Difficulty of Learning within Deep Learning for Stock Trading Action Prediction Due to Data Variances

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Abstract. The abstract should summarize the contents of the paper in short terms, i.e. 150-250 words.

Keywords: First Keyword, Second Keyword, Third Keyword.

1 Introduction

The application of Artificial Intelligence models in the domain of Financial technology, or more commonly known as Fintech, has been widely studied by researchers throughout the years. Over the past few decades, researchers have proposed a variety of computational intelligence models for Fintech tasks such as: support vector machines (SVMs)[1, 2], genetic algorithms[3], and Deep Learning models[4, 5]. With Deep Neural Networks gaining traction in the field of Artificial Intelligence, the use of Deep Neural Networks, or Deep Learning models, for Fintech applications has become more prevalent in recent years. Deep Learning models have been used for Fintech applications such as Algorithmic Trading[6], Financial Risk Assessment[7], as well as Cryptocurrency and Blockchain Studies[8].

In this paper, we first present the survey findings of past research conducted on Deep Learning(DL) implementations for Fintech applications, with focus on the utilization of DL models for Fintech tasks surrounding the trading and investing of financial instruments such as Stocks, or Forex. Some of these tasks include the prediction of next-day stock prices, stock portfolio management, valuation of assets, etc. Our paper aims to highlight the various different DL methodologies employed in past papers for Algorithmic Trading applications, and their key findings.

From the survey of past research conducted on DL implementations for Algorithmic Trading applications, we discovered that past research often do not take into consideration if the data used to train the DL models, fully captured the variations and economic trends present in stock data necessary for learning the task of Algorithmic Trading, and minimal work has been done to study the effects of variations present in the training data on the ability of the models to learn the task of Algorithmic Trading. Therefore, in the subsequent part of this paper, we will present the findings of our study on the effects of introducing different variations to the data used to train DL models, towards the ability of these models to learn the task of stock trading action prediction. The variations were introduced in a manner that allowed us to better understand how various variations present in the training data affect the ability of DL models to learn the task of stock trading action prediction, taking into consideration stock market specific factors likely to affect stock prices and movement. The aim of our study is to better understand the effects of introducing certain types of data variation on the ability of DL models to learn the task of stock trading action prediction. The results of our study will be of assistance towards future studies conducted on the use of DL models for Algorithmic Trading, by providing insights on how to improve the training of DL models for Algorithmic Trading tasks with the use of training data induced with variations beneficial towards helping the models better overcome the difficulty of learning.

2 Survey of Related Work

In this section, we review past research conducted on DL implementations for Fintech applications, their main findings, as well as their significance towards the study of Deep Learning for Fintech applications. The survey then further focus on DL implementations for Algorithmic Trading applications. In addition, we will also review past research conducted on how different training data characteristics affects the ability of DL models to generalize and learn the task given to them.

2.1 Deep Learning for Fintech Applications

Before the advent of DL, traditional Machine Learning(ML) models such as SVMs, have been popular in financial applications research, where they have produced favorable results[9], even outperforming shallow Artificial Neural Networks (ANNs)[9, 10].

In more recent years, the use of DL models has gained traction in the field of Fintech. DL is a specific type of ANN that consists of multiple layers, where each layer provides dissimilar contributions, such that the overall network performs better than its shallow counterparts. DL architectures utilized in past papers include but not limited to: Deep Multilayer Perceptron (DMLP), Convolutional neural networks (CNN), Recurrent neural network (RNN), Long short-term memory (LSTM), Restricted Boltzmann Machines (RBMs), and Deep Belief Networks (DBNs). DL models have shown potential for financial time-series prediction, with results surpassing shallow ML models such as shallow MLP(ANN with only one hidden layer), SVM, K-nearest neighbors[11], which can be attributed to the ability of DL models in handling the non-linear, high-frequency polynomial components of financial time-series data. Past papers also provided evidence that DL models perform better than other forms of ML algorithms in other financial applications such as, Bankruptcy Prediction[12], and Credit Risk Assessment[13]. In Table 1 below, we summarize the findings of past research conducted using DL models for various financial applications in general.

Table 1. Deep Learning Studies on Financial Applications

Ref.	Data set	Publication Year	Data Features	ML Architectures Studied	Financial Application	Key Findings
[12]	Nikkei NEEDS FinancialQUEST	2018	Financial Ratios	CNN,CART, LDA, SVM, MLP, AdaBoost	Bankruptcy Prediction	Application of CNN to bankruptcy prediction, using financial ratios represented as grayscale images for training, outperforms representative conventional methods using CART, LDA, SVM, MLP, AdaBoost and Altman Z-Score.
[13]	Kaggle Credit Dataset	2017	Personal financial variables	Logistic Regression(LR), ANN, SVM, DNN	Credit Risk Assessment (CRA)	DNN models are able to achieve higher classification accuracy, true negative rate, G-mean higher than that of LR, ANN and SVM, with true positive rate slightly lower than ANN for CRA. Proving the superiority of DNN for CRA when compared against other ML algorithms.
[14]	CRSP, COMPUSTAT, TAQ	2019	Financial Ratios	LSTM, MLP, LSTM-MLP Hybrid	Stock Returns Prediction	Provided evidence that 2-layer LSTM and LSTM-MLP hybrid model performs better than MLP-only, hand-engineering momentum, and short-term reversal double sort trading strategy, for predicting stock returns.
[15]	Bucharest Stock Exchange	2019	Stock trading Indicators	LSTM, CNN	Stock Price Prediction	In a trading simulation, LSTM has higher gain in terms of the sum of money earned, CNN has higher number of times gained than lost for the 25 companies watched, HC(hill climbing)-LSTM reaches a better value for the annualized return, and HC-CNN leads to a better sharpe ratio.
[16]	S&P 500 index	2017	Stock Returns	LSTM, RF, LR, DNN	Stock Returns Prediction	LSTM networks outperform memory-free classification methods such as, standard DNN, and traditional ML models such as Random Forest(RF) and LR.
[17]	FRED database & S&P Global Market Intelligence	2018	Financial Indicators	LR, CART, RF, SVM, NN, DL, XGBoost	Forecasting Stock Market Crisis	Deep Neural Networks consistently outperform the rest of the employed approaches (LR, CART, RF, SVM, NN, XGBoost). In addition, provide evidence that nonlinear methods are better in capturing global shocks as well as isolated crash events.
[18]	KSE-100 Index, Financial News, Oil, FX, Gold, Silver	2016	Oil, Gold, Silver, FX rates, News, Index Price	Single Layer Perceptron (SLP), MLP, RBF, SVM	Stock Market Prediction	Provide evidence that MLP is more efficient in predicting market performance as compared to SLP, RBF, and SVM when verified against the test dataset.
[19]	iShares MSCI United Kingdom Close Price	2019	iShares MSCI United Kingdom Close Price	SVM, RF, ANN, LSTM	Stock Price Prediction	The results of the study show that the LSTM recurrent network functions better in prediction of the close price of iShares MSCI United Kingdom than the other methods (SVM, RF, ANN).

[20]	NSE Listed Companies Data	2017	Stock Price Data	RNN, LSTM, CNN	Stock Price Prediction	For stock price prediction, the research results shows that CNN architecture is capable of identifying the changes in stock trends and CNN is identified as the best model out of the three models used in the paper.
[21]	US SEC Filings	2018	10-K Financial Factors	CNN, SVM, RF	Financial Text Classification	For classifying banks as failed or non-failed from text data, the paper find that CNN does well on this task, with an accuracy of 96.8%.

2.2 LSTM for Fintech Applications

Long Short-Term Memory (LSTM) networks is a type of DL recurrent neural network capable of learning order dependence in sequence prediction problems. LSTMs were developed to deal with the vanishing gradient problem that can be encountered when training traditional RNNs. LSTMs are able to remember both short term and long term values in the network which makes them well-suited for classifying, processing, and making predictions based on time-series or sequential data. Therefore, they are often used in Financial applications research involving sequential data such as financial text, stock technical indicators time-series data etc. In Table 2 below, we summarize the findings of past research conducted using LSTMs for various financial applications in general.

Table 2. LSTM Studies on Financial Applications

Ref.	Data set	Publication Year	Data Features	ML Architectures Studied	Financial Application	Key Findings
[22]	Bombay Stock Exchange Index, Tech Mahindra stock	2018	Stock Close Prices	LSTM, DNN	Stock Price Prediction	The research results shows that the LSTM and DNN models performed well in making daily predictions, however, the LSTM RNN outperformed the DNN in making weekly predictions.
[23]	Historical Stock Data for China Stock Market	2015	Stock Technical Indicators, Market Index	LSTM	Stock Returns Prediction	The research results revealed that normalization was very useful for improving LSTM prediction accuracy, and that the inclusion of market index price improves the model accuracy, consistent with the notion that the market indexes affect stock return.
[24]	NYSE TAQ database	2019	Stock Prices	LSTM ensemble, LR	Stock Market Classification	The research shows that an ensemble model that combines multiple LSTM neural networks through a performance-evaluated weighting method outperformed equally weighted and best model LSTM ensemble methods, as well as lasso and ridge logistic regressions models.
[25]	German DAX30 Blue-Chip Stock BMW	2019	Stock Technical Indicators	LSTM, Decision Tree (DT), SVM, KNN	Stock Trading Prediction	The research shows that LSTM network outperforms all benchmarking (passive, RSI, MACD and MLC) trading strategies for automated stock trading.
[26]	Shanghai composite index, PetroChina Stock	2019	Stock Technical Indicators	LSTM, RNN, Associated Neural Network	Stock Price Prediction	The research proposed a multi-value associated network model of LSTM-based deep-recurrent neural network to predict multiple prices of a stock. Experiments in the research show that the average accuracy of the Associated Net model is better than that of the LSTM and RNN models.
[27]	Dow Jones Industrial Average	2018	Stock Technical Indicators	LSTM, Feed-Forward (FF) DNN	Stock Price Prediction	The research provided evidence that LSTM models perform better than Feed-Forward (FF) DNN models for stock price prediction. .
[28]	S&P500 Index	2018	Stock Closing Price	LSTM, Bidirectional LSTM, MLP	Stock Market Prediction	The results showed that Bidirectional LSTM and stacked LSTM networks produced better performance for predicting short-term prices as opposed to the long-term prices. The results also showed superiority of DL methodology over shallow NN.
[29]	Financial Indexes, FX rate, stock & gold prices	2018	Financial Technical Indicators	LSTM, SVM	Trading Financial Indices	The research experiments results shows that LSTM is advantageous in most of the scenarios against GA-SVR for modelling and trading financial indices.

[30]	Bitcoin	2018	Crypto Currency Technical Indicators	LSTM, RNN	Crypto Currency	The research shows that DL models such as RNN and LSTM are effective for Bitcoin prediction, with LSTM showing better performance for recognizing longer-term dependencies.
[31]	Shanghai Composite Index, Shenzhen Component Index, CSI 300, SSE 50	2019	Financial Technical Indicators, Implicit Image Features of Index Data	LSTM	Prediction of Index Trend	The paper extracts implicit features of the graphical representation of index data and calculate the cosine similarity between other implicit features of its historical images, combine the image similarity feature other data features as the input variables of the LSTM network model, and proved that the prediction model with image similarity feature can get better performance.
[32]	China's A-Share Market Stocks	2018	Stock Technical Indicators	LSTM, MLP, SVM, RBM	Stock Returns Ranking	The paper demonstrates that their proposed method of Stocks Returns Ranking using LSTM outperforms other state-of-the-art techniques for stock selection strategy.
[33]	CSI 603899 Index	2018	Stock Technical Indicators	LSTM	Stock Trend Prediction	The paper uses a LSTM network to extract feature value and analyze the stock data and is able to achieve a 72% prediction accuracy for predicting next-day stock trend.
[34]	Shanghai 50 ETF	2019	Stock Options Data	LSTM, RF, LSTM-SVR Hybrid	Quantitativ e Investment Strategies	From the experiments conducted for the paper, the performance of LSTM model is generally better than RF model for asset price prediction. In addition, the paper also provided evidence that the accuracy of LSTM-SVR models are much higher than that of the LSTM model when predicting a relatively stable market.
[35]	Nasdaq Nordic	2017	Price and Volume Data in LOB	LSTM, MLP, SVM	Price Movement Prediction	The paper shows that the proposed LSTM method utilized in the paper performs significantly better than other techniques, such as Linear SVMs and MLPs, when trying to predict short term price movements.
[36]	IBovespa Index	2017	Stock Technical Indicators	LSTM, RF, MLP	Price Movement Prediction	The paper shows that when compared to the other machine learning models, the LSTM model displays considerable gains in terms of accuracy.

2.3 CNN for Fintech Applications

Convolutional Neural Network (CNN) is a type of Deep Neural Networks, most commonly applied to analyzing visual imagery Convolutional networks are inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the human visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field. In Table 3 below, we summarize the findings of past research conducted using CNNs for various financial applications in general.

Table 3.CNN Studies on Financial Applications

Ref.	Data set	Publication Year	Data Features	ML Architectures Studied	Financial Application	Key Findings
[37]	NYSE ETFs	2017	Stock Technical Indicators	CNN	Stock Trend Detection	The paper proposes the use of a 2D CNN model for Stock Trend Forecasting, which utilizes 2-D images generated from technical analysis time series values as input features. The results indicate that the proposed model significantly outperforms Buy & Hold Strategy as a trading strategy.
[38]	Poloniex Crypto Currencies	2017	Asset Historical Prices	CNN, LSTM, RNN	Financial Portfolio Manageme nt	The paper shows that Deep Reinforcement Ensemble of Identical Independent Evaluators (EIIE) topology framework that utilizes CNN outperforms frameworks that utilizes LSTM and RNN, in terms of portfolio value for Portfolio Management.
[4]	Dow 30 Stocks & ETFs	2018	Stock Technical Indicators	CNN	Algorithmi c Trading	The paper utilized a 2D CNN model for developing an algorithmic trading system, utilizing financial time series data converted into 2D images as input. The results indicate their

						approach performs very well against Buy & Hold and other models over long periods of out-of-sample test periods.
[12]	Nikkei NEEDS FinancialQUE ST	2018	Financial Ratios	CNN,CART, LDA, SVM, MLP, AdaBoost	Bankruptcy Prediction	Application of CNN to bankruptcy prediction, using financial ratios represented as grayscale images for training, outperforms representative conventional methods using CART, LDA, SVM, MLP, AdaBoost and Altman Z-Score.
[39]	S&P 500 Minute Data	2019	Stock Technical Indicators	CNN, ANN, SVM	Stock Price Prediction	The results of the paper's empirical experiments demonstrate the potential usefulness of CNNs using input images for Stock Price Prediction by outperforming ANN and SVM models.
[40]	DNB Mortgage Customers Data	2018	Personal financial variables	CNN, LR, MLP, RF	Mortgage Default Prediction	The paper's experimental results shows that their best performing CNN with two convolutional and two fully connected layers achieved an AUC of 0.915 for Mortgage Default Prediction, outperforming LR, MLP, RF models.
[41]	FTSE 100	2018	Stock Historical Prices	CNN	Investment Decision Strategy	The paper propose a Convolutional AutoEncoder (CAE) based model for investment portfolio construction, with experimental results of portfolio outperforming the FTSE 100 index and many well-known funds in terms of total return.
[42]	Various Composite and Market Indices	2019	Financial Technical Indicators	CNN, ANN	Stock Market Prediction	The paper's experimental results shows that their proposed models that utilizes 2D and 3D CNN statistically outperform baseline algorithms.
[43]	Taiwan Stock Index Futures	2018	Price Data Image Representation	CNN	Intelligent Arbitrage Trading System	Utilizing time series visualization method and CNN, the paper's intelligent trading system is able to capture the arbitrage signal and enhance profitability with up to 67% accuracy and improves up to 15% accuracy in the comparison of traditional rule-based strategy.
[44]	London Stock Exchange	2017	Limit order book state, trades, buy/sell orders	CNN	Financial Forecasting	The paper showed that their CNN based model works well in solving financial forecasting problems and DL seems is a potential analysis method and is applicable for high-frequency market data.
[45]	German Credit Dataset	2018	Customer Personal Variables	CNN, MLP	Credit Scoring	The paper's experimental results shows that the CNN approach outperforms the MLP approach with the CNN model having better evaluation scores as compared to the MLP model.
[46]	Technical, Economic Data	2017	Stock Technical Indicators	CNN	Financial Time Series Forecasting	The paper's experimental results shows that their CNN model is able to achieve an accuracy of 65% when forecasting the next month price direction and 60% for the next week price direction forecast.
[47]	Nasdaq Nordic	2017	Price and Volume Data in LOB	CNN MLP, SVM	Stock Price Forecasting	The paper shows that the proposed CNN model outperforms SVM and MLP models for stock price forecasting.

2.4 Effects of training Data Variances on Deep Learning

From the survey of past work done on DL implementations for Fintech applications, we notice that past research on similar financial applications often use differing data features for their DL models and do not take into consideration if the data used to train the DL models consider variance in the training data that may affect the learning of the models. This is especially prominent for research regarding DL implementations for Algorithmic Trading tasks where different research utilize differing data features and data representation for their DL models.

Past research regarding the use of DL for other applications have shown that the characteristics of the training samples in the dataset used to train DL models affect the ability of the models to learn the tasks they are given. In the ObjectNet paper by Barbu et al[48], when DL object detectors are tested on the ObjectNet dataset with real-world objects imaged in many rotations, on different backgrounds, from multiple viewpoints, the object detectors show a 40-45% drop in performance. Past work also proves that CNN for image classification can easily fit a random labeling of the training data[49], and that CNN models trained on the ImageNet dataset are strongly biased towards recognizing textures rather than shapes[50]. In another research regarding the use of LSTM models for language processing[51], the experiments provided evidence that the distribution of lengths of sequences in the training set affects the performance of the models.

In addition, there is evidence from past research that the quality of the training data used to train DL models is more important than the quantity of the training samples. A study regarding ImageNet pre-training[52] shows that ImageNet pre-training may not be required as models trained from scratch do not necessarily perform worse off, and that training models using data more relevant to the task is more important than training with more data. Similarly, a research on Word Sense Disambiguation with LSTM[53] showed that they are able to achieve similar results for a reproduction study with much less data than the study they are reproducing. This is also the case in another research on rainfall–runoff modeling using LSTM[54] which proves that the LSTM model is efficient even when using 3 years of data compared to its benchmarked model which require 9 years for similar results.
In the paper by Liang et al[55], results suggests that variances of visual objects in images affects the amount of learning or information gained by the Deep Learning models significantly. Therefore, there is a possibility that the same observation applies for the use of Deep Learning models for Fintech tasks, where data variance present in financial data affects the ability of Deep Learning models to learn various Fintech tasks. In Table 4 below, we highlight the findings of past research conducted using DL models for various financial applications which shows that data variance or data representation affects the performance of DL models.

Table 3.CNN Studies on Financial Applications

Ref.	Data set	Publication Year	Data Features	ML Architectures Studied	Financial Application	Key Findings
[12]	Nikkei NEEDS FinancialQUEST	2018	Financial Ratios	CNN,CART, LDA, SVM, MLP, AdaBoost	Bankruptcy Prediction	In the paper, a numerical evaluation revealed that allocating neighboring pixel positions to highly correlated financial ratios is more appropriate for their research than placing them at random for the training images used to train the CNN model.
[56]	Taiwan Stock Index Futures & Options	2020	Future and Options Transaction Data	LSTM	Option Trading Strategy	The experimental results in the paper show that different training set lengths will give different prediction results and cause different position sizes; the final profit and loss results are also different.
[57]	SPY Ticker Data	2019	Stock Technical Indicators	CNN, LSTM	Stock Price Forecasting	The paper utilizes different representations of financial time series data for forecasting stock prices and the experimental results shows that models trained on some representations of data perform better than others with the same data used.
[58]	NYSE TAQ Database	2016	Stock Technical Indicators	DNN	High Frequency Trading	The paper provided evidence that adding time as an input feature allows it to differential atypical events and small data window sizes are able to better explain future prices.
[31]	Chinese Market Indices & Composites	2019	Technical Indicators, Image Features of Index Data	LSTM	Prediction of Index Trend	The paper proved that the prediction model with image similarity feature can get better performance.
[59]	Tokyo Stock Exchange & Osaka Exchange	2018	Analyst Reports	CNN, LSTM, Naïve Bayes	Stock Returns Prediction	The paper provided evidence that the inclusion of topic tones of analyst reports improves the performance of the DL models for predicting stock returns.
[60]	NASDAQ Data	2019	Limit Order Book Data	LSTM	Financial Price Formation	The paper provided evidence that partitioning training data into sectors or categories such as large/small tick stocks, do not improve training results, while inclusion of price and order flow history improves forecasting performance.

Sample Heading (Third Level). Only two levels of headings should be numbered. Lower level headings remain unnumbered; they are formatted as run-in headings.

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