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# Algorithmic financial trading with deep convolutional neural networks: Time series to image conversion approach

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ABSTRACT

Computational intelligence techniques for financial trading systems have always been quite popular. In the last decade, deep learning models start getting more attention, especially within the image processing community. In this study, we propose a novel algorithmic trading model CNN-TA using a 2-D convolutional neural network based on image processing properties. In order to convert financial time series into 2-D images, 15 different technical indicators each with different parameter selections are utilized. Each indicator instance generates data for a 15 day period. As a result, 15 × 15 sized 2-D images are constructed. Each image is then labeled as Buy, Sell or Hold depending on the hills and valleys of the original time series. The results indicate that when compared with the Buy & Hold Strategy and other common trading systems over a long out-of-sample period, the trained model provides better results for stocks and ETFs.



## 1. Introduction

Stock market forecasting based on computational intelligence models have been part of stock trading systems for the last few decades. At the same time, more financial instruments, such as ETFs, options, leveraged systems (like forex) have been introduced for individual investors and traders. As a result, trading systems based on autonomous intelligent decision making models are getting more attention in various different financial markets globally [1].

In recent years, deep learning based prediction/classification models started emerging as the best performance achievers in various applications, outperforming classical computational intelligence methods like SVM. However, image processing and vision based problems dominate the type of applications that these deep learning models outperform the other techniques [2].

In literature, deep learning methods have started appearing on financial studies. There are some implementations of deep learning techniques such as recurrent neural network (RNN) [3], convolutional neural network (CNN) [4], and long short term memory (LSTM) [5]. In particular, the application of deep neural networks on financial forecasting models have been very limited.

CNNs have been by far, the most commonly adapted deep learning model [2]. Meanwhile, majority of the CNN implementations in the literature were chosen for addressing computer vision and image analysis challenges. With successful implementations of CNN models, the model error rates keep dropping over years. Despite being one of the early proposed models, AlexNet achieved ~50–55% success rate. More recently, different versions of Inception (v3, v4) and ResNet (v50, v101, v152) algorithms achieved approximately ~75–80% success rate [2]. Nowadays, almost all computer vision researchers, one way or another, implement CNN in image classification problems.

In this study, we propose a novel approach that converts 1-D financial time series into a 2-D image-like data representation in order to be able to utilize the power of deep convolutional neural network for an algorithmic trading system. In order to come up with such a representation, 15 different technical indicator instances with various parameter settings each with a 15 day span are adapted to represent the values in each column. Likewise, *x* axis consists of the time series of 15 days worth of data for each particular technical indicator at each row. Also the rows are ordered in such a way that similar indicators are clustered together to accomplish the locality requirements along the *y*-axis. As a result, 15 × 15 pixels sized images are generated and fed into the deep convolutional neural network. To the best of our knowledge, a 2-D representation of financial technical analysis time series data and feeding it as the input for a 2-D image classification based deep CNN, namely CNN-TA, for a financial trading system is novel; since it has not been used

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not only for any trading system, but also in any financial prediction model the way we have proposed here. Performance evaluation indicates, such an approach actually performs remarkably well even over long periods. The proposed model outperformed Buy & Hold, common technical indicator based models, most widely used neural network, namely MLP, and the state of the art deep learning time series forecasting model, namely LSTM, on short and long out-of-sample periods. Even though, this is probably one of the first attempts using such an unconventional technique, we believe, the proposed model is promising. Moreover, parameter optimization and model fine tuning might even boost the performance even further.

The rest of the paper is structured as follows: After this brief introduction, the related work is presented in Section 2 followed by the model features described in Section 3. The implementation methodology is given in Section 4 where the data, model and the algorithm details are explained. Financial evaluation of the proposed model is analyzed in Section 5. Finally we conclude in Section 6.

## 2. Related work

### 2.1. Time series data analytics

In literature, there are different adapted methodologies for time series data analysis. These can be listed as follows: statistical and mathematical analysis, signal processing, extracting features, pattern recognition, and machine learning. Statistical and mathematical analysis in time series data can be achieved through determining the mathematical parameters such as maximum, minimum, average, moving average, variance, covariance, standard deviation, autocorrelation, crosscorrelation and convolution in the sliding window [6]. Curve fitting, regression analysis, autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), Bayesian analysis, Kalman filter methods are the mathematical methods that are generally used to analyze and forecast time series data in literature [7]. In addition, signal processing methods such as Fourier and wavelet transforms are used to analyze the time series data. Discrete Fourier transform (DFT), discrete wavelet transform (DWT), piecewise aggregate approximation (PAA) are also used to analyze time series data to extract features and find the similarities within the data [8]. Unlike traditional approaches, machine learning models are also used in analyzing time series data and predictions. Machine learning algorithms that are mostly used in time series data analytics are listed as follows: clustering algorithms [9], hidden Markov models [10], support vector machines (SVM) [11–13], artificial neural networks (ANNs) [14–17] self organizing maps (SOM) [18–20].

Time-series forecasting is implemented in various fields such as wind speed forecasting, stock price forecasting, electricity demand forecasting, pollen concentrations forecasting in airborne, human activity recognition forecasting, user behavior forecasting in internet of things applications, and so on. In literature, there are many applications and usage of machine learning on time series data analytics. Arizmendi et al. [14] used ANN in the time series data to predict pollens concentrations in the atmosphere and observed that predictions using ANN performed better than traditional approaches. Srinivasan et al. [15] used a four-layer feedforward ANN to estimate the hourly electrical charge in the power system. Kaastra and Boyd [16] developed an eight-step procedure involving an ANN model in predicting financial and economic time series data. Bezerianos et al. [21] estimated and evaluated the pulse rate change with radial-based function neural network (RBF). Li et al. [22] used a back-propagation artificial neural network (BPANN) and autoregressive (AR) models for estimating the highest values of vibrations in high buildings, which are difficult to measure with instruments. Guan et al. [23] analyzed the sensor data acquired by 40 motion sensors on human legs, by using ANN. With this mechanism, human activities (running, walking, lying, jumping, etc.) are estimated with 97% accuracy. Choi et al. [24] used ANN in the learning part of smart home system. Mohandes et al. [13] applied SVM and MLP on time varying wind speed data and compared the results. In the field of medicine, Morchen [19] used SOM for the extraction of patterns of muscle activities and for the identification of extracted patterns. An et al. [25] proposed a new electricity demand forecasting model called "MFES" that uses feed forward ANN. In their proposal, after application of filtering and seasonal adjustment process, ANN is used to predict future demand. In finance, different machine learning models are also used for forecasting future values. Next subsection covers the financial time series analytics methods in literature.

### 2.2. Financial time series data analytics

For stock market forecasting, traditional machine learning models have been quite popular. Some researchers directly implemented time-series forecasting based on the financial data, whereas others used technical and/or fundamental analysis data in order to achieve good forecasting performance. ANN, genetic algorithms (GA), fuzzy rule-based systems, as well as hybrid models are among the preferred choices.

Cavalcante et al. [1] surveyed all forecasting model approaches such as ANN, SVM, hybrid mechanisms, optimization and ensemble methods in their survey. Besides, Krollner et al. [26] reviewed machine learning based stock market forecasting papers in different categories such as ANN based models, evolutionary & optimization techniques, and multiple/hybrid methods. Most of the researchers used ANN models to forecast stock market index values [27,28]. Chen et al. [29] proposed a neural network model for forecasting and trading the Taiwan Stock Index. Guresen et al. [30] evaluated the neural network models in particular multi-layer perceptron (MLP) and dynamic ANN to predict NASDAQ stock index. In addition, Sezer et al. [31] proposed an ANN that uses the financial technical analysis indicators (MACD, RSI, Williams%R) to predict Dow30 stock prices turning points. Dhar and Mukherjee [32] used a classical three layer MLP network in their studies to estimate the closing values of the Indian Stock Exchange stocks. Researchers also studied various combinations of network parameters (number of neurons in the input and hidden layers, learning rate) to find the best MLP configuration. Vanstone et al. [33] used MLP to create a system that can give buy/sell points for the Australian market. Fundamental analysis data (price earning ratio, book value, return on equity (ROE) and dividend payout ratio) are used as inputs for MLP.

In addition, genetic and evolutionary approaches are used to predict stock prices and trends [34,35]. Kwon and Moon [36] proposed a RNN with GA optimization to forecast stock values. They tested their proposals with 36 companies in NYSE and NASDAQ from 1992 to 2004. Sezer et al. [37] proposed a deep MLP approach with GA optimization to predict Dow Jones 30 companies' stock prices. In their studies, RSI parameters (buy value, buy interval, sell value, sell interval) are determined with GA. Best points are used as training data set in deep MLP. Evans et al. [38] used a GA to correct prediction errors and find the best network topology of MLP for forecasting foreign exchange (FOREX) data. Huang [39] used GA to optimize the support vector regression (SVR) parameters and to find which stock should be used as input for method. Pulido et al. [40] used particle swarm optimization (PSO) for the MLP network structure parameters (number of hidden layers and number of neurons in layers and linkage) for time series prediction of the Mexican Stock Exchange.