predictions, adjusted the portfolio allocation weights for the stocks for enhanced indexing. In [129], an ML framework including DMLP was constructed and the stock selection problem was implemented.

Portfolio selection and smart indexing were the main focuses of [130] and [131] using AE and LSTM networks. Lin et al. [132] used the Elman network for optimal portfolio selection by predicting the stock returns for t+1 and then constructing the optimum portfolio according to the returns. Meanwhile, Maknickiene et al. [133] used Evolino RNN for portfolio selection and return prediction accordingly. The selected portfolio components (stocks) were orthogonal in nature.

In [134], through predicting the next month's return, top to be performed portfolios were constructed and good monthly returns were achieved with LSTM and LSTM-DMLP combined DL models. Similarly, Batres et al. [135] combined DBN and MLP for constructing a stock portfolio by predicting each stock's monthly log-return and choosing the only stocks that were expected to perform better than the performance of the median stock. Lee et al. [136] compared 3 RNN models (S-RNN, LSTM, GRU) for stock price prediction and then constructed a threshold-based portfolio with selecting the stocks according to the predictions. With a different approach, Iwasaki et al. [137] used the analyst reports for sentiment analyses through text mining and word embeddings and used the sentiment features as inputs to

Deep Feedforward Neural Network (DFNN) model for the stock price prediction. After that, different portfolio selections were implemented based on the projected stock returns.

Table 7: Portfolio Management Studies

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[66]	Cryptocurrencies, Bitcoin	2014-2017	Price data	CNN, RNN, LSTM	Accumulative portfolio value, MDD, SR	-
[127]	Stocks from NYSE, AMEX, NASDAQ	1965-2009	Price data	Autoencoder + RBM	Accuracy, confusion matrix	-
[128]	20 stocks from S&P500	2012-2015	Technical indicators	DMLP	Accuracy	Python, Scikit Learn, Keras, Theano
[129]	Chinese stock data	2012-2013	Technical, fundamental data	Logistic Regression, RF, DMLP	AUC, accuracy, precision, recall, f1, tpr, fpr	Keras, Tensorflow, Python, Scikit learn
[130]	Top 5 companies in S&P500	-	Price data and Financial ratios	LSTM, Auto-encoding, Smart indexing	CAGR	-
[131]	IBB biotechnology index, stocks	2012-2016	Price data	Auto-encoding, Calibrating, Validating, Verifying	Returns	-
[132]	Taiwans stock market	-	Price data	Elman RNN	MSE, return	-
[138]	FOREX (EUR/USD, etc), Gold	2013	Price data	Evolino RNN	Return	Python
[134]	Stocks in NYSE, AMEX, NASDAQ, TAQ intraday trade	1993-2017	Price, 15 firm characteristics	LSTM+DMLP	Monthly return, SR	Python,Keras, Tensorflow in AWS
[135]	S&P500	1985-2006	monthly and daily log-returns	DBN+MLP	Validation, Test Error	Theano, Python, Matlab
[136]	10 stocks in S&P500	1997-2016	OCHLV, Price data	RNN, LSTM, GRU	Accuracy, Monthly return	Keras, Tensorflow
[137]	Analyst reports on the TSE and Osaka Exchange	2016-2018	Text	LSTM, CNN, Bi-LSTM	Accuracy, R^2	R, Python, MeCab
[139]	Stocks from Chinese/American stock market	2015-2018	OCHLV, Fundamental data	DDPG, PPO	SR, MDD	-
[140]	Hedge fund monthly return data	1996-2015	Return, SR, STD, Skewness, Kurtosis, Omega ratio, Fund alpha	DMLP	Sharpe ratio, Annual return, Cum. return	-
[141]	12 most-volumed cryptocurrency	2015-2016	Price data	CNN + RL	SR, portfolio value, MDD	-

DRL was selected as the main DL model for [139]. Liang et al. [139] used DRL for portfolio allocation by adjusting the stocks weights using various RL models. Chen et al. [140] compared different ML models (including DFFN) for hedge fund return prediction and hedge fund selection. DL and RF models had the best performance.

Cryptocurrency portfolio management also started getting attention from DL researchers. In [141], portfolio management (allocation and adjustment of weights) was implemented by CNN and DRL on selected cryptocurrencies. Similarly, Jiang et al. [66] implemented cryptocurrency portfolio management (allocation) based on 3 different proposed models, namely RNN, LSTM and CNN.

4.4.1. Model, Feature and Dataset selections for Portfolio Management

In some ways, portfolio management can be considered similar to algorithmic trading except the corresponding timeframes are very different. Algorithmic trading is implemented in relatively shorter durations, i.e. milliseconds to hours or days at most, meanwhile the typical timeframes for portfolio management are in the order of days, months or years. However, when we compare the models, features and datasets that were used for algorithmic trading studies, we saw, more or less, a very similar pattern for portfolio management. Meanwhile, even though spatial properties or features were almost nonexistent for algorithmic trading models, there were a few spatial features and datasets that were used for portfolio management studies. Since most portfolio managers rely on analyst reports for their allocation decisions, it is logical that some DL models also use similar features or datasets for training.

Full distribution of models, features and datasets used by the portfolio management implementations are presented in Figures 10, 11 and 12.

4.5. Asset Pricing and Derivatives Market (options, futures, forward contracts)

Accurate pricing or valuation of an asset is a fundamental study area in finance. There are a vast number of ML models developed for banks, corporates, real estate, derivative products, etc. However, DL has not been applied to this particular field and there are some possible implementation areas that DL models can assist the asset pricing researchers or valuation experts. There were only a handful of studies that we were able to pinpoint within the DL and finance community. There are vast opportunities in this field for future studies and publications.

Meanwhile, financial models based on derivative products is quite common. Options pricing, hedging strategy development, financial engineering with options, futures, forward contracts are among some of the studies that can benefit from developing DL models. Some recent studies indicate that researchers started showing interest in DL models that can provide solutions to this complex and challenging field. Table 8 summarizes these studies with their intended purposes.

Table 8: Asset Pricing and Derivatives Market Studies

Art.	Der.Type	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[137]	Asset pricing	Analyst reports on the TSE and Osaka Exchange	2016-2018	Text	LSTM, CNN, Bi-LSTM	Accuracy, R^2	R, Python, MeCab
[142]	Options	Simulated a range of call option prices	-	Price data, option strike/maturity, dividend/risk free rates, volatility	DMLP	RMSE, the average percentage pricing error	Tensorflow
[143]	Futures, Options	TAIEX Options	2017	OCHLV, fundamental analysis, option price	DMLP, DMLP with Black scholes	RMSE, MAE, MAPE	-
[144]	Equity returns	Returns in NYSE, AMEX, NASDAQ	1975-2017	57 firm characteristics	Fama-French n-factor model DL	R^2,RMSE	Tensorflow

Iwasaki et al. [137] used a DFNN model and the analyst reports for sentiment analyses to predict the stock prices. Different portfolio selection approaches were implemented after the prediction of the stock prices. Culkin et al. [142] proposed a novel method that used DMLP model to predict option prices by comparing their results with Black & Scholes option pricing formula. Similarly, Hsu et al. [143] proposed a novel method that predicted TAIEX option prices using bid-ask spreads and Black & Scholes option price model parameters with 3-layer DMLP. In [144], characteristic features such as Asset growth, Industry momentum, Market equity, Market Beta, etc. were used as inputs to a Fama-French n-factor model DL to predict US equity returns in National Association of Securities Dealers Automated Quotations (NASDAQ), American Stock Exchange (AMEX), New York Stock Exchange (NYSE) indices.

4.5.1. Model, Feature and Dataset selections for Derivatives Market

There are a lot of options studies with machine learning, mostly pricing and volatility estimation research. Meanwhile, when compared with the other areas of finance, this area can still be considered mostly untouched, since it did not attract the researchers from a wider perspective. The other derivative products are even more scarce compared to the options. The trend still continues for the deep learning era.

There might be several reasons behind this scarcity of publications for derivative products: Lack of openly available historic data, the implicit ambiguity using the implied volatility for options pricing, the price irregularities at the tail-ends for the options, too many possibilities for complex formations resulting in too many potential features to consider, etc. Hence the intrinsic dynamics are quite complex in the derivatives market. Even though not many academic papers are published, one might think the financial institutions and their quantitative strategy development departments might be working on these products without publishing their results. This is probably a valid concern, meanwhile these firms may be reluctant to openly publish their models to the public for business protection, so it might not be possible to find openly accessible studies on this topic as easy as the other financial application areas. However, this is an exciting area with tremendous opportunities for professionals and researchers, but the readers should carefully assess the rewards and risks associated with the model development using these highly volatile and often complex products.

Full distribution of models, features and datasets used by the derivatives market implementations are presented in Figures 10, 11 and 12.

4.6. Cryptocurrency and Blockchain Studies

In the last few years, cryptocurrencies have been very popular due to their incredible price gain and loss within short periods. Even though price forecasting dominates the area of interest, some other studies also exist, such as cryptocurrency Algo-trading models.

Meanwhile, Blockchain is a new technology that provides a distributed decentralized ledger system that fits well with the cryptocurrency world. As a matter of fact, cryptocurrency and blockchain are highly coupled, even though blockchain technology has a much wider span for various implementation possibilities that need to be studied. It is still in its early development phase, hence there is a lot of hype in its potentials.

Some DL models have already appeared about cryptocurrency studies, mostly price prediction or trading systems. However, still there is a lack of studies for blockchain research within the DL community. Given the attention that the underlying technology has attracted, there is a great chance that some new studies will start appearing in the near future. Table 9 tabulates the studies for the cryptocurrency and blockchain research.

Table 9: Cryptocurrency and Blockchain Studies

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[48]	Bitcoin, Dash, Ripple, Monero, Litecoin, Dogecoin, Nxt, Namecoin	2014-2017	MA, BOLL, the CRIX daily returns, Euribor interest rates, OCHLV of EURO/UK, EURO/USD, US/JPY	LSTM, RNN, DMLP	Accuracy, F1-measure	Python, Tensorflow
[66]	Cryptocurrencies, Bitcoin	2014-2017	Price data	CNN	Accumulative portfolio value, MDD, SR	-
[141]	12 most-volumed cryptocurrency	2015-2016	Price data	CNN + RL	SR, portfolio value, MDD	
[145]	Bitcoin data	2010-2017	Hash value, bitcoin address, public/private key, digital signature, etc.	Takagi–Sugeno Fuzzy cognitive maps	Analytical hierarchy process	-
[146]	Bitcoin data	2012, 2013, 2016	TransactionId, input/output Addresses, timestamp	Graph embedding using heuristic, laplacian eigen-map, deep AE	F1-score	-
[147]	Bitcoin, Litecoin, StockTwits	2015-2018	OCHLV, technical indicators, sentiment analysis	CNN, LSTM, State Frequency Model	MSE	Keras, Tensorflow
[148]	Bitcoin	2013-2016	Price data	Bayesian optimized RNN, LSTM	Sensitivity, specificity, precision, accuracy, RMSE	Keras, Python, Hyperas

Chen et al. [145] proposed a blockchain transaction traceability algorithm using Takagi-Sugeno fuzzy cognitive map and 3-layer DMLP. Bitcoin data (Hash value, bitcoin address, public/private key, digital signature, etc.) was used as the dataset. Nan et al. [146] proposed a method for bitcoin mixing detection that consisted of different stages: Constructing the Bitcoin transaction graph, implementing node embedding, detecting outliers through AE. Lopes et al. [147] combined the opinion market and price prediction for cryptocurrency trading. Text mining combined with 2 models, CNN and LSTM were used to extract the opinion. Bitcoin, Litecoin, StockTwits were used as the dataset. Open,Close,High, Low, Volume (OCHLV) of prices, technical indicators, and sentiment analysis were used as the feature set. In another study, Jiang et al. [66] presented a financial-model-free RL framework for the Cryptocurrency portfolio management that was based on 3 different proposed models, basic RNN, LSTM and CNN. In [141], portfolio management was implemented by CNN and DRL on 12 most-volumed cryptocurrencies. Bitcoin, Ethereum, Bitcoin Cash and Digital Cash were used as the dataset. In addition, Spilak et al. [48] used 8 cryptocurrencies (Bitcoin, Dash, Ripple, Monero, Litecoin, Dogecoin, Nxt, Namecoin) to construct a dynamic portfolio using LSTM, RNN, DMLP methods. McNally et al. [148] compared Bayesian optimized RNN, LSTM and Autoregressive Integrated Moving Average (ARIMA) to predict the bitcoin price direction. Sensitivity, specificity, precision, accuracy, Root Mean Square Error (RMSE) were used as the performance metrics.

4.6.1. Model, Feature and Dataset selections for Cryptocurrency and Blockchain Studies

Since most of the cryptocurrency studies were focused on cryptocurrency price forecasting or trading systems, the choice of models and features are similar to the algotrading selections. Meanwhile in some studies ([145] and [146]) cryptocurrency specific features were selected. Also, for the datasets, the price data of the most popular cryptocurrency coins were used.

Full distribution of models, features and datasets used by the cryptocurrency implementations are presented in Figures 10, 11 and 12.

4.7. Financial Sentiment Analysis and Behavioral Finance

One of the most important components of behavioral finance is emotion or investor sentiment. Lately, advancements in text mining techniques opened up the possibilities for successful sentiment extraction through social media feeds. There is a growing interest in Financial Sentiment Analysis, especially for trend forecasting and Algo-trading model development. Kearney et al. [149] surveyed ML-based financial sentiment analysis studies that use textual data. Nowadays there is broad interest in the sentiment analysis for financial forecasting research using DL models. Table 10 provides information about the sentiment analysis studies that are focused on financial forecasting and based on text mining.

In [150], technical analysis (MACD, Moving Average (MA), Directional Movement Index (DMI), Exponential Moving Average (EMA), Triple Exponential Moving Average (TEMA), Momentum, RSI, Commodity Channel Index (CCI), Stochastic Oscillator, Price of Change (ROC)) and sentiment analysis (using social media) were used to predict the price of stocks. Shi et al. [151] proposed a method that visually interpreted text-based DL models in predicting the stock price movements. They used the financial news from Reuters and Bloomberg. In [152], text mining and word embeddings were used to extract information from the financial news from Reuters and Bloomberg to predict the stock price movements. In addition, in [153], the prices of index data and emotional data from text posts were used to predict the stock opening price of the next day. Wang [154] performed classification and stock price prediction using text and price data. Das et al. [155] used Twitter sentiment data and stock price data to predict the prices of Google, Microsoft and Apple stocks. Prosky et al. [156] performed sentiment, mood prediction using news from Reuters and used these sentiments for price prediction. Li et al. [157] used sentiment classification (neutral, positive, negative) for the stock open or close price prediction with LSTM (various models). They compared their results with SVM and achieved higher overall performance. Iwasaki et al. [137] used analyst reports for sentiment analysis through text mining and word embeddings. They used the sentiment features as inputs to DFNN model for price prediction. Finally, different portfolio selections were implemented based on the projected stock returns.

In a different study, Huang et al. [158] used several models including Hidden Markov Model (HMM), DMLP and CNN using Twitter moods along with the financial price data for prediction of the next day's move (up or down). CNN achieved the best result.

Table 10: Financial Sentiment Studies coupled with Text Mining for Forecasting

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[137]	Analyst reports on the TSE and Osaka Exchange	2016-2018	Text	LSTM, CNN, Bi-LSTM	Accuracy, R^2	R, Python, MeCab
[150]	Sina Weibo, Stock market records	2012-2015	Technical indicators, sentences	DRSE	F1-score, precision, recall, accuracy, AUROC	Python
[151]	News from Reuters and Bloomberg for S&P500 stocks	2006-2015	Financial news, price data	DeepClue	Accuracy	Dynet software
[152]	News from Reuters and Bloomberg, Historical stock security data	2006-2013	News, price data	DMLP	Accuracy	-
[153]	SCI prices	2008-2015	OCHL of change rate, price	Emotional Analysis + LSTM	MSE	-
[154]	SCI prices	2013-2016	Text data and Price data	LSTM	Accuracy, F1-Measure	Python, Keras
[155]	Stocks of Google, Microsoft and Apple	2016-2017	Twitter sentiment and stock prices	RNN	-	Spark, Flume,Twitter API,
[156]	30 DJIA stocks, S&P500, DJI, news from Reuters	2002-2016	Price data and features from news articles	LSTM, NN, CNN and word2vec	Accuracy	VADER
[157]	Stocks of CSI300 index, OCHLV of CSI300 index	2009-2014	Sentiment Posts, Price data	Naive Bayes + LSTM	Precision, Recall, F1-score, Accuracy	Python, Keras
[158]	S&P500, NYSE Composite, DJIA, NASDAQ Composite	2009-2011	Twitter moods, index data	DNN, CNN	Error rate	Keras, Theano

Even though financial sentiment is highly coupled with text mining, we decided to represent those two topics in different subsections. The main reason for such a choice is not only the existence of some financial sentiment studies which do not directly depend on financial textual data (like [158]) but also the existence of some financial text mining studies that are not automatically used for sentiment analysis which will be covered in section 4.8.

4.7.1. Model, Feature and Dataset selections for Financial Sentiment Analysis

Financial sentiment analysis is mostly used along with financial text mining and algotrading models. As a result, the model choices were highly correlated with the aforementioned financial application areas. Meanwhile, even though the model choices were highly similar, there were significant differences in the feature and dataset choices. For the features, text related ones such as extracted text from various sources like microblogs, news, reports dominated the studies. Also some papers directly used the sentiment feature extracted through APIs. The rest of the used features were similar to the algotrading features, like price data and technical indicators. For the datasets, news and tweet/microblog repositories were the most popular choices. However, stock and index datasets were also used. There were also some studies that used financial reports as their data sources.

Full distribution of models, features and datasets used by the financial sentiment analysis implementations are presented in Figures 10, 11 and 12.

4.8. Financial Text Mining

With the rapid spreading of social media and real-time streaming news/tweets, instant text-based information retrieval became available for financial model development. As a result, financial text mining studies became very popular in recent years. Even though some of these studies are directly interested in the sentiment analysis through crowdsourcing, there are a lot of implementations that are interested in the content retrieval of news, financial statements, disclosures, etc. through analyzing the text context. There are a few ML surveys focused on text mining and news analytics. Among the noteworthy studies of such, Mitra et al. [159] edited a book on news analytics in finance, whereas Li et al. [160], Loughran et al. [161], Kumar et al. [162] surveyed the studies of textual analysis of financial documents, news and corporate disclosures. It is worth to mention that there are also some studies [163, 164] of text mining for financial prediction models.

Previous section was focused on DL models using sentiment analysis specifically tailored for the financial forecasting implementations, whereas this section will include DL studies that have text Mining without Sentiment Analysis for Forecasting (Table 11), financial sentiment analysis coupled with text mining without forecasting intent (Table 12) and finally other text mining implementations (Table 13), respectively.

Huynh et al. [165] used the financial news from Reuters, Bloomberg and stock prices data to predict the stock movements in the future. In [166], different event-types on Chinese companies are classified based on a novel event-type pattern classification algorithm. Besides, the stock prices were predicted using additional inputs. Kraus et al. [167] implemented LSTM with transfer learning using text mining through financial news and stock market data. Dang et al. [168] used Stock2Vec and Two-stream GRU (TGRU) models to generate the input data from the financial news and stock prices for classification.

In [169], events were detected from Reuters and Bloomberg news through text mining. The extracted information was used for price prediction and stock trading with the CNN model. Vargas et al. [170] used text mining and price prediction together for intraday directional movement estimation. Akita et al. [171] implemented a method that used text mining and price prediction together for forecasting prices. Verma et al. [172] combined news data with financial data to classify the stock price movement. Bari et al. [69] used text mining for extracting information from the tweets and news. In the method, time series models were used for stock trade signal generation. In [173], a method that performed information fusion from news and social media sources was proposed to predict the trend of the stocks.

In [174], social media news were used to predict the index price and the index direction with RNN-Boost through Latent Dirichlet Allocation (LDA) features. Hu et al. [175] proposed a novel method that used text mining techniques and Hybrid Attention Networks based on the financial news for forecasting the trend of stocks. Li et al. [176] implemented intraday stock price direction classification using the financial news and stocks prices. In

[177], financial news data and word embedding with Word2vec were implemented to create the inputs for Recurrent CNN (RCNN) to predict the stock price.

Table 11: Text Mining Studies without Sentiment Analysis for Forecasting

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[69]	Energy-Sector/ Company-Centric Tweets in S&P500	2015-2016	Text and Price data	RNN, KNN, SVR, LinR	Return, SR, precision, recall, accuracy	Python, Tweepy API
[165]	News from Reuters, Bloomberg	2006-2013	Financial news, price data	Bi-GRU	Accuracy	Python, Keras
[166]	News from Sina.com, ACE2005 Chinese corpus	2012-2016	A set of news text	Their unique algorithm	Precision, Recall, F1-score	-
[167]	CDAX stock market data	2010-2013	Financial news, stock market data	LSTM	MSE, RMSE, MAE, Accuracy, AUC	TensorFlow, Theano, Python, Scikit-Learn
[168]	Apple, Airbus, Amazon news from Reuters, Bloomberg, S&P500 stock prices	2006-2013	Price data, news, technical indicators	TGRU, stock2vec	Accuracy, precision, AUROC	Keras, Python
[169]	S&P500 Index, 15 stocks in S&P500	2006-2013	News from Reuters and Bloomberg	CNN	Accuracy, MCC	-
[170]	S&P500 index news from Reuters	2006-2013	Financial news titles, Technical indicators	SI-RCNN (LSTM + CNN)	Accuracy	-
[171]	10 stocks in Nikkei 225 and news	2001-2008	Textual information and Stock prices	Paragraph Vector + LSTM	Profit	-
[172]	NIFTY50 Index, NIFTY Bank/Auto/IT/Energy Index, News	2013-2017	Index data, news	LSTM	MCC, Accuracy	-
[173]	Price data, index data, news, social media data	2015	Price data, news from articles and social media	Coupled matrix and tensor	Accuracy, MCC	Jieba
[174]	HS300	2015-2017	Social media news, price data	RNN-Boost with LDA	Accuracy, MAE, MAPE, RMSE	Python, Scikit-learn
[175]	News and Chinese stock data	2014-2017	Selected words in a news	HAN	Accuracy, Annual return	-
[176]	News, stock prices from Hong Kong Stock Exchange	2001	Price data and TF-IDF from news	ELM, DLR, PCA, BELM, KELM, NN	Accuracy	Matlab
[177]	TWSE index, 4 stocks in TWSE	2001-2017	Technical indicators, Price data, News	CNN + LSTM	RMSE, Profit	Keras, Python, TALIB
[178]	Stock of Tsugami Corporation	2013	Price data	LSTM	RMSE	Keras, Tensorflow
[179]	News, Nikkei Stock Average and 10-Nikkei companies	1999-2008	news, MACD	RNN, RBM+DBN	Accuracy, P-value	-
[180]	ISMIS 2017 Data Mining Competition dataset	-	Expert identifier, classes	LSTM + GRU + FFNN	Accuracy	-
[181]	Reuters, Bloomberg News, S&P500 price	2006-2013	News and sentences	LSTM	Accuracy	-
[182]	APPL from S&P500 and news from Reuters	2011-2017	Input news, OCHLV, Technical indicators	CNN + LSTM, CNN+SVM	Accuracy, F1-score	Tensorflow
[183]	Nikkei225, S&P500, news from Reuters and Bloomberg	2001-2013	Stock price data and news	DGM	Accuracy, MCC, %profit	-
[184]	Stocks from S&P500	2006-2013	Text (news) and Price data	LAR+News, RF+News	MAPE, RMSE	-

Minami et al. [178] proposed a method that predicted the stock price with corporate action event information and macro-economic index data using LSTM. In [179], a novel method that used a combination of RBM, DBN and word embeddings to create word vectors for RNN-RBM-DBN network was proposed to predict the stock prices. Buczkowski et al. [180] proposed a novel method that used expert recommendations, ensemble of GRU and LSTM for prediction of the prices.

In [181] a novel method that used character-based neural language model using financial news and LSTM was proposed. Liu et al. [182] proposed a method that used word embeddings with word2Vec, technical analysis features and stock prices for price prediction. In [183], Deep Neural Generative Model (DGM) with news articles using Paragraph Vector algorithm was used for creation of the input vector to predict the stock prices. In [184], the stock price data and word embeddings were used for stock price prediction. The results showed that the extracted information from embedding news improves the performance.

Table 12: Financial Sentiment Studies coupled with Text Mining without Forecasting

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[95]	883 BHC from EDGAR	2006-2017	Tokens, weighted sentiment polarity, leverage and ROA	CNN, LSTM, SVM, Random Forest	Accuracy, Precision, Recall, F1-score	Keras, Python, Scikit-learn
[185]	SemEval-2017 dataset, financial text, news, stock market data	2017	Sentiments in Tweets, News headlines	Ensemble SVR, CNN, LSTM, GRU	Cosine similarity score, agreement score, class score	Python, Keras, Scikit Learn
[186]	Financial news from Reuters	2006-2015	Word vector, Lexical and Contextual input	Targeted dependency tree LSTM	Cumulative abnormal return	-
[187]	Stock sentiment analysis from StockTwits	2015	StockTwits messages	LSTM, Doc2Vec, CNN	Accuracy, precision, recall, f-measure, AUC	-
[188]	Sina Weibo, Stock market records	2012-2015	Technical indicators, sentences	DRSE	F1-score, precision, recall, accuracy, AUROC	Python
[189]	News from NowNews, AppleDaily, LTN, MoneyDJ for 18 stocks	2013-2014	Text, Sentiment	LSTM, CNN	Return	Python, Tensorflow
[190]	StockTwits	2008-2016	Sentences, StockTwits messages	CNN, LSTM, GRU	MCC, WSURT	Keras, Tensorflow
[191]	Financial statements of Japan companies	-	Sentences, text	DMLP	Precision, recall, f-score	-
[192]	Twitter posts, news headlines	-	Sentences, text	Deep-FASP	Accuracy, MSE, R^2	-
[193]	Forums data	2004-2013	Sentences and keywords	Recursive neural tensor networks	Precision, recall, f-measure	-
[194]	News from Financial Times related US stocks	-	Sentiment of news headlines	SVR, Bidirectional LSTM	Cosine similarity	Python, Scikit Learn, Keras, Tensorflow

Rawte et al. [95] tried to solve three separate problems using CNN, LSTM, SVM, RF: Bank risk classification, sentiment analysis and Return on Assets (ROA) regression. Akhtar et al. [185] compared CNN, LSTM and GRU based DL models against MLP for financial sentiment analysis. Chang et al. [186] implemented the estimation of information content polarity (negative/positive effect) with text mining, word vector, lexical, contextual input and various LSTM models. They used the financial news from Reuters.

Jangid et al. [187] proposed a novel method that is a combination of LSTM and CNN for word embedding and sentiment analysis using Bidirectional LSTM (Bi-LSTM) for aspect extraction. The proposed method used multichannel CNN for financial sentiment analysis. Shijia et al. [188] used an attention-based LSTM for the financial sentiment analysis using news headlines and microblog messages. Sohangir et al. [189] used LSTM, doc2vec, CNN and stock market opinions posted in StockTwits for sentiment analysis. Mahmoudi et al. [190] extracted tweets from StockTwits to identify the user sentiment. In the evaluation approach, they also used emojis for the sentiment analysis. Kitamori et al. [191] extracted the sentiments from financial news and used DMLP to classify positive and negative news.

In [192], the sentiment/aspect prediction was implemented using an ensemble of LSTM, CNN and GRU networks. In a different study, Li et al. [193] proposed a DL based sentiment analysis method using RNN to identify the top sellers in the underground economy. Moore et al. [194] used text mining techniques for sentiment analysis from the financial news.

In [195], individual social security payment types (paid, unpaid, repaid, transferred) were classified and predicted using LSTM, HMM and SVM. Sohangir et al. [196] used two neural network models (doc2Vec, CNN) to find the top authors in StockTwits messages and to classify the authors as expert or non-expert for author classification purposes.

Table 13: Other Text Mining Studies

Art.	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[73]	News from NowNews, AppleDaily, LTN, MoneyDJ for 18 stocks	2013-2014	Text, Sentiment	DMLP	Return	Python, Tensorflow
[96]	The event data set for large European banks, news articles from Reuters	2007-2014	Word, sentence	DMLP +NLP preprocess	Relative usefulness, F1-score	-
[97]	Event dataset on European banks, news from Reuters	2007-2014	Text, sentence	Sentence vector + DFFN	Usefulness, F1-score, AUROC	-
[98]	News from Reuters, fundamental data	2007-2014	Financial ratios and news text	doc2vec + NN	Relative usefulness	Doc2vec
[121]	Real-world data for automobile insurance company labeled as fradulent	-	Car, insurance and accident related features	DMLP + LDA	TP, FP, Accuracy, Precision, F1-score	-
[123]	Financial transactions	-	Transaction data	LSTM	t-SNE	-
[195]	Taiwan's National Pension Insurance	2008-2014	Insured's id, area-code, gender, etc.	RNN	Accuracy, total error	Python
[196]	StockTwits	2015-2016	Sentences, StockTwits messages	Doc2vec, CNN	Accuracy, precision, recall, f-measure, AUC	Python, Tensorflow

In [123], the character sequences in financial transactions and the responses from the other side was used to detect if the transaction was fraud or not with LSTM. Wang et al. [121] used text mining and DMLP models to detect automobile insurance fraud.

In [96], the news semantics were extracted by the word sequence learning, bank stress was determined and classified with the associated events. Day et al. [73] used financial sentiment analysis using text mining and DMLP for stock algorithmic trading.

Cerchiello et al. [98] used the fundamental data and text mining from the financial news (Reuters) to classify the bank distress. In [97], the bank distress was identified by extracting the data from the financial news through text mining. The proposed method used DFNN on semantic sentence vectors to classify if there was an event or not.

4.8.1. Model, Feature and Dataset selections for Financial Text Mining

Financial text mining is highly correlated with financial sentiment analysis. So, most of the highlights described for financial sentiment analysis are also valid for financial text mining. Full distribution of models, features and datasets used by the financial text mining implementations are presented in Figures 10, 11 and 12.

4.9. Theoretical or Conceptual Studies

There were a number of research papers that were either focused on the theoretical concepts of finance or the conceptual designs without model implementation phases; however they still provided valuable information, so we decided to include them in our survey. In Table 14, these studies were tabulated according to their topic of interest.

In [197], the connection between deep AEs and Singular Value Decomposition (SVD) were discussed and compared using stocks from iShares Nasdaq Biotechnology ETF (IBB) index and the stock of Amgen Inc. Bouchti et al. [198] explained the details of DRL and mentioned that DRL could be used for fraud detection/risk management in banking.

Table 14: Other - Theoretical or Conceptual Studies

Art.	**SubTopic**	**IsTimeSeries?**	**Data Set**	**Period**	**Feature Set**	**Method**
[197]	Analysis of AE, SVD	Yes	Selected stocks from the IBB index and stock of Amgen Inc.	2012-2014	Price data	AE, SVD
[198]	Fraud Detection in Banking	No	Risk Management / Fraud Detection	-	-	DRL

4.10. Other Financial Applications

Finally, there were some research papers which did not fit into any of the previously covered topics. Their data set and intended output were different than most of the other studies focused in this survey. These studies include social security payment classification, bank telemarketing success prediction, hardware solutions for faster financial transaction processing, etc. There were some anomaly detection implementations like tax evasion, money laundering that could have been included in this group; however we decided to cover them in a different subsection, fraud detection. Table 15 shows all these aforementioned studies with their differences.

Dixon et al. [199] used Intel Xeon Phi to speedup the price movement direction prediction problem using DFFN. The main contribution of the study was the increase in the speed of processing. Alberg et al. [200] used several company financials data (fundamental data) and price together to predict the next period's company financials data. Kim et al. [201]

used CNN for predicting the success of bank telemarketing. In their study, they used the phone calls of the bank marketing data and 16 finance-related attributes. Lee et al. [202] used technical indicators and patent information to estimate the revenue and profit for the corporates using RBM based DBN, FFNN and Support Vector Regressor (SVR).

Ying et al.[195] classified and predicted individual social security payment types (paid, unpaid, repaid, transferred) using LSTM, HMM and SVM. Li et al. [193] proposed a deep learning-based sentiment analysis method to identify the top sellers in the underground economy. Jeong et al. [49] combined deep Q-learning and deep NN to implement a model to solve three separate problems: Increasing profit in a market, prediction of the number of shares to trade, and preventing overfitting with insufficient financial data.

Table 15: Other Financial Applications

Art.	Subtopic	Data Set	Period	Feature Set	Method	Performance Criteria	Env.
[49]	Improving trading decisions	S&P500, KOSPI, HSI, and EuroStoxx50	1987-2017	200-days stock price	Deep Q-Learning and DMLP	Total profit, Correlation	-
[193]	Identifying Top Sellers In Underground Economy	Forums data	2004-2013	Sentences and keywords	Recursive neural tensor networks	Precision, recall, f-measure	-
[195]	Predicting Social Ins. Payment Behavior	Taiwan's National Pension Insurance	2008-2014	Insured's id, area-code, gender, etc.	RNN	Accuracy, total error	Python
[199]	Speedup	45 CME listed commodity and FX futures	1991-2014	Price data	DNN	-	-
[200]	Forecasting Fundamentals	Stocks in NYSE, NASDAQ or AMEX exchanges	1970-2017	16 fundamental features from balance sheet	DMLP, LFM	MSE, Compount annual return, SR	-
[201]	Predicting Bank Telemarketing	Phone calls of bank marketing data	2008-2010	16 finance-related attributes	CNN	Accuracy	-
[202]	Corporate Performance Prediction	22 pharmaceutical companies data in US stock market	2000-2015	11 financial and 4 patent indicator	RBM, DBN	RMSE, profit	-

5. Current Snaphot of DL research for Financial Applications

For the survey, we reviewed 144 papers from various financial application areas. Each paper is analyzed according to its topic, publication type, problem type, method, dataset, feature set and performance criteria. Due to space limitations, we will only provide the general summary statistics indicating the current state of the DL for finance research.

First and foremost, we clustered the various topics within the financial applications research and presented them in Figure 8. A quick glance at the figure shows us financial text mining and algorithmic trading are the top two fields that the researchers most worked on followed by risk assessment, sentiment analysis, portfolio management and fraud detection, respectively. The results indicate most of the papers were published within the past 3 years implying the domain is very hot and actively studied.

When the papers were clustered by the DL model type as presented in Figure 9, we observe the dominance of RNN, DMLP and CNN over the remaining models, which might

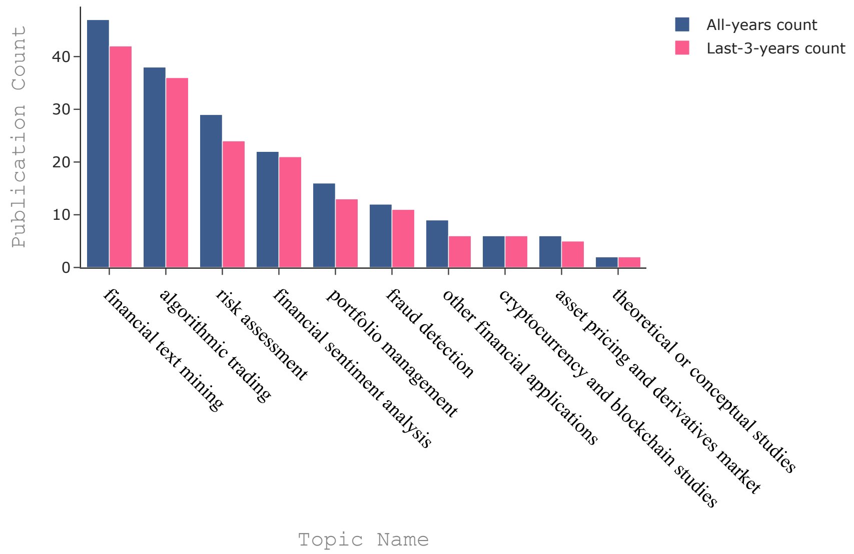

Figure 8: The histogram of Publication Count in Topics

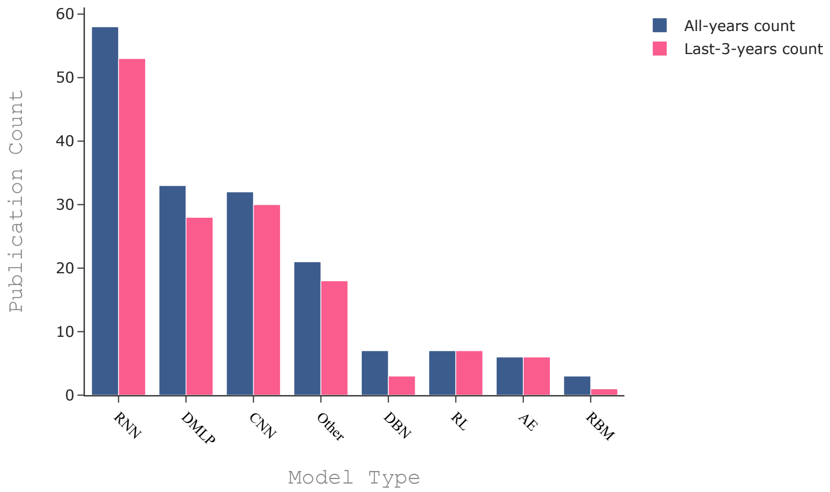

Figure 9: The histogram of Publication Count in Model Types

be expected, since these models are the most commonly preferred ones in general DL implementations. Meanwhile, RNN is a general umbrella model which has several versions including LSTM, GRU, etc. Within the RNN choice, most of the models actually belonged to LSTM, which is very popular in time series forecasting or regression problems. It is also used quite often in algorithmic trading. More than 70% of the RNN papers consisted of

LSTM models.

Meanwhile, DMLP generally fits well for classification problems; hence it is a common choice for most of the financial application areas. However, since it is a natural extension of its shallow counterpart MLP, it has a longer history than the other DL models.

CNN started getting more attention lately since most of the implementations appeared within the past 3 years. Careful analysis of CNN papers indicates that a recent trend of representing financial data with a 2-D image view in order to utilize CNN is growing. Hence CNN based models might overpass the other models in the future. It actually passed DMLP for the past 3 years.

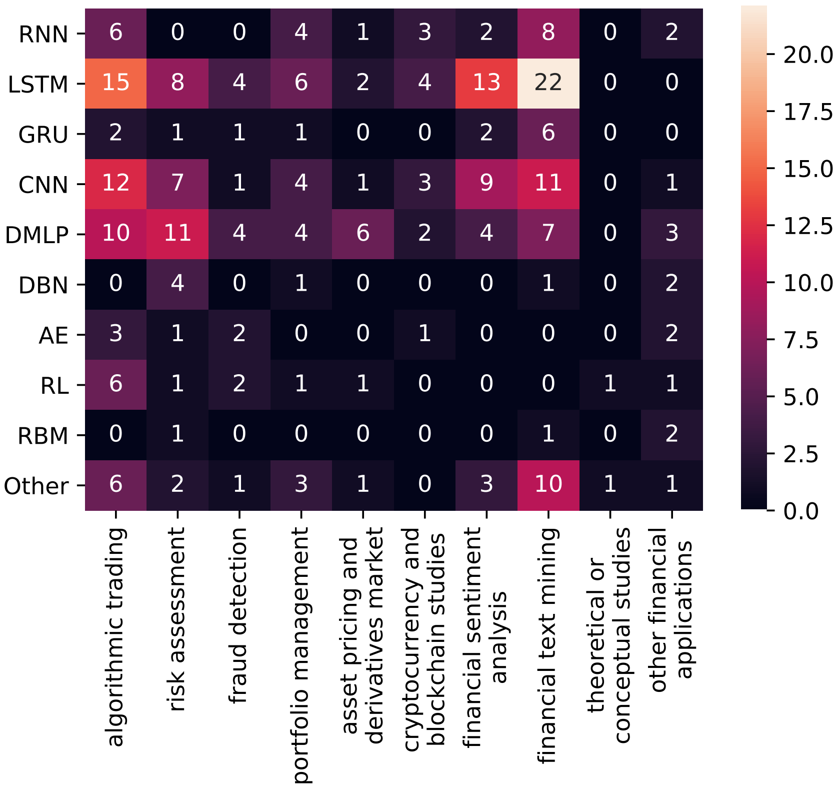

Figure 10: Topic-Model Heatmap

Furthermore, we attempted to provide more details about associations between the DL models and the financial application areas. Figure 10 gives the distribution of the models for the research areas through a model-topic heatmap. Since most of the papers had multiple DL models, the amount of models is more than the number of covered papers. The results indicate the broad acceptance of RNN, DMLP and CNN models in almost all financial application areas.

We also wanted to elaborate on the particular feature selections for each financial application area to see if we could spot any pattern. Figure 11 gives the distribution of the features for the research areas through a feature-topic heatmap. Unlike the model-topic heatmap, in this case, we saw a distinction between the associations. Even though price

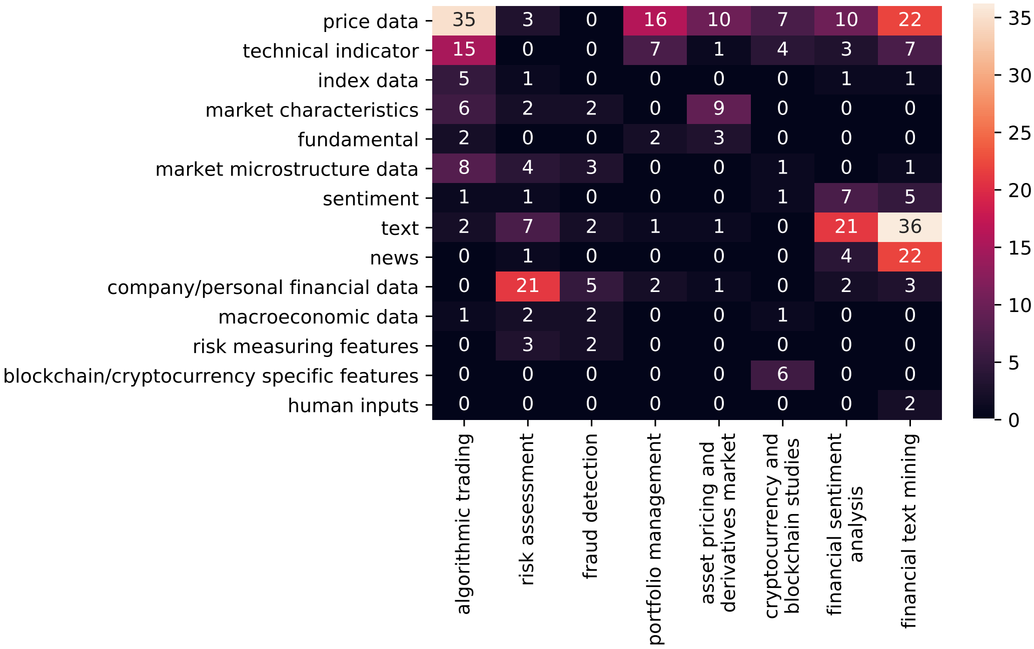

Figure 11: Topic-Feature Heatmap

data and technical indicators have been very popular for most of the resarch areas that are involved with time series forecasting, like algorithmic trading, portfolio management, financial sentiment analysis and financial text mining, the studies that had more significant spatial characteristics like risk assessment and fraud detection did not depend much on these temporal features. One other noteworthy difference came up with the adaptation of text related features. Highly text-based applications like financial sentiment analysis, financial text mining, risk assesssment and fraud detection preferred to use features like text (extracted from tweets, news or financial data) and sentiments during their model development and implementation. However, the temporal characteristics of the financial time series data were also important for financial sentiment analysis and financial text mining, since a significant portion of these models were integrated into algorithmic trading systems.

Figure 12 elaborates on the distribution of the dataset types for the research areas through a dataset-topic heatmap. If we analyze the heatmap, we see similarities with the feature-topic associations. However, this time, we had three main clusters of dataset types, the first one being the temporal datasets like Stock, Index, ETF, Cryptocurrency, Forex and Commodity price datasets, and the second one being the text-based datasets like News, Tweets, Microblogs and Financial Reports, and the last one being the datasets that had both numeric and textual components like Consumer Data, Credit Data and Financial Reports from companies or analysts. As far as the dataset vs. application area associations are concerned, these three main clusters were distributed as follows: Stock, Index, Cryptocurrency, ETF datasets were used almost in every application area except Risk Assessment and Fraud Detection which had less of temporal properties. Meanwhile, Credit Data, Financial

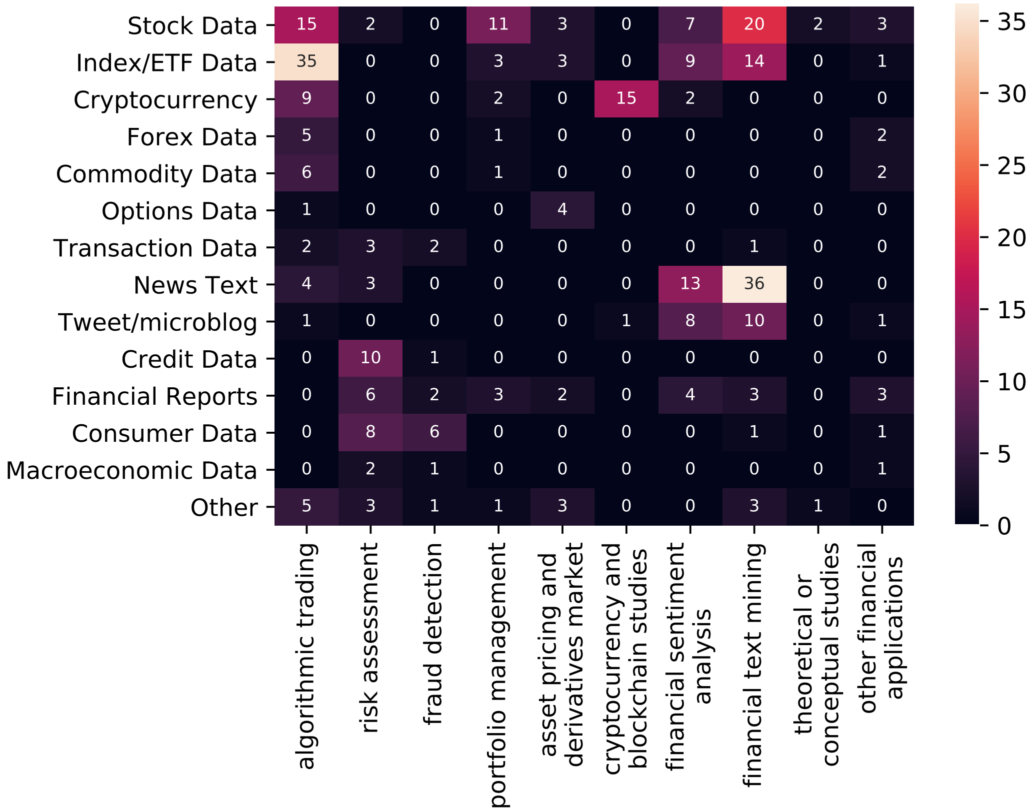

Figure 12: Topic-Dataset Heatmap

Reports and Consumer Data were particularly used by these two application areas, namely Risk Assessment and Fraud Detection. Lastly, pure text based datasets like news, tweets, microblogs were preferred by Financial Sentiment Analysis and Financial Text Mining studies. However, as was the case in the feature-topic associations, temporal datasets like stock, ETF, Index price datasets were also used with these studies since some of them were tied with algorithmic trading models.

6. Discussion and Open Issues

After reviewing all the publications based on the selected criteria explained in the previous section, we wanted to provide our findings of the current state-of-the-art situation. Our discussions are categorized by the DL models and implementation topics.

6.1. Discussions on DL Models

It is possible to claim that LSTM is the dominant DL model that is preferred by most researchers, due to its well-established structure for financial time series data forecasting. Most of the financial implementations have time-varying data representations requiring regression-type approaches which fits very well for LSTM and its derivatives due to their easy adaptations to the problems. As long as the temporal nature of the financial data remains, LSTM and its related family models will maintain their popularities.

Meanwhile, CNN based models started getting more traction among researchers in the last two years. Unlike LSTM, CNN works better for classification problems and is more suitable for either non-time varying or static data representations. However, since most financial data is time-varying, under normal circumstances, CNN is not the natural choice for financial applications. However, in some independent studies, the researchers performed an innovative transformation of 1-D time-varying financial data into 2-D mostly stationary image-like data to be able to utilize the power of CNN through adaptive filtering and implicit dimensionality reduction. This novel approach seems working remarkably well in complex financial patterns regardless of the application area. In the future, more examples of such implementations might be more common; only time will tell.

Another model that has a rising interest is DRL based implementations; in particular, the ones coupled with agent-based modelling. Even though algorithmic trading is the most preferred implementation area for such models, it is possible to develop the working structures for any problem type.

Careful analyses of the reviews indicate in most of the papers hybrid models are preferred over native models for better accomplishments. A lot of researchers configure the topologies and network parameters for achieving higher performance. However, there is also the danger of creating more complex hybrid models that are not easy to build, and their interpretation also might be difficult.

Through the performance evaluation results, it is possible to claim that in general terms, DL models outperform ML counterparts when working on the same problems. DL models also have the advantage of being able to work on larger amount of data. With the growing expansion of open-source DL libraries and frameworks, DL model building and development process is easier than ever.

Also it is worth to mention that, besides the outperformance of DL models over ML, the performance evaluation results are improving every year relatively, even though it is very difficult to explicitly quantifty the amount of improvement. The improvements are most notable in trend prediction based algo-trading implementations and text-mining studies due to deeper and/or more versatile networks and new innovative model developments. This is also reflected through the increasing number of published papers year over year.

6.2. Discussions on Implementation Areas

Price/trend prediction and Algo-trading models have the most interest among all financial applications that use DL models in their implementations. Risk assessment and portfolio management have always been popular within the ML community, and it looks like this is also valid for DL researchers.

Even though broad interest in DL models is on the rise, financial text mining is particularly getting more attention than most of the other financial applications. The streaming flow of financial news, tweets, statements, blogs opened up a whole new world for the financial community allowing them to build better and more versatile prediction and evaluation models integrating numerical and textual data. Meanwhile, the general approach nowadays is to combine text mining with financial sentiment analysis. With that, it is reasonable to assume higher performance will be achieved. A lot of researchers started working on that particular application area. It is quite probable that the next generation of outperforming implementations will be based on models that can successfully integrate text mining with quantified numerical data.

These days, one other hot area within the DL research is the cryptocurrencies. We can also include blockchain research to that, even though it is not necessarily directly related to cryptocurrencies, but generally used together in most implementations. Cryptocurrency price prediction has the most attraction within the field, but since the topic is fairly new, more studies and implementations will probably keep pouring in due to the high expectations and promising rewards.

6.3. Open Issues and Future Work

When we try to extrapolate the current state of research and the achieved accomplishments into the future, a few areas of interests stand out. We will try to elaborate on them and provide a pathway for what can be done or needs to be done within the following few years. We will try to sort out our opinions by analyzing them through the model development and research topic point of view.

6.3.1. Model Development Perspective

We have already mentioned the growing attention on the adaptation of 2-D CNN implementations for various financial application areas. This particular technique looks promising and provides opportunities. It would be beneficial to further explore the possibilities using that approach in different problems. The playfield is still wide open.

Graph CNN is another model that is closely related but still showing some discrepancies. It has not been used much, only one study was published that relates graph-CNN with financial applications. However, versatile transformations of financial data into graphs, integrating sentiment analysis through graph representations and constructing different models can create opportunities for researchers to build better performing financial applications.

There are also recently developed DL models, like GAN, Capsule networks, etc. that can also provide viable alternatives to existing implementations. They have started showing up in various non-financial studies, however to the best of our knowledge, no known implementation of such kind for financial applications exists. It might open up a new window of opportunities for financial researchers and practitioners. In addition to such new models, innovative paradigms like transfer learning, one-shot learning can be tested within the environment.

Since financial text mining is overtaking the other topics in an accelerated fashion, new data models like Stock2Vec [168] can be enhanced for better and more representative models. In addition, Natural Language Processing (NLP) based ensemble models or more integration of data semantics into the picture can increase the accuracy of the existing models.

Finally, according to our observations, hybrid models are preferred more over the native or standalone models in most studies. This trend will likely continue, however, researchers need to introduce more versatile, sometimes unconventional models for better results. Hybrid models integrating various simple DL layers like cascaded CNN-LSTM blocks can have better outcomes since ensembling spatial and temporal information together in a novel way might be an important milestone for researchers seeking for "alpha" in their models.

6.3.2. Implementation Perspective

As far as the application areas are concerned, the usual suspects, algorithmic trading, portfolio management and risk assessment will probably continue on their dominance within the financial research arena in the foreseeable future. Meanwhile, some new shining stars started getting more attention, not only because they represent fairly new research opportunities, but also their forecasted impact on the financial world is noteworthy.

Cryptocurrencies and blockchain technology are among these new research areas. Hence, it is worthwhile to explore the possibilities that these new fields will bring. It will be a while before any of these technologies become widely accepted industry standard, however, that is the sole reason why it provides a great opportunity for the researchers to shape the future of the financial world with new innovative models and hoping that the rest of the world will follow their footsteps.

Another area that can benefit from more innovative models is portfolio management. Robo-advisory systems are on the rise throughout the world and these systems depend on high performing automated decision support systems. Since DL models fit well to that description, it would be logical to assume the utilization of DL implementations will increase in the coming years. As such, the corresponding quant funds will be very interested in the achievements that the DL researchers can offer for the financial community. This might require integrating learning and optimization models together for better-performing systems. Hence, ensemble models that can successfully mix EC and DL components might be what the industry is anticipating for the immediate future. This might also result in new research opportunities.

Yet, one other research area that is generally avoided by soft computing and DL researchers is the financial derivatives market. Even though there are many different products that exist on the market, the corresponding DL research is very scarce. However, for professionals working in the finance industry, these products actually provide incredible flexibilities ranging from hedging their investments to implementing leveraged transactions with minimized risk. Even though, opportunities exist for DL researchers, there was not a broad interest in the topic, since there are only a handful of studies for the derivatives market. Option strategy optimization, futures trading, option pricing, arbitrage trading can be among the areas that might benefit from DL research.

Sentiment analysis, text mining, risk adjusted asset pricing are some of the other implementation areas that attract researchers but not yet fully utilized. It is quite probable we will see more papers in these fields in the near future.

Last, but not least, HFT is one area that has not benefitted from the advancements in ML research to its full potential yet. Since HFT requires lightning-fast transaction processing, the statistical learning model that is embedded into such trading systems must not introduce any extra latency to the existing system. This necessitates careful planning and modelling of such models. For that purpose, DL models embedded within the Graphic Processing

Unit (GPU) or Field Programmable Gate Array (FPGA) based hardware solutions can be studied. The hardware aspects of DL implementations are generally omitted in almost all studies, but as stated above, there might be opportunities also in that field.

6.3.3. Suggestions for Future Research

Careful analysis of Figure 8 indicates the rising overall appetite for applied DL research for finance. Even though the interest is broad, some areas like cryptocurrency and block chain studies might get more attention compared to other areas.

With respect to the promising outlook in text mining and financial sentiment analysis, we believe behavioral finance is also a fairly untouched research area that hides a lot of opportunities within. There is a lack of research work published on behavioral finance using DL models. This might be mainly due to the difficulties of quantifying the inputs and outputs of behavioral finance research to be used with DL models. However, new advancements in text mining, NLP, semantics combined with agent-based computational finance can open up huge opportunities in that field. We would encourage researchers to look further into this for a possible implementation area as it currently seems to be wide open for new studies.

6.4. Responses to Our Initial Research Questions

At this point, since we gathered and processed all the information we need, we are ready to provide answers to our initially stated research questions. The questions and our corresponding answers according to our survey are as follows:

- What financial application areas are of interest to DL community?

  Response: Financial text mining, Algo-trading, risk assessments, sentiment analysis, portfolio management and fraud detection are among the most studied areas of finance research. (Please check Figure 8)

- How mature is the existing research in each of these application areas?

  Response: Even though DL models already had better achievements compared to traditional counterparts in almost all areas, the overall interest is still on the rise in all research areas.

- What are the areas that have promising potentials from an academic/industrial research perspective?

  Response: Cryptocurrencies, blockchain, behavioral finance, HFT and derivatives market have promising potentials for research.

- Which DL models are preferred (and more successful) in different applications?

  Response: RNN based models (in particular LSTM), CNN and DMLP have been used extensively in implementations. From what we have encountered, LSTM is more successful and preferred in time-series forecasting, whereas DMLP and CNN are better suited to applications requiring classification.

- How do DL models pare against traditional soft computing / ML techniques?

  Response: In most of the studies, DL models performed better than their ML counterparts. There were a few occasions where ML had comparable or even better solutions, however the general tendency is the outperformance of the DL methods.

- What is the future direction for DL research in Finance?

  Response: Hybrid models based on Spatio-temporal data representations, NLP, semantics and text mining-based models might become more important in the near future.

7. Conclusions

The financial industry and academia have started realizing the potentials of DL in various application areas. The number of research work keeps on increasing every year with an accelerated fashion. However, we are just in the early years of this new era, more studies will be implemented and new models will keep pouring in. In this survey, we wanted to highlight the state-of-the-art DL research for the financial applications. We not only provided a snapshot of the existing research status but also tried to identify the future roadway for intended researchers. Our findings indicate there are incredible opportunities within the field and it looks like they will not disappear anytime soon. So, we encourage the researchers that are interested in the area to start exploring.

8. Acknowledgement

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Glossary

AE Autoencoder. 4, 8, 9, 11, 13, 15, 19, 20, 24, 31
AI Artificial Intelligence. 15
AMEX American Stock Exchange. 21–23, 32
ANN Artificial Neural Network. 3, 4, 7
ARIMA Autoregressive Integrated Moving Average. 25
AUC Area Under the Curve. 21, 28–30
AUROC Area Under the Receiver Operating Characteristics. 12, 15, 17, 19, 26, 28–30
BA Balanced Accuracy. 17
BELM Basic Extreme Learning Machine. 28
BHC Bank Holding Companies. 17, 29
Bi-GRU Bidirectional Gated Recurrent Unit. 28
Bi-LSTM Bidirectional LSTM. 21, 22, 26, 30
BIST Istanbul Stock Exchange Index. 11
BOLL Bollinger Band. 24
BPTT Backpropagation Through Time. 5
CAE Convolutional Autoencoder. 12
CAGR Compound Annual Growth Rate. 21
CART Classification and Regression Trees. 17
CCI Commodity Channel Index. 25
CDAX German Stock Market Index Calculated by Deutsche Börse. 28
CDS Credit Default Swaps. 15, 16
CGAN Conditional GAN. 17
CME Chicago Mercantile Exchange. 14, 32
CNN Convolutional Neural Network. 2, 4, 5, 10–19, 21, 22, 24–30, 32, 34, 37–40
CRIX The Cryptocurrency Index. 24
CRSP Center for Research in Security Prices. 17
CSI China Securities Index. 11, 26
DAX The Deutscher Aktienindex. 13, 14

DBN Deep Belief Network. 4, 7, 8, 15–17, 20, 21, 28, 29, 32
DCNL Deep Co-investment Network Learning. 14
DCNN Deep Convolutional Neural Network. 15
DDPG Deep Deterministic Policy Gradient. 21
Deep-FASP The Financial Aspect and Sentiment Prediction task with Deep neural networks. 29
DFFN Deep Feed Forward Network. 16, 17, 21, 30, 31
DFNN Deep Feedforward Neural Network. 21, 22, 25, 31
DGM Deep Neural Generative Model. 28, 29
DGP Deep Gaussian Process. 9
DJI Dow Jones Index. 26
DJIA Dow Jones Industrial Average. 11, 26
DL Deep Learning. 1–4, 6–10, 14–16, 18, 20–25, 27, 29, 30, 32–34, 36–41
DLR Deep Learning Representation. 28
DMI Directional Movement Index. 25
DMLP Deep Multilayer Perceptron. 4, 5, 11–26, 29–32, 34, 40
DNN Deep Neural Network. 5, 26, 32
DP Discriminant Power. 17
DQL Deep Q-Learning. 19
DRL Deep Reinforcement Learning. 9, 11, 14, 21, 24, 31, 37
DRSE Deep Random Subspace Ensembles. 26, 29
DTW Dynamic Time Warping. 14
EA Evolutionary Algorithm. 3, 10, 20
EC Evolutionary Computation. 15, 39
ELM Extreme Learning Machine. 28
EMA Exponential Moving Average. 25
ETF Exchange-Traded Fund. 11, 12
FDDR Fuzzy Deep Direct Reinforcement Learning. 10, 11
FE-QAR Fixed Effects Quantile VAR. 17
FFNN Feedforward Neural Network. 5, 8, 12, 18, 28, 32
FN False Negative. 15, 17
FNN Fully Connected Neural Network. 12
FP False Positive. 15, 17, 19, 30
FPGA Field Programmable Gate Array. 40
FTSE London Financial Times Stock Exchange Index. 11–14
G-mean Geometric Mean. 17
GA Genetic Algorithm. 3, 11, 12, 42
GAN Generative Adversarial Network. 9, 38, 41
GASVR GA with a SVR. 11
GBDT Gradient-Boosted-DecisionTrees. 19
GBT Gradient Boosted Trees. 11
GP Genetic Programming. 3, 13, 15, 16
GPU Graphic Processing Unit. 39
GRU Gated-Recurrent Unit. 13, 14, 19–21, 28–30, 33
HAN Hybrid Attention Network. 28
HFT High Frequency Trading. 10, 13, 39, 40
HMM Hidden Markov Model. 25, 30, 32
HS China Shanghai Shenzhen Stock Index. 28
HSI Hong Kong Hang Seng Index. 11, 32
IBB iShares Nasdaq Biotechnology ETF. 21, 31
KELM Kernel Extreme Learning Machine. 28
KNN K-Nearest Neighbors. 28
KOSPI The Korea Composite Stock Price Index. 11, 32
KS Kolmogorov–Smirnov. 17
LAR Linear Auto-regression Predictor. 28
LDA Latent Dirichlet Allocation. 19, 27, 28, 30
LFM Lookahead Factor Models. 32
LinR Linear Regression. 28
LOB Limit Order Book Data. 12
LR Logistic Regression. 16
LSTM Long-Short Term Memory. 2, 4, 6, 7, 10–14, 16–22, 24–30, 32–34, 36, 37, 39, 40
MA Moving Average. 24, 25
MACD Moving Average Convergence and Divergence. 12, 25, 28
MAE Mean Absolute Error. 11, 22, 28
MAPE Mean Absolute Percentage Error. 11, 22, 28
MCC Matthew Correlation Coefficient. 28, 29
MDA Multilinear Discriminant Analysis. 11
MDD Maximum Drawdown. 11, 12, 21, 24
ML Machine Learning. 1–4, 10, 15, 16, 18, 20–22, 25, 27, 37, 39, 41
MLP Multilayer Perceptron. 4, 20, 21, 29, 34
MODRL Multi-objective Deep Reinforcement Learning. 11
MOEA Multiobjective Evolutionary Algorithm. 3, 20
MSE Mean Squared Error. 11, 12, 19, 21, 24, 26, 28, 29, 32
MV-t Multivariate t Distribution. 17
MVN Multivariate Normal Distribution. 17
NASDAQ National Association of Securities Dealers Automated Quotations. 14, 21–23, 26, 32
NES Natural Evolution Strategies. 11
NIFTY National Stock Exchange of India. 28
NIKKEI Tokyo Nikkei Index. 11
NLP Natural Language Processing. 17, 30, 38, 40, 41

NN Neural Network. 3, 17, 26, 28, 30, 32
NYSE New York Stock Exchange. 11, 21–23, 26, 32
OCHL Open,Close,High, Low. 11, 26
OCHLV Open,Close,High, Low, Volume. 11, 12, 14, 21, 22, 24, 26, 28
PCA Principal Component Analysis. 3, 19, 28
PCC Pearson's Correlation Coefficient. 14
PLR Piecewise Linear Representation. 11
PNN Probabilistic Neural Network. 12, 13
PPO Proximal Policy Optimization. 21
PSO Particle Swarm Optimization. 3
$\mathbf{R^2}$ Squared correlation, Non-linear regression multiple correlation. 21, 22, 26, 29
RBM Restricted Boltzmann Machine. 4, 7, 15–17, 20, 21, 28, 29, 32
RCNN Recurrent CNN. 28
ReLU Rectified Linear Unit. 4
RF Random Forest. 11, 16, 17, 19, 21, 28, 29
RL Reinforcement Learning. 11–14, 19, 21, 24
RMSE Root Mean Square Error. 11, 17, 19, 22, 24, 25, 28, 32
RNN Recurrent Neural Network. 2, 4, 5, 10–14, 20, 21, 24–30, 32–34, 40
ROA Return on Assets. 17, 29
ROC Price of Change. 25
RSE Relative Squared Error. 11
RSI Relative Strength Index. 12, 25
S&P500 Standard's & Poor's 500 Index. 11, 12, 14, 21, 26, 28, 32
SAE Stacked Autoencoder. 10, 16, 17
SCI SSE Composite Index. 26
SFM State Frequency Memory. 10, 11
SGD Stochastic Gradient Descent. 5
SPY SPDR S&P 500 ETF. 12
SR Sharpe-ratio. 11, 12, 14, 21, 24, 28, 32
STD Standard Deviation. 11, 21
SVD Singular Value Decomposition. 31
SVM Support Vector Machine. 3, 15–17, 25, 28–30, 32
SVR Support Vector Regressor. 11, 28, 29, 32, 42
SZSE Shenzhen Stock Exchange Composite Index. 11
TAIEX Taiwan Capitalization Weighted Stock Index. 22
TALIB Technical Analysis Library Package. 12, 28
TAQ Trade and Quote. 21
TDNN Timedelay Neural Network. 12, 13
TEMA Triple Exponential Moving Average. 25
TF-IDF Term Frequency-Inverse Document Frequency. 28
TGRU Two-stream GRU. 27, 28
THEIL-U Theil's inequality coefficient. 11
TN True Negative. 15
TP True Positive. 15, 19, 30
TR Total Return. 12
TSE Tokyo Stock Exchange. 21, 22, 26
TWSE Taiwan Stock Exchange. 28
VAR Vector Auto Regression. 17
VWL WL Kernel-based Method. 14
WBA Weighted Balanced Accuracy. 17
WMTR Weighted Multichannel Time-series Regression. 11
WSURT Wilcoxon Sum-rank Test. 29
WT Wavelet Transforms. 10, 11
XGBoost eXtreme Gradient Boosting. 16, 17

References

[1] Omer Berat Sezer, Mehmet Ugur Gudelek, and Ahmet Murat Ozbayoglu. Financial time series forecasting with deep learning : A systematic literature review: 2005-2019. *arXiv preprint arXiv:1911.13288*.

[2] Arash Bahrammirzaee. 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, June 2010.

[3] D. Zhang and L. Zhou. Discovering golden nuggets: Data mining in financial application. *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)*, 34(4):513–522, November 2004.

[4] Asunción Mochón, David Quintana, Yago Sáez, and Pedro Isasi Viñuela. Soft computing techniques applied to finance. *Applied Intelligence*, 29:111–115, 2007.

[5] Pulakkazhy. Mining in banking and its applications: A review. *Journal of Computer Science*, 9(10): 1252–1259, October 2013.

[6] Sendhil Mullainathan and Jann Spiess. Machine learning: An applied econometric approach. *Journal of Economic Perspectives*, 31(2):87–106, May 2017.

[7] Keke Gai, Meikang Qiu, and Xiaotong Sun. A survey on fintech. *Journal of Network and Computer Applications*, 103:262–273, 2018.

[8] Boris Kovalerchuk and Evgenii Vityaev. *Data Mining in Finance: Advances in Relational and Hybrid Methods*. Kluwer Academic Publishers, Norwell, MA, USA, 2000.

[9] Rafik A. Aliev, Bijan Fazlollahi, and Rashad R. Aliev. Soft computing and its applications in business and economics. In *Studies in Fuzziness and Soft Computing*, 2004.

[10] Anthony Brabazon and Michael O'Neill, editors. *Natural Computing in Computational Finance*. Springer Berlin Heidelberg, 2008.

[11] Ludmila Dymowa. *Soft Computing in Economics and Finance*. Springer Berlin Heidelberg, 2011.

[12] Shu-Heng Chen, editor. *Genetic Algorithms and Genetic Programming in Computational Finance*. Springer US, 2002.

[13] Ma. Guadalupe Castillo Tapia and Carlos A. Coello Coello. Applications of multi-objective evolutionary algorithms in economics and finance: A survey. In *2007 IEEE Congress on Evolutionary Computation*. IEEE, September 2007.

[14] Antonin Ponsich, Antonio Lopez Jaimes, and Carlos A. Coello Coello. A survey on multiobjective evolutionary algorithms for the solution of the portfolio optimization problem and other finance and economics applications. *IEEE Transactions on Evolutionary Computation*, 17(3):321–344, June 2013.

[15] Ruben Aguilar-Rivera, Manuel Valenzuela-Rendon, and J.J. Rodriguez-Ortiz. Genetic algorithms and darwinian approaches in financial applications: A survey. *Expert Systems with Applications*, 42(21): 7684–7697, November 2015.

[16] Bo K Wong and Yakup Selvi. Neural network applications in finance: A review and analysis of literature (1990–1996). *Information & Management*, 34(3):129–139, October 1998.

[17] Yuhong Li and Weihua Ma. Applications of artificial neural networks in financial economics: A survey. In *2010 International Symposium on Computational Intelligence and Design*. IEEE, October 2010.

[18] B. Elmsili and B. Outtaj. Artificial neural networks applications in economics and management research: An exploratory literature review. In *2018 4th International Conference on Optimization and Applications (ICOA)*, pages 1–6, April 2018.

[19] Blake LeBaron. Chapter 24 agent-based computational finance. In L. Tesfatsion and K.L. Judd, editors, *Handbook of Computational Economics*, volume 2 of *Handbook of Computational Economics*, pages 1187–1233. Elsevier, 2006.

[20] Stephan K. Chalup and Andreas Mitschele. Kernel methods in finance. In *Handbook on Information Technology in Finance*, pages 655–687. Springer Berlin Heidelberg, 2008.

[21] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. *Nature*, 521(7553):436–444, 2015.

[22] George Cybenko. Approximation by superpositions of a sigmoidal function. *Mathematics of control, signals and systems*, 2(4):303–314, 1989.

[23] Barry L Kalman and Stan C Kwasny. Why tanh: choosing a sigmoidal function. In *[Proceedings 1992] IJCNN International Joint Conference on Neural Networks*, volume 4, pages 578–581. IEEE, 1992.

[24] Vinod Nair and Geoffrey E Hinton. Rectified linear units improve restricted boltzmann machines. In *Proceedings of the 27th international conference on machine learning (ICML-10)*, pages 807–814, 2010.

[25] Andrew L Maas, Awni Y Hannun, and Andrew Y Ng. Rectifier nonlinearities improve neural network acoustic models. In *Proc. icml*, volume 30, page 3, 2013.

[26] Prajit Ramachandran, Barret Zoph, and Quoc V Le. Searching for activation functions. *arXiv preprint arXiv:1710.05941*, 2017.

[27] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning*. MIT Press, 2016. http://www.deeplearningbook.org.

[28] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

[29] Xueheng Qiu, Le Zhang, Ye Ren, P. Suganthan, and Gehan Amaratunga. Ensemble deep learning for regression and time series forecasting. In *2014 IEEE Symposium on Computational Intelligence in Ensemble Learning (CIEL)*, pages 1–6, 2014.

[30] Yoshua Bengio. Deep learning of representations for unsupervised and transfer learning. In *Proceedings of ICML workshop on unsupervised and transfer learning*, pages 17–36, 2012.

[31] Geoffrey E. Hinton, Simon Osindero, and Yee-Whye Teh. A fast learning algorithm for deep belief nets. *Neural Computation*, 18(7):1527–1554, 2006.

[32] Pascal Vincent, Hugo Larochelle, Yoshua Bengio, and Pierre-Antoine Manzagol. Extracting and composing robust features with denoising autoencoders. In *Proceedings of the 25th international conference on Machine learning*, pages 1096–1103. ACM, 2008.

[33] Qinxue Meng, Daniel Catchpoole, David Skillicom, and Paul J Kennedy. Relational autoencoder for feature extraction. In *2017 International Joint Conference on Neural Networks (IJCNN)*, pages 364–371. IEEE, 2017.

[34] Yong Hu, Kang Liu, Xiangzhou Zhang, Lijun Su, E.W.T. Ngai, and Mei Liu. Application of evolutionary computation for rule discovery in stock algorithmic trading: A literature review. *Applied Soft Computing*, 36:534–551, November 2015.

[35] Sercan Karaoglu and Ugur Arpaci. A deep learning approach for optimization of systematic signal detection in financial trading systems with big data. *International Journal of Intelligent Systems and Applications in Engineering*, SpecialIssue(SpecialIssue):31–36, July 2017.

[36] Wei Bao, Jun Yue, and Yulei Rao. A deep learning framework for financial time series using stacked autoencoders and long-short term memory. *PLOS ONE*, 12(7):e0180944, July 2017.

[37] Shuanglong Liu, Chao Zhang, and Jinwen Ma. Cnn-lstm neural network model for quantitative strategy analysis in stock markets. In *Neural Information Processing*, pages 198–206. Springer International Publishing, 2017.

[38] Liheng Zhang, Charu Aggarwal, and Guo-Jun Qi. Stock price prediction via discovering multi-frequency trading patterns. In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD17*. ACM Press, 2017.

[39] Dat Thanh Tran, Martin Magris, Juho Kanniainen, Moncef Gabbouj, and Alexandros Iosifidis. Tensor representation in high-frequency financial data for price change prediction. In *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*. IEEE, November 2017.

[40] Yue Deng, Feng Bao, Youyong Kong, Zhiquan Ren, and Qionghai Dai. Deep direct reinforcement learning for financial signal representation and trading. *IEEE Transactions on Neural Networks and Learning Systems*, 28(3):653–664, March 2017.

[41] Thomas Fischer and Christopher Krauss. Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research*, 270(2):654–669, October 2018.

[42] Marios Mourelatos, Christos Alexakos, Thomas Amorgianiotis, and Spiridon Likothanassis. Financial indices modelling and trading utilizing deep learning techniques: The athens se ftse/ase large cap use

case. In *2018 Innovations in Intelligent Systems and Applications (INISTA)*. IEEE, July 2018.

[43] Weiyu Si, Jinke Li, Peng Ding, and Ruonan Rao. A multi-objective deep reinforcement learning approach for stock index future's intraday trading. In *2017 10th International Symposium on Computational Intelligence and Design (ISCID)*. IEEE, December 2017.

[44] Bang Xiang Yong, Mohd Rozaini Abdul Rahim, and Ahmad Shahidan Abdullah. A stock market trading system using deep neural network. In *Communications in Computer and Information Science*, pages 356–364. Springer Singapore, 2017.

[45] David W. Lu. Agent inspired trading using recurrent reinforcement learning and lstm neural networks, 2017.

[46] Matthew Francis Dixon, Diego Klabjan, and Jin Hoon Bang. Classification-based financial markets prediction using deep neural networks. *SSRN Electronic Journal*, 2016.

[47] Jerzy Korczak and Marcin Hernes. Deep learning for financial time series forecasting in a-trader system. In *Proceedings of the 2017 Federated Conference on Computer Science and Information Systems*. IEEE, September 2017.

[48] Bruno Spilak. Deep neural networks for cryptocurrencies price prediction. Master's thesis, Humboldt-Universitat zu Berlin, Wirtschaftswissenschaftliche Fakultat, 2018.

[49] Gyeeun Jeong and Ha Young Kim. Improving financial trading decisions using deep q-learning: Predicting the number of shares, action strategies, and transfer learning. *Expert Systems with Applications*, 117:125–138, March 2019.

[50] Christopher Krauss, Xuan Anh Do, and Nicolas Huck. Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the s&p 500. *European Journal of Operational Research*, 259 (2):689–702, June 2017.

[51] Google. System and method for computer managed funds to outperform benchmarks.

[52] Omer Berat Sezer, Murat Ozbayoglu, and Erdogan Dogdu. A deep neural-network based stock trading system based on evolutionary optimized technical analysis parameters. *Procedia Computer Science*, 114:473–480, 2017.

[53] Ariel Navon and Yosi Keller. Financial time series prediction using deep learning, 2017.

[54] Luigi Troiano, Elena Mejuto Villa, and Vincenzo Loia. Replicating a trading strategy by means of lstm for financial industry applications. *IEEE Transactions on Industrial Informatics*, 14(7):3226–3234, July 2018.

[55] Justin Sirignano and Rama Cont. Universal features of price formation in financial markets: Perspectives from deep learning. *SSRN Electronic Journal*, 2018.

[56] Avraam Tsantekidis, Nikolaos Passalis, Anastasios Tefas, Juho Kanniainen, Moncef Gabbouj, and Alexandros Iosifidis. Using deep learning to detect price change indications in financial markets. In *2017 25th European Signal Processing Conference (EUSIPCO)*. IEEE, August 2017.

[57] M. Ugur Gudelek, S. Arda Boluk, and A. Murat Ozbayoglu. A deep learning based stock trading model with 2-d cnn trend detection. In *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*. IEEE, November 2017.

[58] Omer Berat Sezer and Ahmet Murat Ozbayoglu. Algorithmic financial trading with deep convolutional neural networks: Time series to image conversion approach. *Applied Soft Computing*, 70:525–538, September 2018.

[59] Guosheng Hu, Yuxin Hu, Kai Yang, Zehao Yu, Flood Sung, Zhihong Zhang, Fei Xie, Jianguo Liu, Neil Robertson, Timpathy Hospedales, and Qiangwei Miemie. Deep stock representation learning: From candlestick charts to investment decisions. In *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, April 2018.

[60] Avraam Tsantekidis, Nikolaos Passalis, Anastasios Tefas, Juho Kanniainen, Moncef Gabbouj, and Alexandros Iosifidis. Forecasting stock prices from the limit order book using convolutional neural networks. In *2017 IEEE 19th Conference on Business Informatics (CBI)*. IEEE, July 2017.

[61] Hakan Gunduz, Yusuf Yaslan, and Zehra Cataltepe. Intraday prediction of borsa istanbul using convolutional neural networks and feature correlations. *Knowledge-Based Systems*, 137:138–148, December 2017.

[62] Omer Berat Sezer and Ahmet Murat Ozbayoglu. Financial trading model with stock bar chart image time series with deep convolutional neural networks. *arXiv preprint arXiv:1903.04610*, 2019.

[63] Will Serrano. Fintech model: The random neural network with genetic algorithm. *Procedia Computer Science*, 126:537–546, 2018.

[64] E.W. Saad, D.V. Prokhorov, and D.C. Wunsch. Comparative study of stock trend prediction using time delay, recurrent and probabilistic neural networks. *IEEE Transactions on Neural Networks*, 9 (6):1456–1470, 1998.

[65] Jonathan Doering, Michael Fairbank, and Sheri Markose. Convolutional neural networks applied to high-frequency market microstructure forecasting. In *2017 9th Computer Science and Electronic Engineering (CEEC)*. IEEE, September 2017.

[66] Zhengyao Jiang, Dixing Xu, and Jinjun Liang. A deep reinforcement learning framework for the financial portfolio management problem. *arXiv preprint arXiv:1706.10059*, 2017.

[67] P. Tino, C. Schittenkopf, and G. Dorffner. Financial volatility trading using recurrent neural networks. *IEEE Transactions on Neural Networks*, 12(4):865–874, July 2001.

[68] Yu-Ying Chen, Wei-Lun Chen, and Szu-Hao Huang. Developing arbitrage strategy in high-frequency pairs trading with filterbank cnn algorithm. In *2018 IEEE International Conference on Agents (ICA)*. IEEE, July 2018.

[69] Omar A. Bari and Arvin Agah. Ensembles of text and time-series models for automatic generation of financial trading signals from social media content. *Journal of Intelligent Systems*, 2018.

[70] Matthew Francis Dixon. Sequence classification of the limit order book using recurrent neural networks. *SSRN Electronic Journal*, 2017.

[71] Chiao-Ting Chen, An-Pin Chen, and Szu-Hao Huang. Cloning strategies from trading records using agent-based reinforcement learning algorithm. In *2018 IEEE International Conference on Agents (ICA)*. IEEE, July 2018.

[72] Yue Wang, Chenwei Zhang, Shen Wang, Philip S. Yu, Lu Bai, and Lixin Cui. Deep co-investment network learning for financial assets, 2018.

[73] Min-Yuh Day and Chia-Chou Lee. Deep learning for financial sentiment analysis on finance news providers. In *2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*. IEEE, August 2016.

[74] Justin Sirignano. Deep learning for limit order books, 2016.

[75] Xiang Gao. Deep reinforcement learning for time series: playing idealized trading games, 2018.

[76] Martin Neil Baily, Robert E. Litan, and Johnson Matthew S. The origins of the financial crisis. *Initiative on Business and Public Policy at Brookings, Fixing Finance Series - Paper 3*, 2008.

[77] Cuicui Luo, Desheng Wu, and Dexiang Wu. A deep learning approach for credit scoring using credit default swaps. *Engineering Applications of Artificial Intelligence*, 65:465–470, October 2017.

[78] Lean Yu, Rongtian Zhou, Ling Tang, and Rongda Chen. A dbn-based resampling svm ensemble learning paradigm for credit classification with imbalanced data. *Applied Soft Computing*, 69:192–202, August 2018.

[79] Ying Li, Xianghong Lin, Xiangwen Wang, Fanqi Shen, and Zuzheng Gong. Credit risk assessment algorithm using deep neural networks with clustering and merging. In *2017 13th International Conference on Computational Intelligence and Security (CIS)*. IEEE, December 2017.

[80] Khiem Tran, Thanh Duong, and Quyen Ho. Credit scoring model: A combination of genetic programming and deep learning. In *2016 Future Technologies Conference (FTC)*. IEEE, December 2016.

[81] Victor-Emil Neagoe, Adrian-Dumitru Ciotec, and George-Sorin Cucu. Deep convolutional neural networks versus multilayer perceptron for financial prediction. In *2018 International Conference on Communications (COMM)*. IEEE, June 2018.

[82] Bing Zhu, Wenchuan Yang, Huaxuan Wang, and Yuan Yuan. A hybrid deep learning model for consumer credit scoring. In *2018 International Conference on Artificial Intelligence and Big Data (ICAIBD)*. IEEE, May 2018.

[83] Ayahiko Niimi. Deep learning for credit card data analysis. In *2015 World Congress on Internet Security (WorldCIS)*. IEEE, October 2015.

[84] Efstathios Kirkos and Yannis Manolopoulos. Data mining in finance and accounting: A review of current research trends. In *Proceedings of the 1 st International Conference on Enterprise Systems and Accounting (ICESAcc*, pages 63–78, 2004.

[85] V. Ravi, H. Kurniawan, Peter Nwee Kok Thai, and P. Ravi Kumar. Soft computing system for bank performance prediction. *Applied Soft Computing*, 8(1):305–315, January 2008.

[86] Meryem Duygun Fethi and Fotios Pasiouras. Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. *European Journal of Operational Research*, 204(2):189–198, July 2010.

[87] Adel Lahsasna, Raja Noor Ainon, and Ying Wah Teh. Credit scoring models using soft computing methods: A survey. *Int. Arab J. Inf. Technol.*, 7:115–123, 2010.

[88] Ning Chen, Bernardete Ribeiro, and An Chen. Financial credit risk assessment: a recent review. *Artificial Intelligence Review*, 45(1):1–23, October 2015.

[89] AI Marques, Vicente García, and José Salvador Sánchez. A literature review on the application of evolutionary computing to credit scoring. *Journal of the Operational Research Society*, 64(9):1384–1399, 2013.

[90] P. Ravi Kumar and V. Ravi. Bankruptcy prediction in banks and firms via statistical and intelligent techniques – a review. *European Journal of Operational Research*, 180(1):1–28, July 2007.

[91] Antanas Verikas, Zivile Kalsyte, Marija Bacauskiene, and Adas Gelzinis. Hybrid and ensemble-based soft computing techniques in bankruptcy prediction: a survey. *Soft Computing*, 14(9):995–1010, September 2009.

[92] Jie Sun, Hui Li, Qing-Hua Huang, and Kai-Yu He. Predicting financial distress and corporate failure: A review from the state-of-the-art definitions, modeling, sampling, and featuring approaches. *Knowledge-Based Systems*, 57:41–56, February 2014.

[93] W. Lin, Y. Hu, and C. Tsai. Machine learning in financial crisis prediction: A survey. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 42(4):421–436, July 2012.

[94] Zineb Lanbouri and Said Achchab. A hybrid deep belief network approach for financial distress prediction. In *2015 10th International Conference on Intelligent Systems: Theories and Applications (SITA)*. IEEE, October 2015.

[95] Vipula Rawte, Aparna Gupta, and Mohammed J. Zaki. Analysis of year-over-year changes in risk factors disclosure in 10-k filings. In *Proceedings of the Fourth International Workshop on Data Science for Macro-Modeling with Financial and Economic Datasets - DSMM18*. ACM Press, 2018.

[96] Samuel Ronnqvist and Peter Sarlin. Detect & describe: Deep learning of bank stress in the news. In *2015 IEEE Symposium Series on Computational Intelligence*. IEEE, December 2015.

[97] Samuel Ronnqvist and Peter Sarlin. Bank distress in the news: Describing events through deep learning. *Neurocomputing*, 264:57–70, November 2017.

[98] Paola Cerchiello, Giancarlo Nicola, Samuel Rönnqvist, and Peter Sarlin. Deep learning bank distress from news and numerical financial data. *CoRR*, abs/1706.09627, 2017.

[99] Nikhil Malik, Param Vir Singh, and Urooj Khan. Can banks survive the next financial crisis? an adversarial deep learning model for bank stress testing. *An Adversarial Deep Learning Model for Bank Stress Testing (June 30, 2018)*, 2018.

[100] Bernardete Ribeiro and Noel Lopes. Deep belief networks for financial prediction. In *Neural Information Processing*, pages 766–773. Springer Berlin Heidelberg, 2011.

[101] Shu-Hao Yeh, Chuan-Ju Wang, and Ming-Feng Tsai. Deep belief networks for predicting corporate defaults. In *2015 24th Wireless and Optical Communication Conference (WOCC)*. IEEE, October 2015.

[102] Tadaaki Hosaka. Bankruptcy prediction using imaged financial ratios and convolutional neural networks. *Expert Systems with Applications*, September 2018.

[103] Justin Sirignano, Apaar Sadhwani, and Kay Giesecke. Deep learning for mortgage risk. *SSRN Electronic Journal*, 2018.

[104] Håvard Kvamme, Nikolai Sellereite, Kjersti Aas, and Steffen Sjursen. Predicting mortgage default

using convolutional neural networks. *Expert Systems with Applications*, 102:207–217, July 2018.

[105] Narek Abroyan and. Neural networks for financial market risk classification. *Frontiers in Signal Processing*, 1(2), August 2017.

[106] Sotirios P. Chatzis, Vassilis Siakoulis, Anastasios Petropoulos, Evangelos Stavroulakis, and Nikos Vlachogiannakis. Forecasting stock market crisis events using deep and statistical machine learning techniques. *Expert Systems with Applications*, 112:353–371, December 2018.

[107] E Kirkos, C Spathis, and Y Manolopoulos. Data mining techniques for the detection of fraudulent financial statements. *Expert Systems with Applications*, 32(4):995–1003, May 2007.

[108] Dianmin Yue, Xiaodan Wu, Yunfeng Wang, Yue Li, and Chao-Hsien Chu. A review of data mining-based financial fraud detection research. In *2007 International Conference on Wireless Communications, Networking and Mobile Computing*. IEEE, September 2007.

[109] Shiguo Wang. A comprehensive survey of data mining-based accounting-fraud detection research. In *2010 International Conference on Intelligent Computation Technology and Automation*. IEEE, May 2010.

[110] Clifton Phua, Vincent C. S. Lee, Kate Smith-Miles, and Ross W. Gayler. A comprehensive survey of data mining-based fraud detection research. *CoRR*, abs/1009.6119, 2010.

[111] E.W.T. Ngai, Yong Hu, Y.H. Wong, Yijun Chen, and Xin Sun. The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature. *Decision Support Systems*, 50(3):559–569, February 2011.

[112] Anuj Sharma and Prabin Kumar Panigrahi. A review of financial accounting fraud detection based on data mining techniques. *International Journal of Computer Applications*, 39(1):37–47, February 2012.

[113] Jarrod West and Maumita Bhattacharya. Intelligent financial fraud detection: A comprehensive review. *Computers & Security*, 57:47–66, March 2016.

[114] Yaya Heryadi and Harco Leslie Hendric Spits Warnars. Learning temporal representation of transaction amount for fraudulent transaction recognition using cnn, stacked lstm, and cnn-lstm. In *2017 IEEE International Conference on Cybernetics and Computational Intelligence (CyberneticsCom)*. IEEE, November 2017.

[115] Abhimanyu Roy, Jingyi Sun, Robert Mahoney, Loreto Alonzi, Stephen Adams, and Peter Beling. Deep learning detecting fraud in credit card transactions. In *2018 Systems and Information Engineering Design Symposium (SIEDS)*. IEEE, April 2018.

[116] Jon Ander Gómez, Juan Arévalo, Roberto Paredes, and Jordi Nin. End-to-end neural network architecture for fraud scoring in card payments. *Pattern Recognition Letters*, 105:175–181, April 2018.

[117] Ishan Sohony, Rameshwar Pratap, and Ullas Nambiar. Ensemble learning for credit card fraud detection. In *Proceedings of the ACM India Joint International Conference on Data Science and Management of Data - CoDS-COMAD18*. ACM Press, 2018.

[118] Johannes Jurgovsky, Michael Granitzer, Konstantin Ziegler, Sylvie Calabretto, Pierre-Edouard Portier, Liyun He-Guelton, and Olivier Caelen. Sequence classification for credit-card fraud detection. *Expert Systems with Applications*, 100:234–245, June 2018.

[119] Ebberth L. Paula, Marcelo Ladeira, Rommel N. Carvalho, and Thiago Marzagao. Deep learning anomaly detection as support fraud investigation in brazilian exports and anti-money laundering. In *2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA)*. IEEE, December 2016.

[120] Thiago Alencar Gomes, Rommel Novaes Carvalho, and Ricardo Silva Carvalho. Identifying anomalies in parliamentary expenditures of brazilian chamber of deputies with deep autoencoders. In *2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA)*. IEEE, December 2017.

[121] Yibo Wang and Wei Xu. Leveraging deep learning with lda-based text analytics to detect automobile insurance fraud. *Decision Support Systems*, 105:87–95, January 2018.

[122] Longfei Li, Jun Zhou, Xiaolong Li, and Tao Chen. Poster: Practical fraud transaction prediction. In *ACM Conference on Computer and Communications Security*, 2017.

[123] Allan Inocencio de Souza Costa and Luis Silva. Sequence classification of the limit order book using recurrent neural networks. 2016.
[124] Nikolaos D. Goumagias, Dimitrios Hristu-Varsakelis, and Yannis M. Assael. Using deep q-learning to understand the tax evasion behavior of risk-averse firms. *Expert Systems with Applications*, 101: 258–270, July 2018.
[125] Bin Li and Steven C. H. Hoi. Online portfolio selection: A survey. *ACM Comput. Surv.*, 46(3): 35:1–35:36, January 2014.
[126] K. Metaxiotis and K. Liagkouras. Multiobjective evolutionary algorithms for portfolio management: A comprehensive literature review. *Expert Systems with Applications*, 39(14):11685–11698, October 2012.
[127] Lawrence Takeuchi. Applying deep learning to enhance momentum trading strategies in stocks. 2013.
[128] Anthony Grace. Can deep learning techniques improve the risk adjusted returns from enhanced indexing investment strategies. Master's thesis, 2017.
[129] XingYu Fu, JinHong Du, YiFeng Guo, MingWen Liu, Tao Dong, and XiuWen Duan. A machine learning framework for stock selection, 2018.
[130] Saurabh Aggarwal and Somya Aggarwal. Deep investment in financial markets using deep learning models. *International Journal of Computer Applications*, 162(2):40–43, March 2017.
[131] J.B. Heaton and Nick Polson. Deep learning for finance: Deep portfolios. *SSRN Electronic Journal*, 2016.
[132] Chi-Ming Lin, Jih-Jeng Huang, Mitsuo Gen, and Gwo-Hshiung Tzeng. Recurrent neural network for dynamic portfolio selection. *Applied Mathematics and Computation*, 175(2):1139–1146, April 2006.
[133] Nijole Maknickiene, Aleksandras Vytautas Rutkauskas, and Algirdas Maknickas. Investigation of financial market prediction by recurrent neural network. 2014.
[134] Bo Zhou. Deep learning and the cross-section of stock returns: Neural networks combining price and fundamental information. *SSRN Electronic Journal*, 2018.
[135] Bilberto Batres-Estrada. Deep learning for multivariate financial time series. Master's thesis, KTH, Mathematical Statistics, 2015.
[136] Sang Il Lee and Seong Joon Yoo. Threshold-based portfolio: the role of the threshold and its applications. *The Journal of Supercomputing*, September 2018.
[137] Hitoshi Iwasaki and Ying Chen. Topic sentiment asset pricing with dnn supervised learning. *SSRN Electronic Journal*, 2018.
[138] Nijolė Maknickienė. Selection of orthogonal investment portfolio using evolino rnn trading model. *Procedia - Social and Behavioral Sciences*, 110:1158–1165, January 2014.
[139] Zhipeng Liang, Hao Chen, Junhao Zhu, Kangkang Jiang, and Yanran Li. Adversarial deep reinforcement learning in portfolio management, 2018.
[140] Jiaqi Chen, Wenbo Wu, and Michael Tindall. Hedge fund return prediction and fund selection: A machine-learning approach. Occasional Papers 16-4, Federal Reserve Bank of Dallas, November 2016.
[141] Zhengyao Jiang and Jinjun Liang. Cryptocurrency portfolio management with deep reinforcement learning. In *2017 Intelligent Systems Conference (IntelliSys)*. IEEE, September 2017.
[142] Robert Culkin and Sanjiv R. Das. Machine learning in finance: The case of deep learning in option pricing. 2017.
[143] Pei-Ying Hsu, Chin Chou, Szu-Hao Huang, and An-Pin Chen. A market making quotation strategy based on dual deep learning agents for option pricing and bid-ask spread estimation. In *2018 IEEE International Conference on Agents (ICA)*. IEEE, July 2018.
[144] Guanhao Feng, Nicholas G. Polson, and Jianeng Xu. Deep factor alpha, 2018.
[145] Rui-Yang Chen. A traceability chain algorithm for artificial neural networks using t–s fuzzy cognitive maps in blockchain. *Future Generation Computer Systems*, 80:198–210, March 2018.
[146] Lihao Nan and Dacheng Tao. Bitcoin mixing detection using deep autoencoder. In *2018 IEEE Third International Conference on Data Science in Cyberspace (DSC)*. IEEE, June 2018.
[147] Gonçalo Duarte Lima Freire Lopes. Deep learning for market forecasts. 2018.
[148] Sean McNally, Jason Roche, and Simon Caton. Predicting the price of bitcoin using machine learn-

ing. In *2018 26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP)*. IEEE, March 2018.

[149] Colm Kearney and Sha Liu. Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis*, 33:171–185, May 2014.

[150] Qili Wang, Wei Xu, and Han Zheng. Combining the wisdom of crowds and technical analysis for financial market prediction using deep random subspace ensembles. *Neurocomputing*, 299:51–61, July 2018.

[151] Lei Shi, Zhiyang Teng, Le Wang, Yue Zhang, and Alexander Binder. Deepclue: Visual interpretation of text-based deep stock prediction. *IEEE Transactions on Knowledge and Data Engineering*, pages 1–1, 2018.

[152] Yangtuo Peng and Hui Jiang. Leverage financial news to predict stock price movements using word embeddings and deep neural networks. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. Association for Computational Linguistics, 2016.

[153] Qun Zhuge, Lingyu Xu, and Gaowei Zhang. Lstm neural network with emotional analysis for prediction of stock price. 2017.

[154] Wang Zhongsheng. Measuring financial crisis index for risk warning through analysis of social network. Master's thesis, 2018.

[155] Sushree Das, Ranjan Kumar Behera, Mukesh Kumar, and Santanu Kumar Rath. Real-time sentiment analysis of twitter streaming data for stock prediction. *Procedia Computer Science*, 132:956–964, 2018.

[156] Jordan Prosky, Xingyou Song, Andrew Tan, and Michael Zhao. Sentiment predictability for stocks. *CoRR*, abs/1712.05785, 2017.

[157] Jiahong Li, Hui Bu, and Junjie Wu. Sentiment-aware stock market prediction: A deep learning method. In *2017 International Conference on Service Systems and Service Management*. IEEE, June 2017.

[158] Yifu Huang, Kai Huang, Yang Wang, Hao Zhang, Jihong Guan, and Shuigeng Zhou. Exploiting twitter moods to boost financial trend prediction based on deep network models. In *Intelligent Computing Methodologies*, pages 449–460. Springer International Publishing, 2016.

[159] Leela Mitra and Gautam Mitra. Applications of news analytics in finance: A review. In *The Handbook of News Analytics in Finance*, pages 1–39. John Wiley & Sons, Ltd., May 2012.

[160] Feng Li. Textual analysis of corporate disclosures: A survey of the literature. *Journal of Accounting Literature*, 29, February 2011.

[161] Tim Loughran and Bill McDonald. Textual analysis in accounting and finance: A survey. *Journal of Accounting Research*, 54(4):1187–1230, June 2016.

[162] B. Shravan Kumar and Vadlamani Ravi. A survey of the applications of text mining in financial domain. *Knowledge-Based Systems*, 114:128–147, December 2016.

[163] Marc-André Mittermayer and Gerhard F Knolmayer. Text mining systems for market response to news: A survey. September 2006.

[164] Arman Khadjeh Nassirtoussi, Saeed Aghabozorgi, Teh Ying Wah, and David Chek Ling Ngo. Text mining for market prediction: A systematic review. *Expert Systems with Applications*, 41(16):7653–7670, November 2014.

[165] Huy D. Huynh, L. Minh Dang, and Duc Duong. A new model for stock price movements prediction using deep neural network. In *Proceedings of the Eighth International Symposium on Information and Communication Technology - SoICT 2017*. ACM Press, 2017.

[166] Songqiao Han, Xiaoling Hao, and Hailiang Huang. An event-extraction approach for business analysis from online chinese news. *Electronic Commerce Research and Applications*, 28:244–260, March 2018.

[167] Mathias Kraus and Stefan Feuerriegel. Decision support from financial disclosures with deep neural networks and transfer learning. *Decision Support Systems*, 104:38–48, December 2017.

[168] L. Minh Dang, Abolghasem Sadeghi-Niaraki, Huy D. Huynh, Kyungbok Min, and Hyeonjoon Moon. Deep learning approach for short-term stock trends prediction based on two-stream gated recurrent unit network. *IEEE Access*, pages 1–1, 2018.

[169] Xiao Ding, Yue Zhang, Ting Liu, and Junwen Duan. Deep learning for event-driven stock prediction. In *Proceedings of the 24th International Conference on Artificial Intelligence*, IJCAI'15, pages 2327–2333. AAAI Press, 2015.

[170] Manuel R. Vargas, Beatriz S. L. P. de Lima, and Alexandre G. Evsukoff. Deep learning for stock market prediction from financial news articles. In *2017 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA)*. IEEE, June 2017.

[171] Ryo Akita, Akira Yoshihara, Takashi Matsubara, and Kuniaki Uehara. Deep learning for stock prediction using numerical and textual information. In *2016 IEEE/ACIS 15th International Conference on Computer and Information Science (ICIS)*. IEEE, June 2016.

[172] Ishan Verma, Lipika Dey, and Hardik Meisheri. Detecting, quantifying and accessing impact of news events on indian stock indices. In *Proceedings of the International Conference on Web Intelligence - WI17*. ACM Press, 2017.

[173] Xi Zhang, Yunjia Zhang, Senzhang Wang, Yuntao Yao, Binxing Fang, and Philip S. Yu. Improving stock market prediction via heterogeneous information fusion. *Knowledge-Based Systems*, 143:236–247, March 2018.

[174] Weiling Chen, Chai Kiat Yeo, Chiew Tong Lau, and Bu Sung Lee. Leveraging social media news to predict stock index movement using rnn-boost. *Data & Knowledge Engineering*, August 2018.

[175] Ziniu Hu, Weiqing Liu, Jiang Bian, Xuanzhe Liu, and Tie-Yan Liu. Listening to chaotic whispers: A deep learning framework for news-oriented stock trend prediction. In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining*, WSDM '18, pages 261–269, New York, NY, USA, 2018. ACM.

[176] Xiaodong Li, Jingjing Cao, and Zhaoqing Pan. Market impact analysis via deep learned architectures. *Neural Computing and Applications*, March 2018.

[177] Che-Yu Lee and Von-Wun Soo. Predict stock price with financial news based on recurrent convolutional neural networks. In *2017 Conference on Technologies and Applications of Artificial Intelligence (TAAI)*. IEEE, December 2017.

[178] Shotaro Minami. Predicting equity price with corporate action events using lstm-rnn. *Journal of Mathematical Finance*, 08(01):58–63, 2018.

[179] Akira Yoshihara, Kazuki Fujikawa, Kazuhiro Seki, and Kuniaki Uehara. Predicting stock market trends by recurrent deep neural networks. In *Lecture Notes in Computer Science*, pages 759–769. Springer International Publishing, 2014.

[180] Przemyslaw Buczkowski. Predicting stock trends based on expert recommendations using gru/lstm neural networks. In *Lecture Notes in Computer Science*, pages 708–717. Springer International Publishing, 2017.

[181] Leonardo dos Santos Pinheiro and Mark Dras. Stock market prediction with deep learning: A character-based neural language model for event-based trading. In *Proceedings of the Australasian Language Technology Association Workshop 2017*, pages 6–15, 2017.

[182] Yang Liu, Qingguo Zeng, Huanrui Yang, and Adrian Carrio. Stock price movement prediction from financial news with deep learning and knowledge graph embedding. In *Knowledge Management and Acquisition for Intelligent Systems*, pages 102–113. Springer International Publishing, 2018.

[183] Takashi Matsubara, Ryo Akita, and Kuniaki Uehara. Stock price prediction by deep neural generative model of news articles. *IEICE Transactions on Information and Systems*, E101.D(4):901–908, 2018.

[184] Janderson B. Nascimento and Marco Cristo. The impact of structured event embeddings on scalable stock forecasting models. In *Proceedings of the 21st Brazilian Symposium on Multimedia and the Web - WebMedia15*. ACM Press, 2015.

[185] Md Shad Akhtar, Abhishek Kumar, Deepanway Ghosal, Asif Ekbal, and Pushpak Bhattacharyya. A multilayer perceptron based ensemble technique for fine-grained financial sentiment analysis. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 540–546. Association for Computational Linguistics, 2017.

[186] Ching-Yun Chang, Yue Zhang, Zhiyang Teng, Zahn Bozanic, and Bin Ke. Measuring the information

content of financial news. In *COLING*, 2016.

[187] Hitkul Jangid, Shivangi Singhal, Rajiv Ratn Shah, and Roger Zimmermann. Aspect-based financial sentiment analysis using deep learning. In *Companion of the The Web Conference 2018 on The Web Conference 2018 - WWW18*. ACM Press, 2018.

[188] Shijia E., Li Yang, Mohan Zhang, and Yang Xiang. Aspect-based financial sentiment analysis with deep neural networks. In *Companion of the The Web Conference 2018 on The Web Conference 2018 - WWW18*. ACM Press, 2018.

[189] Sahar Sohangir, Dingding Wang, Anna Pomeranets, and Taghi M. Khoshgoftaar. Big data: Deep learning for financial sentiment analysis. *Journal of Big Data*, 5(1), January 2018.

[190] Nader Mahmoudi, Paul Docherty, and Pablo Moscato. Deep neural networks understand investors better. *Decision Support Systems*, 112:23–34, August 2018.

[191] Shiori Kitamori, Hiroyuki Sakai, and Hiroki Sakaji. Extraction of sentences concerning business performance forecast and economic forecast from summaries of financial statements by deep learning. In *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*. IEEE, November 2017.

[192] Guangyuan Piao and John G. Breslin. Financial aspect and sentiment predictions with deep neural networks. In *Companion of the The Web Conference 2018 on The Web Conference 2018 - WWW18*. ACM Press, 2018.

[193] Weifeng Li and Hsinchun Chen. Identifying top sellers in underground economy using deep learning-based sentiment analysis. In *2014 IEEE Joint Intelligence and Security Informatics Conference*. IEEE, September 2014.

[194] Andrew Moore and Paul Rayson. Lancaster a at semeval-2017 task 5: Evaluation metrics matter: predicting sentiment from financial news headlines. In *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017)*, pages 581–585, Vancouver, Canada, August 2017. Association for Computational Linguistics.

[195] Josh Jia-Ching Ying, Po-Yu Huang, Chih-Kai Chang, and Don-Lin Yang. A preliminary study on deep learning for predicting social insurance payment behavior. In *2017 IEEE International Conference on Big Data (Big Data)*. IEEE, December 2017.

[196] Sahar Sohangir and Dingding Wang. Finding expert authors in financial forum using deep learning methods. In *2018 Second IEEE International Conference on Robotic Computing (IRC)*. IEEE, January 2018.

[197] Vadim Sokolov. Discussion of 'deep learning for finance: deep portfolios'. *Applied Stochastic Models in Business and Industry*, 33(1):16–18, 2017.

[198] Abdelali El Bouchti, Ahmed Chakroun, Hassan Abbar, and Chafik Okar. Fraud detection in banking using deep reinforcement learning. In *2017 Seventh International Conference on Innovative Computing Technology (INTECH)*. IEEE, August 2017.

[199] Matthew Dixon, Diego Klabjan, and Jin Hoon Bang. Implementing deep neural networks for financial market prediction on the intel xeon phi. In *Proceedings of the 8th Workshop on High Performance Computational Finance - WHPCF15*. ACM Press, 2015.

[200] John Alberg and Zachary Chase Lipton. Improving factor-based quantitative investing by forecasting company fundamentals. *CoRR*, abs/1711.04837, 2017.

[201] Kee-Hoon Kim, Chang-Seok Lee, Sang-Muk Jo, and Sung-Bae Cho. Predicting the success of bank telemarketing using deep convolutional neural network. In *2015 7th International Conference of Soft Computing and Pattern Recognition (SoCPaR)*. IEEE, November 2015.

[202] Joonhyuck Lee, Dong Sik Jang, and Sangsung Park. Deep learning-based corporate performance prediction model considering technical capability. *Sustainability*, 9(6), May 2017.

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