Expert Systems With Applications 177 (2021) 114800

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Review

A comprehensive survey on deep neural networks for stock market: The need, challenges, and future directions

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ARTICLE INFO

Keywords:
Stock market prediction
Deep neural network
Convolutional neural network
Recurrent neural network
Challenges
Future research directions

ABSTRACT

The stock market has been an attractive field for a large number of organizers and investors to derive useful predictions. Fundamental knowledge of stock market can be utilised with technical indicators to investigate different perspectives of the financial market; also, the influence of various events, financial news, and/or opinions on investors' decisions and hence, market trends have been observed. Such information can be exploited to make reliable predictions and achieve higher profitability. Computational intelligence has emerged with various deep neural network (DNN) techniques to address complex stock market problems. In this article, we aim to review the significance and need of DNNs in the field of stock price and trend prediction; we discuss the applicability of DNN variations to the temporal stock market data and also extend our survey to include hybrid, as well as metaheuristic, approaches with DNNs. We observe the potential limitations for stock market prediction using various DNNs. To provide an experimental evaluation, we also conduct a series of experiments for stock market prediction using nine deep learning-based models; we analyse the impact of these models on forecasting the stock market data. We also evaluate the performance of individual models with different number of features. We discuss challenges, as well as potential future research directions, and conclude our survey with the experimental study. This survey can be referred for the recent perspectives of DNN-based stock market prediction, primarily covering research spanning over years 2017 –2020.

1. Introduction

The financial markets greatly influence economic and social organizations where the associated assets can be valuable as well as vulnerable. A stock market, also known as an equity market, represents a collective approach of buying and selling various instruments publicly and/or privately. An ownership may be claimed on the traded stocks wherein careful trading may aid investors to gain higher returns of their investment; in contrast to that, it may induce loss of the investment as well. The stock market introduces volatility, i.e., random fluctuations over time, and hence, analysis of the market behaviour is a challenging task. Fundamental analysis can be carried out by investigating quantitative data such as stock price, volume, portfolio, etc. and qualitative information of the associated organizations, their profiles, and strategies (Zhang et al., 2018b); on the other hand, technical analysis can be performed using stock features and the derived correlations to predict future market behaviour. Such analyses can be helpful in studying market liquidity and therefore, development of reliable computational approaches are highly desirable.

Several methods proposed in economics as well as computer science to predict future market behaviour include stock trend direction (up or down, i.e., bull market or bear market, respectively), intraday or interday stock price, associated risk and return, to name a few. The time-series data of stock market represents an ordered sequence or a set of data points collected at specific time interval. It provides information about the given stock on a stock exchange during the defined trading cycle; such historical data in its raw form include the opening and closing prices, the highest and lowest prices attained, and the total number of traded stocks, i.e., volume, for the given trading period. Various econometrics-based statistical methods (Engle et al., 2003; Cakra & Trisedya, 2015; Afeef, Ihsan, & Zada, 2018) as well as computational intelligence-based techniques (Abraham, Elayidom, & Santhanakrishnan, 2019; Karia, 2018; Fischer & Krauss, 2018) have been integrated with such temporal stock data to derive useful predictions. While the statistical methods are likely to be dependent on the initial assumptions, the machine learning approaches encounter limited

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https://doi.org/10.1016/j.eswa.2021.114800
Received 14 October 2020; Received in revised form 31 January 2021; Accepted 25 February 2021
Available online 11 March 2021
0957-4174/

intepretability, manual feature selection-dependent performance, and over-fitting problems; this encourages integration of neural network (NN)-based deep learning methods to enhance stock market predictions (Long, Lu, & Cui, 2019). The complex inherent patterns of a stock price movement can be studied using such NNs by extracting essential characteristics of the highly unstructured data (Fadlalla & Lin, 2001).

While the financial markets are largely affected by several events, it is a challenging task to identify the impact of various domains (Thakkar et al., 2020); such domains can be studied and analysed for a detailed evaluation of the economic markets. The research studies have provided evidence against the impact of political influences (Maqbool, Hameed, & Habib, 2018), information security events (Spanos et al., 2016), specific news and/or announcements (Schumaker & Chen, 2009, 2011, 2011, Baker, Bloom, Davis, & Kost, 2019), national policies (Bomfim, 2003; Zussman & Zussman, 2006; Christiano, Ilut, Motto, & Rostagno, 2010), to name a few. The analysis through this aspect is critical; also, the potential security aspects on domains associated with the financial markets are crucial in order to maintain the integrity of the collected information as well as its fair analysis (Chaudhari & Prajapati, 2020; Prajapati & Chaudhari, 2020). On the other hand, there can be several domains associated with the financial markets such that it is important to understand the possible implications on the market volatility. There are several problems such as edge continuity-based shape descriptor (Susan, Agrawal, Mittal, & Bansal, 2019), kernel-clustering for radial basis function network (RBFN) (Zhu & Miao, 2019), clustering-based approach to prolong wireless sensor network lifetime (Thakkar, 2016c), speech recognition (Seyedin & Ahadi, 2009), sentiment classification (Mungra, Agrawal, & Thakkar, 2020), Electroencephalogram (EEG) signals classification (Kocadagli et al., 2017), credit risk evaluation (Shen, Zhao, Li, Li, & Meng, 2019), energy-efficient power management (Thakkar, Chaudhari, & Shah, 2020), travel recommendation (Chaudhari & Thakkar, 2019), intrusion detection (Lohiya, 2020a, 2019, 2020; Lohiya & Thakkar, 2021), texture analysis (Patel, Patel, & Thakkar, 2012b), web data extraction (Patel & Thakkar, 2015), internet of things (IoT) for various applications (Desai & Thakkar, 2019; Patel, Narmawala, & Thakkar, 2019; Lohiya, Thakkar, & Domains, 2020), text-based captcha verification (Patel & Thakkar, 2017; Thakkar & Patel, 2020), cognitive tutoring (Vora, Shah, Harsoda, Sheth, & Thakkar, 2020), etc. that represented diverse applications of learning models. The controlling mechanism can be a useful aspect for identifying a trade-off between the given metrics; such controllers have potential applications even in the field of hydraulic machinery to reduce the engine speed with the help of predictive algorithms (Wiens, 2019). Also, the analytical analysis can be carried out for pressure relief valves (PRVs) (Osterland & Weber, 2019). The neural network-based learning models have a vast range of applications such as age estimation (Tingting, Junqian, Lintai, & Yong, 2019), seismic damage detection evaluation in infrastructure (Shokri et al., 2019), etc. One of the significant domain for such applications can be wireless sensor network (Thakkar & Kotecha, 2013; Thakkar & Kotecha, 2014; Thakkar & Kotecha, 2014a; Thakkar & Kotecha, 2014b) where the network can be optimised using various approaches; also, the concepts included in the existing methodologies can be further useful for other domains (Thakkar & Pradhan, 2009; Thakkar & Kotecha, 2011; Thakkar & Kotecha, 2012; Thakkar & Kotecha, 2012a; Thakkar & Kotecha, 2012b). Human activity recognition (HAR) is one of the widely explored real-world applications (Pareek et al., 2020); several machine learning and deep learning approaches have been developed to address this domain such as spatio-temporal and angular-geometric descriptors-based human interaction recognition (Mahmood, Jalal, & Kim, 2019), skeleton joints features-based HAR of the daily activities for elderly healthcare application within indoor environments (Kim, Jalal, & Mahmood, 2019), depth-based life logging system for HAR in living/indoor environments (Jalal et al., 2012; Jalal, Kamal, & Kim, 2014a), depth silhouettes-based HAR for residents monitoring services (Jalal, Sarif, Kim, & Kim, 2013), shape and motion features-based human silhoutte recognition for HAR (Jalal, Kamal, & Kim, 2015b), multidimensional features-based tracking and recognition of human body actions (Nadeem, Jalal, & Kim, 2020); on the other hand, human behavioural patterns can also been identified using wearable sensors (Quaid et al., 2020). Also, identification of important features is a crucial task; several algorithms and methods have been proposed to analyse the features for different applications (Khalid et al., 2014; Bozdogan & Baek, 2018; Thakkar & Lohiya, 2020b). In view to the performance of such models, there are several functions that may play a considerable role during forecasting; hence, for a time-series data such as stock market, evaluation of various membership functions (Kocadağli, 2015; Aljawarneh, Radhakrishna, & Cheruvu, 2017; Jalota, Thakur, & Mittal, 2017) is a subject of interest for many researchers. It can also be motivating to see how the basic concepts of stock markets can be adapted to optimise problems from other domains, for example, a routing protocol for wireless sensor network was developed based on the concepts of Bollinger Band (Thakkar & Kotecha, 2015). Thus, it is of a critical importance to review the significance of DNNs from a panoramic perspective as well as with a scope-specific point-of-view towards the stock market applications.

1.1. The need of DNNs for stock market

The behaviours and inductive capabilities of human brains motivated the development of NNs; they can be understood as computerised intelligent systems. NNs can be largely categorised into artificial NN (ANN) and deep NN (DNN); while ANN considers input and output layers, along with hidden layer(s) between them, DNN contains an extension with dense hidden layers with a hierarchical topology. This article considers increasing demand for building a robust stock market prediction model and conducts a comprehensive survey using DNN perspectives.

The primary motivation behind reviewing DNNs as compared to other statistical as well as machine learning approaches is due to their representation-learning characteristics; the transformations of raw input data can be useful to learn complex functions (LeCun, Bengio, & Hinton, 2015). During such transformations, feature extraction is carried out automatically in CNN, for example, to map input data to the output; such flexibility can also be utilised to derive complex patterns from the non-linear stock data. The multiple levels of features can correspond with the multiple layers of a DNN architecture; such levels represent abstract features derived from the previous levels and hence, increase the extent of abstraction. As compared to a shallow network with a single hidden layer, a deep network exhibits higher levels of feature extraction capability with respect to each added hidden layer (Sun, Wang, & Tang, 2014; Yong, Rahim, & Abdullah, 2017). For a volatile stock market, an appropriate data representation is a crucial task to derive inherent patterns. Hence, the adaptability of DNNs for non-linear financial markets provides the primary motivation to review the integration of DNNs with stock market data; this survey presents various DNN architectures and their suitability to extract deeper information to increase prediction performance. A graphical overview of the primary contents of this survey article is given in Fig. 1.

1.2. Survey strategy

In this article, we aim to provide a focused survey on the recent advances of DNNs for stock market prediction. To collect the relevant research articles for our survey, we carried out a systematic survey strategy. We approached Google Scholar and initialised our search using the keywords "stock" along with various DNN approaches. The associated DNNs were searched using terms "deep neural network", "convolutional neural network" (CNN), "deep Q-network" (DQN), "recurrent neural network" (RNN), "long short-term memory" (LSTM), "gated recurrent unit" (GRU), "echo state network" (ESN), "restricted Boltzmann machine" (RBM), and "deep belief network" (DBN); also, these keywords were paired with "stock price" and "stock trend" along with

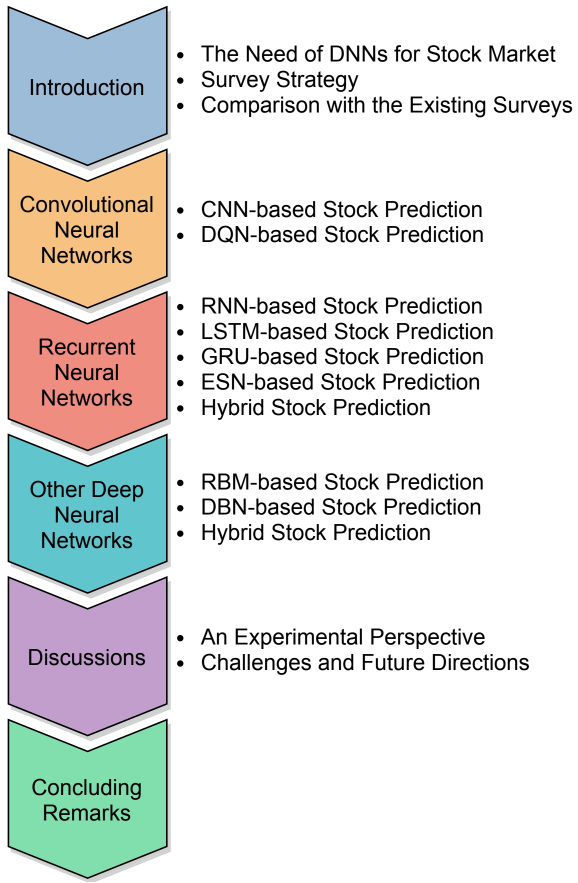

Fig. 1. A graphical oveview of the primary contents of this survey.

"prediction" and "forecasting" terms given in possible combinations. In order to prepare a focused survey with recent enhancements using DNN perspectives, we restricted our search to years 2017 –2020. The derived results included various tradings such as algorithmic, quantitative, momentum, portfolio-based, foreign exchange-based, bot-based, as well as derivative-based such as futures and exchange-traded funds which, in turn, indicated the spread of DNNs applications in financial domain. To concentrate on the major aspects of stock price and trend prediction, we excluded articles based on the other applications; the rationale behind such restriction is due to the significance of forecasting stock price and its future movement. It can be considered as one of the major deciding factors and various other applications can be further enhanced using the market trends. Hence, a set of articles selected for this survey were collected with the aim to analyse the need of DNNs in stock markets along with the associated challenges and potential future directions. We believe this survey can serve to researchers as well as traders who are interested in stock tradings for providing a broader perspective towards the market dynamics.

1.3. Comparison with the existing surveys

Along with various machine learning techniques, DNNs and their variations have been adopted for the financial market applications. The properties of various time-series problems such as video, stock prediction, music and speech recognition were reviewed in Längkvist, Karlsson, and Loutfi (2014) by considering unsupervised feature learning and deep learning approaches for different time-series data. For building an intelligent trading system, financial markets were studied with computational intelligence in terms of machine learning and NNs (Cavalcante, Brasileiro, Souza, Nobrega, & Oliveira, 2016); authors reviewed applications of computational intelligence in finance, including pre-processing, clustering, text mining, and other forecasting methods and defined a systematic procedure to build such systems and discussed challenges and open problems. For stock market analysis and forecasting, authors conducted a systematic analysis on some of the deep learning and data representation methods in Chong, Han, and Park (2017). One of the recent surveys on deep learning discussed financial market analysis for various machine learning and deep learning architectures in Hatcher et al. (2018). On the other hand, deep learning approaches were reviewed using diverse categories of time-series classification and an empirical comparative study was provided (Fawaz et al., 2018). Considering the potential spread of machine learning techniques in financial domain, bibliographic survey techniques were reviewed in Ref. Henrique, Sobreiro, and Kimura (2019). Many metaheuristics have played a vital role in improving the prediction accuracies, however, the same has not been sufficiently experimented with DNNs. We focus on various types of DNNs and explained their applications in stock predictions; these recent advances mainly include research work from year 2017 –2020.

The summary of comparing our survey with the existing surveys based on DNN perspectives is given in Table 1 which includes CNN, DQN, RNN, LSTM, GRU, ESN, DNN, RBM, DBN, metaheuristics, as well as sentiment analysis-based stock market prediction. The highly fluctuating financial market predictions may include stock price value/ range prediction, trend prediction, return profit forecasting, to name a few. To develop a thorough understanding of the existing DNN-based approaches in the field of stock market, this article discusses how CNNs, RNNs, and other DNNs are integrated with time-series stock market data. This survey also provides the challneges and potential future research directions.

The organization of the remaining article is as follows: we study CNNs for stock market prediction along with related approaches in Section 2; RNNs and corresponding variations for stock market are provided in Section 3; we collectively discuss other DNN methods along with the hybrid approaches in Section 4; we provide an experimental perspective of the DNN-based models as well as discuss various aspects of stock market along with a detailed summary of the reviewed articles, existing challenges, and potential future research directions in Section 5; we conclude our survey in Section 6.

2. Convolutional neural networks

One of the important aspects of DNNs is the automatic feature selection strategy that can reduce possible limitations of manual approach. Feature selection demands an understanding of the target environment and knowledge of its significance; network performance can be largely affected by the selected features. For time-series as well as image data which represents grid-like topology, CNN is developed as a specialised NN (Goodfellow, Bengio, & Courville, 2016).

A generalised structure of CNN is given in Fig. 2 (Liu et al., 2017b); the architecture includes neurons arranged in width, height, and depth dimensions; it has an input layer, hidden layers that typically have convolutional layer, pooling layer, and a fully connected (FC) layer, followed by an output layer. Here, a mathematical operation, convolution, is performed with the input and kernel arguments to develop a feature map (Goodfellow et al., 2016); considering the complexity of non-linear stock market data, identification of useful features can be a significant task. Three major properties of a convolution include sparse interactions among layers, parameter sharing, and equivariant representations. They are capable of leveraging performance improvements over other machine learning methods; the capability of CNNs to learn complex inherent structures (Liu et al., 2017b) can be adopted for stock markets. The complex stock market consists of a vast number of features; to automatically identify contributing features from such time-series data, CNN-based various prediction models have been built.

Along with the financial markets, there are several domains where CNNs can be potentially integrated for various applications such as

Table 1
Comparative analysis of our survey with existing stock-related surveys for DNN-based various criteria.

Criteria (→) Reference (↓)	CNN	DQN	RNN	LSTM	GRU	ESN	DNN	RBM	DBN	Metaheuristics	Sentiment Analysis
Längkvist et al. (2014)	✓		✓	✓			✓	✓	✓		
Cavalcante et al. (2016)	✓						✓	✓	✓	✓	✓
Chong et al. (2017)							✓	✓		✓	
Hatcher et al. (2018)	✓		✓	✓			✓		✓		✓
Fawaz et al. (2018)	✓		✓			✓	✓		✓	✓	
Henrique et al. (2019)							✓				
Our Survey	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

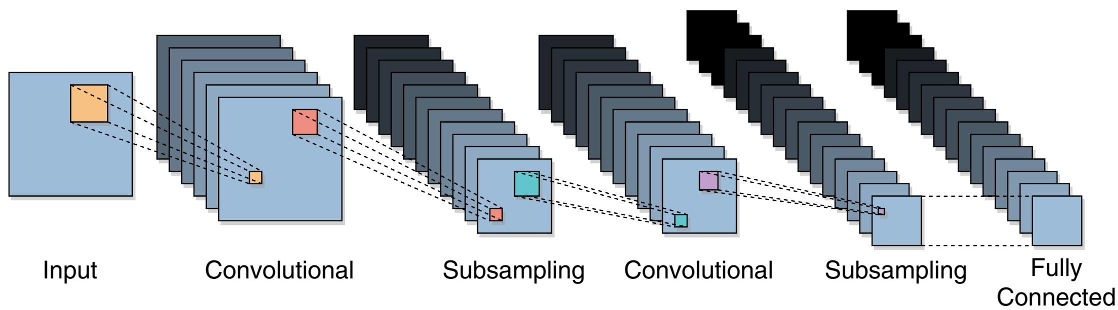

Fig. 2. A generalised CNN structure (Liu et al., 2017b).

object localisation and recognition (Patel, Patel, & Thakkar, 2012a; Ahmed, Jalal, & Kim, 2020), human tracking and/or activity recognition (Jalal, Kamal, & Kim, 2014b, 2015, 2015a, 2016, 2016, 2017, 2020), human pose tracking (Jalal & Kim, 2014), motion analysis (Jalal, Quaid, & Kim, 2019), face recognition (Thakkar, Jivani, Padasumbiya, & Patel, 2013), facial expression detection (Rizwan, Jalal, & Kim, 2020), emotion recognition (Sharma, Rajvaidya, Pareek, & Thakkar, 2019; Vora et al., 2019), X-ray image-based coronavirus disease (COVID-19) detection (Apostolopoulos, 2020; Narin et al., 2020), motif-fold recognition (Li & Liu, 2020), leaf disease identification (Ji, Zhang, & Wu, 2020), speech recognition (Han et al., 2020), handwriting recognition (Chaudhari & Thakkar, 2019; Altwaijry & Al-Turaiki, 2020; Sufian et al., 2020), text classification (Xu et al., 2020; Yousef, Hussain, & Mohammed, 2020), wireless sensor networks (Thakkar, 2016b; Ilal & Thakkar, 2016; Thakkar, 2016a; Thakkar, 2017), to name a few. The wider applicability of CNNs can be motivating to evaluate their performance for financial market prediction problems.

2.1. CNN-based stock prediction

In financial market, an exchange-traded fund (ETF) may be considered as a marketable security, i.e., a liquid financial instrument; it is traded similar to the regular stock, however, a combination of such ETFs may aid to lower volatility. Adopting the concepts of ETFs as primary financial assets, CNN was used in Ref. Gudelek et al. (2017) to predict stock price movement. Authors created 2D images with the sliding window approach using agglomerative clustering and evaluated 2-class (buy, sell) and 3-class (buy, hold, sell) regressions.

Another important factor in stock market is a limit order; it can be understood as a condition that one may put on stock buying or selling price which is yet not available in the market. Such limit order data were utilised to forecast mid-price movements of future stocks using CNN in Ref. Tsantekidis et al. (2017). On the other hand, five of the most liquid stocks listed on London stock exchange were used in Ref. Zhang et al. (2018); authors proposed DeepLOB model with a standard convolutional layer, inception module, and an LSTM layer. The historical data of LOBs were utilised along with price and volume (size) information and an extended micro-price from the feature maps of the first convolutional layer was defined. Using leaky ReLU as the activation function and a max-pooling layer inside the inception module, dynamic behaviours were captured over multiple time-scales; due to the temporal dependencies within the extracted features, LSTM units were used instead of FC layers and a softmax activation function was applied in the output layer. Authors proposed to use five levels on each side of LOBs, called DeepLOB5; the results indicated performance improvement in predicting short-term price movements.

In analysing stock trends, identification of patterns is an important task. Dynamic time warping (DTW) is one of the methods to retrieve pattern similarity between temporal sequences. For two time-series Q and C, the best alignment is identified to calculate a DTW distance as given by Eq. (1) (Kate, 2016); here, alignment is represented by a warping path W.

$$DTW\left(Q,C\right) = \underset{W=w_1,\ldots,w_k,\ldots,w_K}{\operatorname{argmin}} \sqrt{\sum_{k=1,w_k=(i,j)}^{K} \left(q_i - c_j\right)^2} \tag{1}$$

where, q_i and c_j present points of time-series Q and C, respectively. The minimum total cost is considered as DTW distance; it may be analysed with varying speed as well. Patterns such as consolidation, cup with handle, double bottom, and saucer may be found in stock price graphs (Zhang et al., 2010; Bulkowski, 2011). A DTW-based approach was demonstrated to identify such patterns in the historical stock price data for forecasting (Jeon, Hong, & Chang, 2018). Using the sliding window method, one day long patterns were generated with five-minute intervals; stepwise regression analysis was adopted for pattern identification. ANN with the selected features predicted the stock price.

2.2. DQN-based stock prediction

Building software agents that maximise progressive rewards by taking actions is the primary goal of reinforcement learning (RL). Q-learning can be considered as a model-free RL algorithm; it learns a policy to direct an agent for taking certain actions in the given circumstances. The stochastic transitions and rewards are used for handling the given problems wherein agents iteratively update their action value. However, in the case of non-linear function approximator, such RL approach may be unstable or divergent. DQN combines CNN with Q-learning concept for learning high-dimensional complex data (Mnih et al., 2015). Such networks are capable of solving instability problem generated because of non-linearity of approximation functions.

DQN was applied with CNN for stock market predictions on a global basis in study (Lee et al., 2019). The proposed approach considered stock chart images as the states and utilised CNN as a function approximator to map such representations to actions. For company c on day t, the input to CNN was S_t^c matrix of W days, i.e., matrix of size $W \times W$; an output action was given based on S_t^c and a reward was calculated. Authors utilised experience replay for correlation reduction and parameter freezing method to hold the target parameters for a temporary period during the training; these methods were adopted to solve non-linearity-based instability in the network. The portfolios were generated to show percentage return per transaction and the results indicated profit predictions on global stock markets.

3. Recurrent neural networks

An enhancement to the NN architectures was provided to include internal state (memory) to process input sequences. RNNs exhibit such a characteristic which is suitable to work with temporal data; they are capable of scaling to long sequences (Goodfellow et al., 2016). RNN can be understood as a directed graph representation which may have cyclic, i.e., finite impulse or acyclic, i.e., infinite impulse temporal behaviours (Miljanovic, 2012). The controlled states, also known as gated memory (states), belong to LSTMs and GRUs along with the given RNN architecture. Other variations include fully recurrent, Elman (Elman, 1990) and Jordan (Jordan et al., 1997) networks, ESN (Jaeger et al., 2004), etc. Fig. 3 demonstrates a generalised RNN structure (Connor, Martin, & Atlas, 1994); it can be significantly applied to domains having consolidated features such as time-series prediction (Han, Xi, Xu, & Yin, 2004; Guo et al., 2016; Qin et al., 2017).

3.1. RNN-based stock prediction

For the temporal stock market data, RNNs have provided a considerable prediction performance. The recurrent hidden state of RNN is given by Eq. (2)–(4) (Connor et al., 1994).

$$h_t = \tanh(Wx_t + Uh_{t-1} + b) \tag{2}$$

$$o_t = c + Vh_t \tag{3}$$

$$y_t = \mathrm{softmax}(o_t) \tag{4}$$

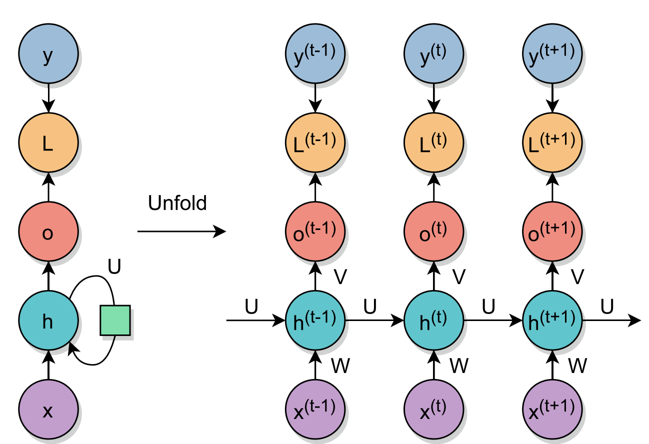

Fig. 3. A generalised RNN structure (Connor et al., 1994).

where, U, V, W denote hidden-to-hidden, hidden-to-output, input-to-hidden weight matrices, respectively; x_t is the input vector at time t; b and c stand for bias values. As shown in Fig. 3, loss (L) is measured as the difference between the targeted and predicted values.

While operating with the time-series data, an attention mechanism can be adopted; it divides the given data region into parts such that only specific parts are utilised by the decoder while generating new values. This may be termed as a task of orient perception. A dual-stage attention-based RNN (DA-RNN) for time-series forecasting was proposed (Qin et al., 2017). Here, the encoder and decoder consisted of input and temporal attention mechanisms for selecting relevant driving series and appropriate hidden encoder states, respectively. The model was trained with mini-batch stochastic gradient descent (SGD) and ADAM optimizer for stock market prediction. Subsequently, with an inspiration from discrete Fourier transform (DFT), authors in Zhang, Aggarwal, and Qi (2017) proposed for a state-frequency memory (SFM) RNN for shot- and long-term predictions. In SFM, number of states implied the number of patterns; predictions were dependent on the frequency of such trading patterns, e.g., short-term predictions were dependent on high-frequency patterns whereas long-term ones on low-frequency patterns.

3.2. LSTM-based stock prediction

As compared to RNN, temporal behaviours and contextual information of LSTM are preserved in the memory. The capability of LSTM in learning longer data dependencies can be exploited for time-series stock market data; the internal operations of single cell LSTM can be explained through Algorithm 1 where, σ indicates logistic sigmoid function, tanh is hyperbolic tangent function, and $\odot$ denotes element-wise multiplication (Hochreiter S., 1997). A generalised single cell LSTM is shown in Fig. 4 (Thakkar & Chaudhari, 2020).

Algorithm 1 Single cell long short-term memory operations

Input: Input vector (x_t) at time step t; previous memory cell state vector (c_{t-1}); previous hidden state vector (h_{t-1})
Given: Input-to–hidden weight matrix (W); hidden-to-hidden weight matrix (U); bias vector (b)
Output: Memory cell state vector (c_t); hidden state vector (h_t)
1: Calculate input gate vector, $i_t = \sigma(W^{(i)}x_t + U^{(i)}h_{t-1} + b^{(i)})$
2: Calculate forget gate vector, $f_t = \sigma(W^{(f)}x_t + U^{(f)}h_{t-1} + b^{(f)})$
3: Calculate output gate vector, $o_t = \sigma(W^{(o)}x_t + U^{(o)}h_{t-1} + b^{(o)})$
4: Calculate memory cell state vector, $c_t = i_t \odot u_t + f_t \odot c_{t-1}$ where, $u_t = \tanh(W^{(u)}x_t + U^{(u)}h_{t-1} + b^{(u)})$
5: Calculate hidden state vector, $h_t = o_t \odot \tanh(c_t)$

In financial aspects, volatility may be considered as the degree of variation of a trading price series over time. It may be seen as big swings in either direction of the stock trend (Li et al., 2017a). Various stocks having different volatilities were analysed using LSTM and SVM approaches in Ref. Li et al. (2017a); authors proposed an LSTM model with a single input layer, followed by sigmoid activation function-based two

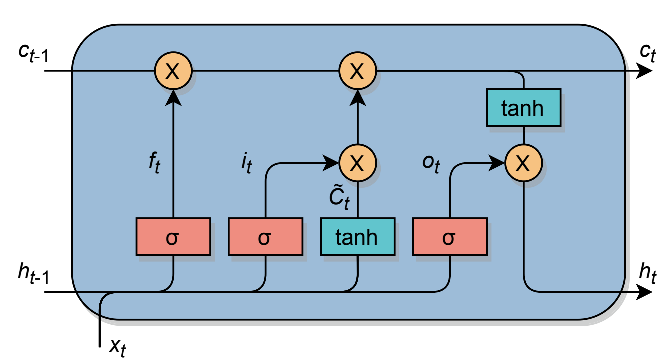

Fig. 4. A generalised single cell LSTM structure (Thakkar & Chaudhari, 2020).

LSTM layers, each followed by dropout, and the dense output layer with softmax function. LSTM resulted into higher accuracy for low-volatility stocks than SVM with the radial basis function (RBF) kernel. Also, using attention-based mechanism, authors in Ref. Cheng et al. (2018) proposed to predict multi-class output based on stock price increase whereas to extract valuable semantic features from the news text, an attention-based LSTM (At-LSTM) model was proposed in Liu (2018). Other applications of LSTM included next-day's close price prediction (Gao et al., 2017), stock indices forecasting (Roondiwala, Patel, & Varma, 2017), stock characteristics analysis (Liu et al., 2018), to name a few.

The concept of word vector in NLP was adopted to conceptualise stock vector and deep LSTM NN was proposed with an embedded layer (ELSTM) to predict stock market in study (Pang, Zhou, Wang, Lin, & Chang, 2018); here, the matrix transformation converted the high-dimensional data into low-dimensional in the embedded layer and the stock vector was created. Three-layer LSTM extracted feature information to predict the stock value; the parameters were updated using EBP and improved prediction results were derived. One of the recent advances proposed to utilise the concept of stock listing on multiple exchanges for cross-reference to exchange-based stock trend (CREST) prediction (Thakkar & Chaudhari, 2020); considering that a company can be listed on multiple exchanges, authors identified the difference between stock open prices of two exchanges within the same country wherein the company was listed and predicted one-day-ahead stock open price. An extension of the same, called iCREST prediction, was proposed by considering companies having been listed on international stock exchanges (Chaudhari & Thakkar, 2021); authors proposed to map time-series stock data of different exchanges and included currency conversion to process the historical stock data. Similar to CREST, the proposed iCREST prediction was conducted using LSTM for one-day-ahead stock open trend prediction.

The sentiment analysis may be given as developing computational intelligence for identifying and categorising sentiments (Thakkar, Mungra, & Agrawal, 2020). Such contextual opinions may be expressed in news articles, social media posts, microblogs, or other textual responses. Sentiments are identified, extracted, quantified, and studied in various domains including stock market responses. An RNN approach based on character-level sequence modelling was proposed for intraday and interday stock market predictions (dos Santos Pinheiro & Dras, 2017) and the proposed event-based strategy, having leaky ReLU activation and LSTM layer, provided comparable results to various other approaches. Considering stock market as a group decision-making system, the network public opinion and actual behaviour data spaces were exploited and LSTM model was proposed for time-series data in Ref. Zhuge, Xu, and Zhang (2017). While Naïve Bayes was used to build an emotional classifier using term frequency-inverse document frequency (TF-IDF) weights, LSTM models were individually applied to opinion and behaviour spaces; the merged outputs were trained using ReLU and performance improvement was attained for the proposed approach.

Subsequently, the temporal stock market data were addressed to be analysed using wavelet transformation (WT). Fundamentally, it allows changes in only time extension and not in shape; specific basis function may be chosen for stock trend analysis. WT provides time–frequency decomposition. Previous approaches that considered one-time WT were not suitable for real-time applications because of having future data in the window filter. Also, different stocks may be subtle to various wavelet functions. Hence, real-time wavelet-based denoising of the stock data and LSTM-based index prediction was proposed in study (Li et al., 2017b). The major trend could be predicted based on the classical wavelet denoising model; multi-resolution decomposition was carried out on discrete WT (DWT) and denoising was conducted on it using sliding window approach. The LSTM predictions indicated performance enhancement.

On the other hand, it is observed that the financial market introduces a derivative as the contract among parties that derived the value of an underlying entity. It is useful in maintaining low transition costs, risk management, increasing market efficiency as well as liquidity, and encouraging short selling in the stock market. While a large number of articles propose to forecast close or open price of the stocks, an LSTM NN-based approach was proposed to predict high and low prices of soybean futures in Ref. Wang et al. (2018). Authors suggested that the lower amount of noise associated with such prices of futures derivatives could be helpful in preparing trading strategies; the results indicated higher trend accuracy using LSTM model. Subsequently, the carbon trading-based futures prices were predicted using a hybrid ARIMA-CNN-LSTM model in study (Ji, Zou, He, & Zhu, 2019). Also, a prototype trading platform was developed based on DNN and LSTM and the futures market movements were predicted in Ref. Sun et al. (2019); authors considered four futures from energy and metal sectors to augment the bar as well as tick data collected from an online broker, namely Interactive Brokers (IB). Authors also evaluated their model using back-testing and paper trading which indicated performance improvement. It can be observed that a considerable amount of information can be fused to derive useful predictions; such fusion may be carried out at information, feature, and/or model-level (Thakkar & Chaudhari, 2021). Also, the potential applicability of the techniques can be adapted to analyse the given data. One of the recent approaches considered TF–IDF to derive feature weight matrix in study (Thakkar & Chaudhari, 2020b); authors experimented the proposed approach with various NNs including backpropagation NN (BPNN), LSTM, and GRU. The impact of features in enhancing a model's prediction accuracy was also demonstrated.

3.3. GRU-based stock prediction

Similar to LSTM, GRU has gating system with comparatively small number of parameters; single cell GRU structure is provided in Fig. 5 (Huynh, Dang, & Duong, 2017) wherein the internal operations of GRU can be given by Algorithm 2 where, σ indicates logistic sigmoid function, tanh is hyperbolic tangent function, and $\odot$ denotes element-wise multiplication (Cho et al., 2014).

Algorithm 2 Single cell gated recurrent unit operations

Input: Input vector (x_t) at time t; previous output vector (h_{t-1})
Given: Input-to–hidden weight matrix (W); hidden-to–hidden weight matrix (U); bias vector (b)
Output: Output vector (h_t)
1: Calculate update gate vector, $z_t = \sigma(W^{(z)}x_t + U^{(z)}h_{t-1} + b^{(z)})$
2: Calculate reset gate vector, $r_t = \sigma(W^{(r)}x_t + U^{(r)}h_{t-1} + b^{(r)})$
3: Calculate output vector, $h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \widetilde{h}_t$ where, candidate activation vector, $\widetilde{h}_t = \tanh(Wx_t + r_t \odot Uh_{t-1} + b^{(h)})$

Considering that financial news may fluctuate stock prices, a dual-layer attention-based GRU was developed in Ref. Yang et al. (2019) to predict stock price movement. The input attention layer captured important news by means of allocating weights from which features

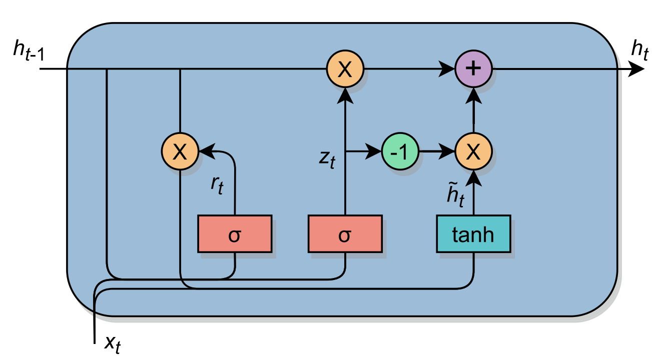

Fig. 5. A generalised single cell GRU structure (Huynh et al., 2017).

were extracted using GRU. Similarly, an output attention layer was adopted to identify long-term influential news. The stock price movement direction was forecasted based on that. The proposed GRU-2ATT approach improved the prediction performance. Based on the concept of GRU, a bidirectional GRU (BGRU) was also proposed in study (Huynh et al., 2017) to predict stock price movements using online financial news and historical stock data. Authors performed word embedding to generate word vectors, followed by dropout mask to reduce overfitting. The internal operations of GRU were applied in forward as well as backward directions separately and the resulted contexts were concatenated, i.e., $h_t = [\overleftarrow{h_t}, \overrightarrow{h_t}]$; an outperforming accuracy was reached using the proposed approach.

It is observed that news reports and/or announcements can provide information on various events; financial news largely covers the stock market aspects whereas reactions on such articles may be helpful in identifying public moods or opinions; authors in Ref. Chen et al. (2017) analysed the public moods from news-based posts written by 100 verified accounts for the sake of authenticity and an overall influence of various daily news on stock market was calculated; the proposed two-layer RNN-GRU approach predicted stock prices with smaller errors as compared to linear regression (LR) and SVR methods.

3.4. ESN-based stock prediction

ESN may be understood as a sparse connection of random hidden layers where weights of only output neurons can be learned for developing specific temporal series (Jaeger, 2001). For $u(t+1)$ input vector at timestep $(t+1)$, the internal state activation and network output are given by Eq. (5) and (6) (Jaeger, 2001), respectively.

$$x(t+1) = f\left(W^{in}u(t+1) + Wx(t) + W^{back}y(t)\right) \tag{5}$$

$$y(t+1) = f^{out}\left(W^{out}(u(t+1), x(t+1), y(t))\right) \tag{6}$$

where, $f = (f_1, \ldots, f_t)$ and $f^{out} = (f_1^{out}, \ldots, f_L^{out})$ denoted the activation function of internal unit and output function, respectively; connection matrices of input-hidden, hidden–hidden, and output-hidden were presented using W^{in}, W, and W^{back}, respectively; L indicated the output units; here, $(u(t+1), x(t+1), y(t)$ was given as a concatenation of input, internal, and output activation vectors. ESN is a variation of RNN, majorly suitable for time-series data. Because the dynamic reservoir structure is not trained, it is capable of resolving slow convergence, computational intractability, and gradient descent instability constraints.

Considering that technical analysis might be dependent on individuals' experiences, the trading rules were studied using GA in study (Lin, Yang, & Song, 2011) and various rules were combined using ESN for further suggestions. Experiments with stock components in terms of average profits in bull and bear markets and comparison with buy & hold (BaH) strategy indicated a significant improvement in the proposed technique. As the higher dimensionality of ESN may affect training performance, authors in study (Zhang, Liang, & Chai, 2013) introduced to use phase space reconstruction with an autocorrelation function for producing an inter-irrelative model sample, followed by principal component analysis (PCA) for dimensionality reduction; the model trained with ESN and internal state activation was analysed in terms of detecting strength, direction, momentum, and duration of stock price trend. Subsequently, for predicting the stock price movement, a multi-objective diversified ESN (MODESN) was proposed in Ref. Liu, Liu, Song, Gong, and Chen (2017a) to maintain generalization ability in the network. The aim was to reduce over-fitting by allowing neurons to encode different information as much as possible. Authors defined the diversity metric. For the experiment, the performance of MODESN was improved using GA in terms of diversity and prediction accuracy.

3.5. Hybrid stock prediction

Apart from the individual applications of RNN-based architectures, the hybrid approaches are also developed to overcome the limitations of the existing techniques. Using Colombo stock exchange (CSE) of three companies, a model was prepared with close, high, and low price data of the past two days to predict the close price for next day in Ref. Samarawickrama and Fernando (2017). Simple RNN (SRNN), LSTM, GRU, and feed-forward MLP architectures were compared with six input neurons and a varying number of hidden neurons; mean absolute deviation (MAD) and mean absolute percentage error (MAPE) were calculated to identify the best model for each company. Similarly, Google stock price movement directions were predicted using multi-layer RNN, LSTM, and GRU models in study (Di Persio et al., 2017).

A higher-level mechanism of generating or identifying a partial search approach that may optimise the problem solution, specifically in the case of insufficient search space information or limited computational capacity, is known as a metaheuristic (Bianchi, Dorigo, Gambardella, & Gutjahr, 2009). It may belong to local search or global search, conducted by a single-solution approach or population-based approach. Nature-inspired metaheuristics include evolutionary algorithms and swarm intelligence-based algorithms. One of the applications of such algorithms is parameter optimization in NNs. While considering stock market-based time-series data prediction, the searching ability of global optimum can be exploited using such metaheuristics. They can be helpful in speeding up the network training without diminishing the prediction performance (Tian & Fong, 2016; Fong, Deb, & Yang, 2018).

A WT-based RNN approach was proposed for stock market prediction in Ref. Hsieh, Hsiao, and Yeh (2011); the Haar wavelet was applied on time-series data to reduce noise, followed by RNN to construct input features. In Karaboga et al. (2007), authors optimised the weights and biases of RNN using artificial bee colony (ABC) due to its ability to find optimal solutions with relatively moderate resources (Chaudhari et al., 2019). RNN, autoregressive moving average (ARMA) (Jenkins, 1970), and exponential smoothing (Smoothing et al., 2004) models were combined to predict stock returns in study (Rather, Agarwal, & Sastry, 2015); the hybrid model weights were optimised using genetic algorithm (GA). Subsequently, optimization of an LSTM approach was demonstrated in Ref. Chung and Shin (2018) using GA for stock market prediction. A self-adapting variant particle swarm optimization (PSO) algorithm was used for weights and threshold value optimization of an Elman NN to predict the opening price of stocks (Zhang, Shen, Zhang, Song, & Zhu, 2017). Various other stock forecasting approaches based on PSO were recently reviewed in study (Thakkar et al., 2020).

4. Other deep neural networks

In general, a DNN can be understood as a combination of input and output layers with multiple hidden layers between them; it is a supervised learning to identify the data relationships which may be linear or non-linear. Due to the inherent complexity of stock-based data, DNNs have shown significant results in learning the relationships and predicting the trends of stock market. DNN may be classified into CNN and RNN, which have derived promising results in stock-related forecasting tasks individually as well. The common issues of overfitting and computational costs while using DNNs may be overcome using various approaches and by tuning the parameters. A generalised DNN structure is given in Fig. 6 where an input layer is followed by multiple dense hidden layers and an output layer.

For stock chart-based trend prediction, $(2D)^2$PCA (Zhang et al., 2005) was integrated to reduce dimensionality and authors in Ref. Singh et al. (2017) proposed to predict using DNN with tanh functions in hidden layers, softmax function for classification, and linear function for regression. On the other hand, an approach was proposed to extract information from the residuals of autoregressive model separately using PCA, autoencoder (AE), and RBM and the stock returns were predicted

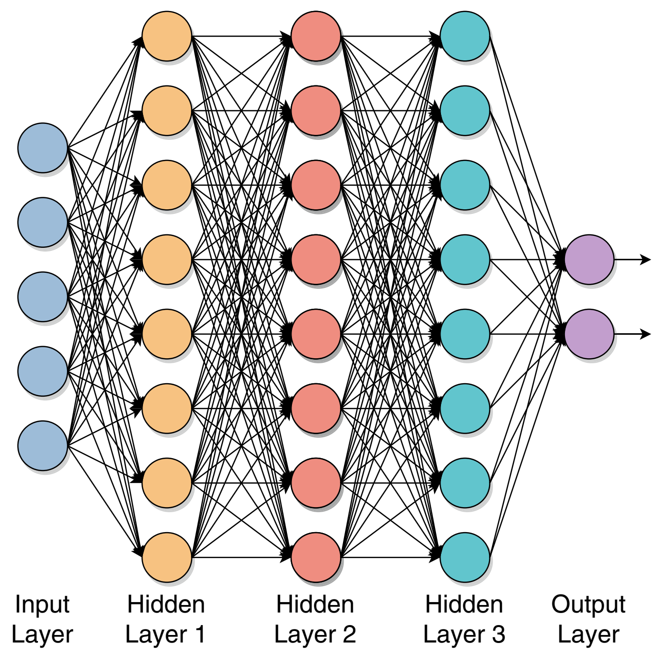

Fig. 6. A generalised DNN structure.

using DNNs; though the empirical results could not provide superiority of the network, authors had discussed positive directions for future work. Seven trading strategies were considered in Ref. Ma (2018) for stock fluctuation classification; deep feed-forward NN was used while experimenting with the sliding window approach and rise or fall of the Shanghai composite index was predicted. While considering various DNN-based approaches to manipulate complex stock data, an important task is to identify influential aspects. It requires understanding the effect of events/news/circumstances that dominate stock market movements. Concatenation of such factors and analysing the associated motives and/or sentiments may be carried out to enhance stock-related predictions. For this purpose, event-specific news articles, social boards having financial discussions, and firm-specific datasets were collected and a tensor-based predictive model was proposed to conceptualise a framework for stock movement prediction (Li, Chen, Jiang, Li, & Chen, 2016).

4.1. RBM-based stock prediction

RBM is a probability distribution-based generative stochastic approach; it is trained for maximising the product of probabilities of the given sample. One of the stock trend prediction approaches considered RBM for feature generation (Liang, Rong, Zhang, Liu, & Xiong, 2017). Authors collected two aggregate stock indices and one individual stock index from Yahoo finance website and eleven technical indicators that were conveyed to binary values. RBM was trained using a k-steps contrastive divergence learning (CD-k) and three classifiers, including SVM with RBF kernel, random forest (RF), and logistic regression, were used for comparative study of stock trend prediction; results indicated higher directional accuracy (DA) while using Bernoulli RBM. Similarly, using RBM for feature extraction, an SVM-based classification approach was proposed for stock trend prediction in study (Assis, Pereira, Carrano, Ramos, & Dias, 2018).

4.2. DBN-based stock prediction

DBN can be created using multiple RBMs stacked together. In Cai et al. (2012), two RBMs were combined such that an output of the bottom RBM served as the input of the top RBM. This approach was carried out to extract features from 20 technical indicators using DBN and the next day closing price was predicted using SVM. In finance, a security position may be decided upon such that an investor would not face losing more than a certain percentage, i.e., stop-loss order. A continuous-valued DBN was proposed and combined with fuzzy granulation (FG) in Ref. Zhang, Shen, and Zhao (2014). Authors experimented with Euro/US dollar and British pound/US dollar exchange rate datasets to predict fluctuation range using stop-loss concept and provided more profitable forecasting. Another CDBN-based exchange rate forecasting approach was proposed with a conjugate gradient optimization method (Shen, Chao, & Zhao, 2015). The proposed method outperformed feed-forward NN when experimented with British pound/US dollar, Indian rupee/US dollar, and Brazilian real/US dollar exchange rate datasets.

4.3. Hybrid stock prediction

Various DNN-based approaches were believed to be suitable for specific application domains, however, research works show their applicability to various financial fields. Combination of such methods can overcome the limitations and hence, they may be utilised for stock market forecasting. Such hybrid techniques may include various NN approaches, along with transformation methods for denoising or data processing, metaheuristics for parameter optimization, or using linear and non-linear models; comparative analysis of various NNs have been studied as well.

A single-layer AE (Bengio et al., 2007) may be illustrated as a three-layer NN having an input layer, hidden layer, and reconstruction layer with an aim to minimise the error between input and reconstruction vectors; stacked AE (SAE) is a stacked sequence of such single-layer AEs. Using WT with LSTM, i.e., WLSTM, LSTM, and RNN models, WSAEs-LSTM was proposed in Bao, Yue, and Rao (2017) where WT denoised time-series using Haar wavelet. To identify the existence of long-term dependency on stock data, Selvin, Vinayakumar, Gopalakrishnan, Menon, and Soman (2017) compared three models, RNN, LSTM, and CNN, for predicting stock prices of three companies of NSE. The sliding window approach was applied for short-term predictions and least root-mean-square error (RMSE) was evaluated. CNN model was independent of previous information and hence, it outperformed in studying the dynamic modifications and relevant patterns occurring in the given window. Another comparative analysis between LSTM, GRU, CNN, and ELM approaches was shown in Balaji, Ram, and Nair (2018) to predict one-step-ahead and four-step-ahead stock predictions of S&P BASE-BANKEX index. The generated predictions were evaluated using RMSE, median APE (MdAPE), and DA. Single-pipeline-based deep learning model consisted of three CNN layers which fed into two LSTM layers, followed by a dense output layer; enhancing the pipeline concept, Quintanilla and Verma (2018) proposed to use a multiple pipeline approach by combining three single-pipeline models; CNN layer was followed by batch normalization, ReLU activation, and max-pooling; output of the last pooling layer was given to LSTM. Three outputs of LSTM from single-pipeline models, individually, were concatenated for performance improvement and given to the output layer. The proposed model enhanced stock prediction accuracy over SVR and single-pipeline approach.

The entity embedding generation based on financial news contents and integration of complex relationships between such contents and stock market movements have been a challenging task; Xu, Zhang, Zhang, Li, and Lin (2018) addressed this issue with a recurrent CNN model. The data collected from Yahoo finance website were pre-processed and labelled on daily, weekly, and monthly matching basis which were given to the proposed RCNN consisting of embedding layer, convolutional layer, and LSTM layer. The words of news contents were embedded into matrix (Guo & Berkhahn, 2016). The output matrix was modelled using CNN followed by LSTM which captured dependency relationships for stock movement prediction. The proposed model, EB-CNN-LSTM (Xu et al., 2018), resulted in improved accuracy and Matthews correlation coefficient (MCC) as compared to existing approaches.

In the everyday routine, many events occur with varying aspects, some of which largely affect the corresponding companies and/or organizations and hence, the stock markets as well. Such influential events have been studied to identify their impact of stock predictions. Long-term, mid-term, and short-term events representing events over the past month, week, and day, respectively, were modelled to predict stock market using event embeddings input and CNN model (Ding et al., 2015). Another approach considered knowledge graph-based event embedding for predicting stock market volatilities (Ding, Zhang, Liu, & Duan, 2016). Concerning that macro-environmental events reported in news influence the stock index movements, Verma, Dey, and Meisheri (2017) analysed news articles belonging to political, economical, social, technological, environmental, and legal (PESTEL) categories and proposed to use LSTM-based approach to predict stock movement. On the

Table 2
Summary of the existing DNN-based stock price prediction approaches.

Paper	Type of NN	Type of Input	Features	Target	Dataset	Training: Validation: Testing	Sampling Period (Frequency)	Result
Gudelek et al. (2017)	CNN	2D matrix	RSI, SMA, MACD, William's %R, stochastic and ultimate oscillators, MFI	Next day stock price	Google finance; 17 ETFs	90%: Unspecified: 10%	06/04/2000 to 17/11/2016 (Daily)	72.9% average accuracy
Lee et al. (2019)	DQN, CNN	Chart images	Closing price, volume	Stock market prediction; portfolio construction	Yahoo finance; data from US and other 30 countries	5: Unspecified: 12 years	01/2001 to 12/2017 (Daily)	Global stock price forecasting
Qin et al. (2017)	RNN	Time-series	Driving series	Time-series stock prediction	NASDAQ 100	35100: 2730: 2730 data points	26/07/2016 to 22/12/2016 (Minute)	Improved MAE, MAPE, RMSE for 64 hidden states
Cheng et al. (2018)	LSTM	Time-series	Open, close, low, high, volume	Multi-class output (stock increase)	TWSE	Unspecified	Unspecified	Improved accuracy, precision, recall, F1-score
Gao et al. (2017)	LSTM	Time-series	Open, close, high, low, adjusted price, volume	Next day closing price	Yahoo finance; S&P 500	Unspecified	03/01/2000 to 10/11/2016 (Daily)	Improved MAE, RMSE, MAPE, AMAPE than MA, EMA, SVM
Roondiwala et al. (2017)	LSTM	Time-series	Date, open, high, low, close, volume	Stock index prediction	NSE; NIFTY 50	90 –95%: -: 10 –5%	01/01/2011 to 31/12/2016 (Daily)	Improved RMSE
Pang et al. (2018)	LSTM	Time-series	Open, close, highest, lowest, volume; five amplitude indicators	Stock price, trend prediction	Shanghai A-shares; Sinopec	70%: 10%: 20%	01/01/2006 to 19/10/2016 (Daily)	Shanghai A-shares composite index: 57.2% accuracy; Sinopec: 52.4% accuracy
Zhuge et al. (2017)	LSTM	Time-series	Time, ticker, open, high, low, close; change, change rate, turnover rate	Opening stock price prediction	Eastmoney; NetEase; Shanghai composite index	02/06/2008 to 05/06/2015 (except last 30 days): Unspecified: 30 days	06/02/2008 to 06/05/2015	Improved MSE, B value than SVR, MLP, RNN
Li et al. (2017b)	LSTM	Time-series	Price, volume, EMA, MA, RSI, MACD, ROC, William's %R, CCI, SAR, MFI	Stock index prediction	East Asian stock indexes	6: Unspecified: 1 year(s)	01/01/2010 to 31/12/2016 (Daily)	Improved MAPE
Wang et al. (2018)	LSTM	Time-series	Open, high, low, close, settlement price, volume, position	Next-day high and low prices; trading strategies	Soybean futures from Dalian Commodity Exchange	2700: Unspecified: 219 days	01/2006 to 12/2017 (Daily)	Trend accuracy: 73.7% for high price, 68.2% for low price
Ji et al. (2019)	ARIMA-CNN-LSTM	Time-series	Futures price	Carbon future prices	EU ETS	400: Unspecified: 173 weekly observations	07/04/2008 to 06/05/2019 (weekly)	Decreased RMSE and MAPE by 19.45% and 32.42%, respectively
Lin et al. (2011)	ESN	Time-series	Open, close, lowest, highest	Market profit	S&P 500	2000 days: Unspecified: 12/2003 to 11/2005 (bull market); 2000 days: Unspecified: 09/2000 to 09/2002 (bear market)	Approxi-mately 2500 days for bull as well as bear market (Daily)	Improved market profit than BaH strategy
Zhang et al. (2013)	ESN	Time-series	Open, close	Stock prediction	Yahoo finance	Unspecified	02/01/2004 to 08/11/2006 (Daily)	Improved prediction than BPNN, HMM, SVM, PNN
Singh et al. (2017)	$(2D)^2$-PCA with DNN	2D matrix	36 indicators	Stock prediction	NASDAQ	19/08/2004 to 31/05/2011 : Unspecified: 01/06/2011 to 10/12/2015	19/08/2004 to 10/12/2015 (Daily)	Improved RMSE, hit rate, total return than RBFNN by 17.1%, RNN by 43.4%
Shen et al. (2015)	DBN	Time-series	Exchange rate	Exchange rate forecasting	GBP/USD; BRL/USD; INR/USD	885: Unspecified: 52; 167: Unspecified: 42; 350: Unspecified: 146	Different periods (Weekly)	Improved RMSE, MAE, MAPE, DA, CORR than RW, ARMA, FFNN

other hand, Oncharoen et al. (2018) used the event embeddings with technical indicators for stock market prediction with CNN and LSTM methods. The relationships between various enterprises have been explored; Zhang, Yang, Du, and Xu (2018a) leveraged enterprise knowledge graph to predict stock price movement using DNN model.

NN learns to update its weights and biases so as to enhance the performance accuracy. Metaheuristic approaches have shown promising improvement in optimising such parameters. Stock-related predictions have been conducted using various NNs and hence, researchers have incorporated evolutionary algorithms to achieve a higher level of stock trading performance. A deep MLP-based approach was enhanced using GA for stock prediction (Sezer, Ozbayoglu, & Dogdu, 2017).

5. Discussions

In this article, we have presented a brief overview of DNNs including CNN and RNN; respective approaches have been classified to demonstrate the widespread of deep learning methods in stock market forecasting. To provide a balanced study of the diverse characteristics of these approaches and their suitability for financial prediction problems, we have provided a brief introduction to DNNs and their recent applications in the stock market (2017 −2020). A brief summary of our survey on stock market prediction using DNNs is provided in Tables 2 and 3 that present articles on stock price forecasting and stock trend prediction, respectively. Here, for the reviewed articles, we present type of NN, type of input data, features, and target output, as well as training, validation (if any), and testing details and dataset specifications; we briefly discuss the results attained in respective articles.

5.1. An experimental perspective

In this survey, we review how various DNNs are applied for stock market prediction. It can be observed that the reviewed articles have adopted diverse prediction models and used various datasets with different specifications. Also, the parameters, set of features, and train-test durations differ in these articles. Hence, it is difficult to conduct a comparative analysis. In order to address this limitation and provide an experimental perspective on how various DNN architectures may result, we demonstrate the prediction capabilities of different DNNs under a specific simulation environment with an adopted common network architecture, one dataset with a given set of features, as well as other parameters to have a fair comparison.

For our experiments, we adopt the network parameters as specified in Sethia et al. (2019) for LSTM and GRU; to conduct an unbiased comparison, we carry forward the same hyperparameters for CNN, DQN, RNN, ESN, DNN, RBM, and DBN models, wherever applicable; details of the same are given in Table 4. Based on the considered approach (Sethia et al., 2019), we take Standard & Poor's 500 (S&P500) dataset for the duration of 01 −01 −2000 to 23 −10 −2017; the dataset is downloaded from Yahoo finance website where we receive the historical time-series data including open, high, low, close, adjusted close, and volume information for the given trading day. It is important to have a balanced dataset in order to derive fair evaluation; it is identified that S&P500 dataset for the considered duration is approximately balanced (i.e., with up and down trends) and hence, we carry forward our experiments with the same. We apply a series of pre-processing steps on the collected data; we calculate technical indicators and derive a total of 48 attributes that serve as features as given in Sethia et al. (2019). To eliminate the error propagation in the subsequent steps, we remove data samples having null or missing information as a part of cleaning operation (Thakkar & Chaudhari, 2020b). It can be understood that these features can have variable data ranges; for example, on 31 −12 −2020, the open price of S&P500 was $3,733.27$ USD whereas the volume was $3,17,25,10,000$ USD; the prediction may get dominated by several features because of large variations in data. Therefore, we consider to normalise each feature within $[0,1]$ range. Here, we have 48 features that can be further sampled into training, validation (optional), and testing data samples.

Identification and/or derivation of useful feature can be an important aspect; in the considered article, authors adopted independent component analysis (ICA) for feature extraction with the number of ICA components $\in \{7,12,18,25,32,45\}$ (Sethia et al., 2019). For an impartial comparison, we also consider the given approach to extract features with the given number of ICA components. The data samples are further provided to individual prediction model to predict five-day-ahead stock trend of the adjusted close price. We evaluate the prediction performance using directional accuracy (DA) metric. These experiments are repeated for ten random initial seed values to ensure that the comparison is unbiased and an average of DAs is calculated. Here, we compare the prediction performance of various DNN models with respect to different number of ICA components as shown in Fig. 7. As given in the reference article (Sethia et al., 2019), there are a total of 48 attributes considered as a set of features; to study the impact of the given attributes, we also carry out a comparison of 48 features with that of 5 features, i.e., open, high, low, adjusted close, and volume, as shown in Fig. 8.

In Fig. 7, we compare the performance of different DNN models with respect to individual number of ICA components; it can be observed that the experience-gathering-based DQN approach indicates the highest performance in handling non-linearity of stock market data as compared to CNN. On the other hand, the recurrent nature of RNN, and its enhancements, LSTM and GRU, demonstrate a near-similar prediction accuracies; the capabilities of handling longer dependencies of the time-series data can be addressed using such networks, however, the sparse connection-based ESN could not provide desirable performance. The ability of DNNs to learn temporal data through their dense networks can be seen in the comparison; while an RBM model delivers an overall lower accuracy, it can be stacked together in order to develop a DBN model which, in our experiments, represents comparable or improved prediction with respect to RBM.

On the other hand, a comparison of the number of input features is illustrated in Fig. 8. We consider 5 features collected in the historical stock market data, i.e., open, high, low, adjusted close, and volume, and compare their prediction results with that attained by the given 48 attributes, i.e., without applying feature extraction using ICA (Sethia et al., 2019). In majority of the cases, a close performance prediction can be observed; using 48 features have given slightly better accuracies than 5 features in case of LSTM, DNN, and DBN models whereas for CNN, DQN, RNN, GRU, and DBN models, the set of 5 features indicates a slightly improved prediction accuracy as compared to using 48 features; ESN model results are closely similar. It can be observed that the highest average DA is attained by DQN model irrespective of the number of features. Apart from these models, RBM shows to have a significant performance enhancement while using 5 features; the results of RBM with 5 features reaches close to that attained by DQN.

While we aim to study and prepare an illustrative experiment, the model architectures and other hyperparameters are adopted as provided in Ref. Sethia et al. (2019), however, the fine-tuning can be a critical aspect in order to find a suitable model and corresponding hyper-parameter settings for the prediction; for example, the number of learnable parameters can be reduced as well as inputs with variable size can be accepted using global average pooling in CNN, however, it may suffer with memory limitations (Yamashita, Nishio, Do, & Togashi, 2018) that may be overcome using RNN-based model(s). The computational complexity of RNNs may limit the size of model in order to learn given data (Sutskever & Hinton, 2010); for stock market prediction, LSTM can be considerably useful to handle long-term dependencies, however, the data processing can affect the prediction performance (Ma, 2020). On the other hand, not learning recurrent weights is advantageous and increases the learning speed of ESN (Sutskever & Hinton, 2010). While DQN has an advantage of enhancing Q-learning stability, its variations and itself may require larger computations (Khanzhahi et al., 2018). The feature extraction without prior knowledge of

Table 3
Summary of the existing DNN-based stock trend prediction approaches.

Paper	Type of NN	Type of Input	Features	Target	Dataset	Training: Validation: Testing	Sampling Period (Frequency)	Result
Tsantekidis et al. (2017)	CNN	2D sequences	LOB	Mid-price movement direction	NASDAQ Nordic; 4.5 million samples	70%: Unspecified: 30%	01/06/2010 to 14/06/2010 (Daily)	Improved recall, precision, F1-score, κ than linear SVM, MLP
Zhang et al. (2018)	CNN	Time-series	LOB	Short-term price movement	5 instruments of London stock exchange; 134 million samples	6: 3: 3 months	03/01/2017 to 24/12/2017 (Daily)	Improved precision, recall, F1-score, average AUC than linear SVM, MLP, Tsantekidis et al. (2017)
Thakkar and Chaudhari (2020)	LSTM	Time-series	Open	Next-day stock trend prediction	WIPRO; INFY; LTI (NSE, BSE)	80%: -: 20%	2009 to 2019 (Daily)	Improved RMSE, DA, precision, recall, F-measure
Li et al. (2017a)	LSTM	Time-series	51 technical indicators	Stock price movement	SSE 50 index	3: Unspecified: 1 year(s)	01/01/2012 to 31/12/2015 (Daily)	High-volatility group: SVM outperformed; low-volatility group: LSTM outperformed
Liu (2018)	Bi-LSTM	News titles, time-series	Character, word, news embeddings; stochastic %K, stochastic %D, momentum, rate of change, William's % R, A/D Oscillator, Disparity 5	Next day closing price directional movement	Financial news: Reuters and Bloomberg; 473 companies listed on S&P 500	20/10/2006 to 27/06/2012 (445262 news): 28/06/2012 to 13/03/2013 (55658 news): 14/03/2013 to 20/11/2013 (55658 news)	10/2006 to 03/2018	63.06% average accuracy
Liu et al. (2018)	LSTM	Time-series	Open, close, high, low, MA, EMA	Stock trend classification	CSI 300 index	18/05/2014 to 25/12/2016 : Unspecified: 26/12/2016 to 29/01/2017	18/05/2014 to 29/01/2017 (Daily)	Single-layer: 0.66% accuracy; three-layer: 0.78% accuracy
Chaudhari and Thakkar (2021)	LSTM	Time-series	Open	Next-day stock trend prediction	DRREDDY; HDFCBANK; ICICIBANK; INFY; WIPRO (NYSE, NSE, BSE)	80%: -: 20%	2009 to 2020 (Daily)	Improved DA, precision, recall, F-measure
dos Santos Pinheiro and Dras (2017)	LSTM	Character-based or multi-channel	Character embedding	Price direction prediction: intraday (after news); interday (close price)	Financial news: Reuters and Bloomberg; S&P 500 companies: Thomson Reuters tick history	157033: 52344: 51476 documents	02/10/2006 to 21/11/2013 (Daily)	Comparable results
Sun et al. (2019)	LSTM	Time-series	227 feature groups	Futures market movement; trading strategy	Bar data, tick data; futures of crude oil, natural gas, copper, and gold	256 weeks: Unspecified: (testing on different durations for backtesting and paper trading)	12 years	Improved prediction results
Thakkar and Chaudhari (2020b)	BPNN, LSTM, GRU	Time-series	Open, high, low, close, volume, Google trends, technical indicators	One-day-ahead open price, five-day-ahead adjusted close price	DJIA, S&P500	1276 : – : 600 records, 3053 : 525 : 847 records	01 –01 –2010 to 16 –06 –2017, 03 –01 –2000 to 30 –10 –2017 (Daily)	Improved directional accuracy (DA)
Chen et al. (2017)	RNN-GRU	Time-series	Open, close, highest, lowest, volume, change and limit of price and volume, amplitude, difference	Stock volatility prediction	Verified Sina Weibo accounts; HS 300 index	Unspecified	01/01/2015 to 08/03/2017 (Daily)	Improved MAE, MAPE, RMSE than LR, SVR
Huynh et al. (2017)	BGRU	Time-series	Word embedding	Stock movement prediction	Reuters and Bloomberg; Yahoo; S&P 500	01/10/2006 to 31/12/2012 : 01/10/2013 to 15/06/2013 : 16/06/2013 to 31/12/2013	01/10/2006 to 31/12/2013	Improved accuracy than LSTM, GRU; 60 –65% accuracy
Yang et al. (2019)	GRU	Embedd-ings	Sentence embedding	Stock price movement	Reuters and Bloomberg; S&P 500	1480: 180: 180 days	10/10/2006 to 14/11/2013 (Weekly)	Improved MCC than EB-NN, EB-CNN
Liu et al. (2017a)	MODESN	Time-series	Open, close, high, low	Stock price movement	Shanghai composite index	04/01/2000 to 01/06/2012 : Unspecified: 04/06/2012 to 21/01/2016	04/01/2000 to 21/01/2016	Accuracy: 77.7% (training), 76.1% (testing)
Liang et al. (2017)	RBM	Time-series	Open, close, lowest, highest; 11 technical indicators	Stock market trend prediction	SSECI (2274 samples), FTSE 100 (4200 samples), PingAn Bank (2319 samples)	80%: 10%: 10%	26/07/1999 to 31/12/2008 for SSECI; 03/01/2000 to 26/02/2016 for FTSE 100; 25/07/2006 to 25/07/2016 for PingAn Bank	Improved DA than Bernoulli RBM
Assis et al. (2018)	RBM	Time-series, candles	Set of features de Campos (2001)	Stock market asset trend	VALE3, ENBR3, BRAP4, USIM5, ABEV3	Sliding window with 20 : – : 10 candles	08/2014 to 08/2015 (Daily)	Improved prediction accuracy compared to SVM

Table 4
Parameter specifications.

Parameter		Value
Prediction frequency		5 days (Sethia et al., 2019)
Dataset		S&P500 (Sethia et al., 2019)
Data specification		03 –01 –2000 to 30 –10 –2017 (Sethia et al., 2019)
Input features	i)	48 features (Sethia et al., 2019)
	ii)	5 features
Target attribute		Adjusted close price (Sethia et al., 2019)
Feature extraction		ICA (number of components $\in \{7, 12, 18, 25, 32, 45\}$) (Sethia et al., 2019)
Model Architecture		64 –128 –256 –512 –1 (Sethia et al., 2019)
NN		CNN, DQN (ϵ: 1.0; γ: 0.97), RNN, LSTM, GRU, ESN (Sparsity: 0.2; Radius: 1.5; Noise: 0.0001; Reservoir: 5000), DNN, RBM (Learning rate: 0.002; C: 6000), DBN
Model weight initialisation		Random (Sethia et al., 2019)
Number of epochs		125 (Sethia et al., 2019)
Batch size		50 (Sethia et al., 2019)
Dropout		0.3 (Sethia et al., 2019)
Normalisation		[0, 1] (Sethia et al., 2019)
Activation function		Linear (Sethia et al., 2019)
Optimizer		ADAM (Sethia et al., 2019)
Loss function		Mean squared error (MSE) (Sethia et al., 2019)
Train: Validate: Test		3053 : 525 : 847 records (Sethia et al., 2019)

predictors can be one of the benefits of using DNN models (Chong et al., 2017), however, their limitations must be overcome using other enhancing model(s) in order to have a robust prediction approach. Hence, it is critical to select a suitable prediction model with an appropriate set of parameters to derive useful prediction results.

5.2. Challenges and future directions

The inherent non-linear characteristics and non-casual behaviour of stock market trend can be approached using different techniques. On a large basis, the historical data of various stocks have been used for building a prediction model in statistical as well as learning algorithms-based methods. DNNs are integrated to predict stock price, stock trend, market profit, and exchange rate using the extracted features; the performance can be evaluated using error estimations methods such as RMSE, mean squared error (MSE), mean absolute error (MAE), and MAPE, accuracy and directional accuracy metrics, precision, recall, and F-measure. Such financial data can be seen as structured time-series wherein data persist dependency. Because of the temporal characteristics of such chronological sequences, random cross-validation is not preferred as it is likely to reduce the performance (Roberts et al., 2017) and hence, majority of the articles have not considered it while training their model; this limitation may be overcome using a block-based cross-validation for the financial time-series data. The prediction duration, i.e., short-term, medium-term, or long-term is an important consideration, however, the rationale behind the selection of specific features, predicted gain for the output duration, or the datasets are given limited attention.

It may be desired to weigh the perception to select a specific method, features, dataset and sampling duration, as well as the evaluation metrics. This may aid to develop implications of the surveyed approaches on other datasets. It has been observed that the rationale behind selection of a specific parameter value may not be well-established; this may also be a concern while selecting an activation function. Evaluation of the impact of selecting a particular hyperparameter as compared to others can be one of the important factors for potential future direction. Subsequently, the amount of time required to train a forecast model and predict the stock price needs to be improved; real-time prediction of

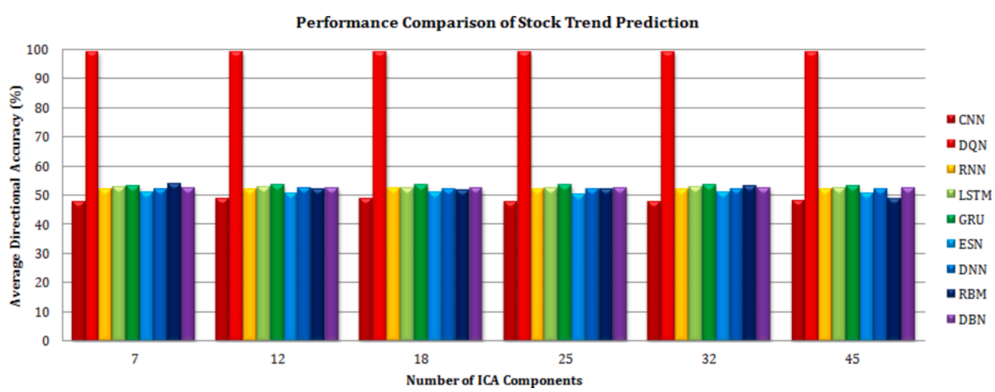

Fig. 7. Performance comparison of five-day-ahead stock trend prediction using various DNN models for different number of ICA components.

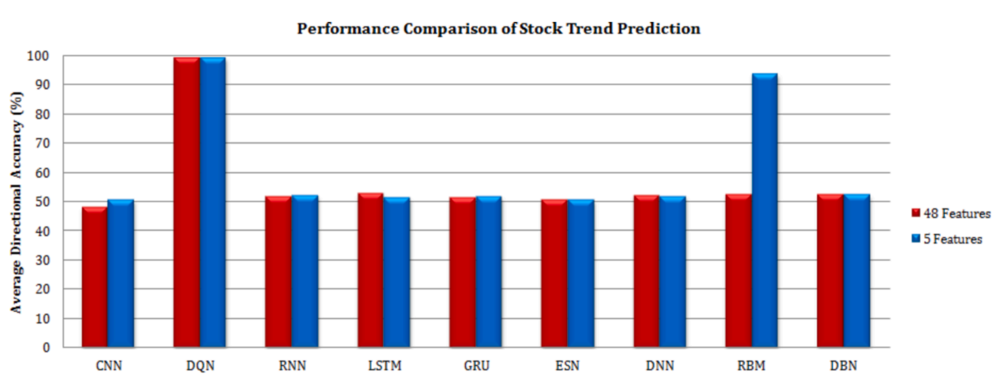

Fig. 8. Performance comparison of five-day-ahead stock trend prediction using various DNN models for different number of features.

stock market is a challenging task. On the other hand, it could be obsereved that limited amount of research is carried out on derivatives-based stock market analysis and prediction; while some machine learning approaches have been applied to forecast various market derivatives (Fang & George, 2017; Lu, Geng, & Yu, 2019; Beytollahi & Zeinali, 2020), DNN-based methods can be exploited on a larger basis to study this perspective.

Though historical data demonstrate trends of respective stocks, the influential factors play a crucial role. It has been observed that an individual's investment in the stock market may be affected by economic, psychological, as well as social aspects. Subsequently, the country perspectives such as political events, government policies, declaration of split or merger of different entities, as well as global occurences can highly influence the stock market. Identification of such factors and their associations with investors in the stock market is a challenging task; such contextual information-based stock market predictions may benefit the community. A financial market is said to be informationally coherent (Fama, 1965); stock price and its movement reflect various aspects of news and events. This kind of events greatly influences the stock market; considering such occurrences while analysing stocks and identifying associated patterns with external events may bring significant improvement in the forecasting. Another observation reveals that for a robust or near-optimal stock prediction model, it may be possible that all the users trade as per the model's suggestions which may lead to equal profit for all; however, this may not be universally true wherein individuals are likely to trade using different aspects in the real-life, for example, their intuitions, experiences, financial conditions, time duration for the projected investment, to name a few. This may be an open research domain to analyse potential hypotheses associated with stock trading and their coordination with computational intelligence to enhance the forecasting ability of the model. In economics, market dynamics such as supply, demand, price, quantity, and other factors are applied to business models (Plott, Roll, Seo, & Zhao, 2019); study of the same and various benchmark models along with computational intelligence may be a subject of future research direction. A potential field of extension may direct financial risks and returns associated with the investment; prediction models may be constructed using efficient market hypotheses. Also, personal aspirations can be useful features to study an individual's expectations and risk-averse etiquettes; the same can be exploited to customise stock prediction recommendations.

The highly non-linear stock markets face fluctuations due to a large number of events that can influence the market trends directly or indirectly. The impact of such trends can be viewed actively or passively over a period of time; also, there are several cases that may result into failure of the market predictions. It can be observed that a stock market is driven by sentiments (Khedr et al., 2017; Ren, Wu, & Liu, 2018; Sohangir, Wang, Pomeranets, & Khoshgoftaar, 2018); prediction through the historical stock market data may provide traces of the resultant effects of public mood at a particular time, however, evaluation of the dominating factors as well as their intensity can be a challneging aspect. While a large number of technical indicators have been used for market analysis, the predictions may be dominated by sudden change of events that may occur nationally and/or globally. In such regard, coverage of a broader area of analysis can be helpful, however, evaluation of the past events and identification of their correlation with stock trend can be a difficult task.

The existing surveyed models adapted various machine learning and/or deep learning approaches; the study reveals that hybrid methods can be used to overcome inherent limitations of any approach in isolation, for example, the vanishing gradient problem of RNN can be largely avoided using deep feed-forward networks (Sussillo, 2014). Hence, integration of complementing techniques may enhance the prediction performance. The NN weights can also be optimised using metaheuristic algorithms (Thakkar & Lohiya, 2020c); it can be perceived as a potential discipline for a large number of applications including stock market prediction. The hyperparameters and NN architecture can play an important role in deriving the model complexity; identification of such complexity for various DNN models can be a potential future research direction (Hu, Liu, Bian, & Pei, 2020). The time-series characteristics of stock market can be given further attention to complement the network settings such as identification of suitable dataset duration to analyse the market trend, selection of appropriate functions to derive useful predictions, hyperparameter tuning, as well as preparation of the network model to learn inherent market patterns for reliable forecasting; while the motivation behind choosing an appropriate setup is required, the implications of such factors on the prediction performance can be a potential future research direction.

6. Concluding remarks

In this article, we studied various deep learning-based NN approaches for stock market forecasting. The existing surveyed articles covered in our survey mainly represented the recent advances between years 2017 and 2020 to primarily focus on the need and challenges for stock prediction; these articles were categorised based on their prediction approach and diversity in derivatives-based market predictions. We mainly concentrated on CNN, RNN, and other DNN approaches and their subsequent variations for stock market prediction and provided the basic concepts and their applicability in the financial market. We also analysed the sentimental, event-driven, attention-based, and meta-heuristic aspects to indicate the appropriateness of NNs in time-series predictions. Along with this review, we argued on some of the limitations which may be analysed to improve the prediction models. We believe it is important to understand the equilibrium between financial concepts and computational intelligence, technical indicators, econometrics, learning approaches, and their integration in order to study and analyse the field of interest. Therefore, this survey can be adopted as a recent enhancement in approaching deep learning-based NNs for stock market.

It has been observed through the literature survey that the experimental comparisons between different models have been explored at a limited extent. To address this challenge, we carried out a series of experiments by considering nine deep learning-based NN models; we evaluated their prediction performance for different number of ICA components; we also analysed the impact of deriving multiple features. The analysis indicated the significance of model enhancements and it could be noticed that the prediction model's hyperparameters can have a significant impact. Our observations for the existing challenges and considerations towards the development of a robust stock prediction model were also discussed with potential future research directions. As the non-linearity of the temporal stock market has been an interesting research domain, this research can be useful to study the diversity of deep learning-based NN approaches, their applicability in the financial markets, and potential research problems that may be addressed to develop a reliable prediction model.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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