2018 IEEE 20th International Conference on High Performance Computing and Communications; IEEE 16th International Conference on Smart City; IEEE 4th Intl. Conference on Data Science and Systems

Comparing Technical and Fundamental indicators in stock price forecasting

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***Abstract*— This paper evaluates whether Fundamental or Technical analysis is better when forecasting stock prices with machine learning models; further, it considers whether combined use of the two approaches is beneficial. Tests run on 140 companies from the S&P 500 indicate that models using indicators based on Fundamental analysis outperform those using indicators from Technical analysis with the level of outperformance varying across industries. Furthermore, in over 95% of cases, using Combined indicators results in lower RMSE compared to using Fundamental or Technical indicators alone.**

Keywords—Supervised Learning; ANN; SVR; Technical Analysis; Fundamental Analysis; Stock Price Forecasting

I. INTRODUCTION

In general, stock prices are determined by forces of supply and demand in the stock market which in turn is driven by traders' decisions to buy or sell a company's stock [1]. The Efficient Market Hypothesis (EMH) states that stock prices reflect all the available information in such a way that it is not possible to profit in a sustainable way by forecasting future stock prices [2-3]. Thus, EMH believes that stock prices follow a random walk [2-3]. In contrast, the Adaptive Market Hypothesis (AMH) states that stock prices are predictable and can be profited from [4].

Technical analysis and Fundamental analysis are the two main schools of thought that finance practitioners subscribe to when making trading decisions and predicting stock prices [1, 6, 7]. Although these approaches have developed as competing, finance practitioners have recently combined both indicators [1,8,14] to obtain increased benefit [9].

Stock price forecasting based on machine learning methods has proven to be both popular and successful [10-11]. However, surveys have shown that much work applying machine learning to stock price forecasting has focused on utilizing Technical Indicators only, and has downplayed Fundamental Indicators [10-13]. Thus, there appears to be a disconnect between the approach taken by finance practitioners and that taken by researchers with respect to the type of inputs that should be utilized to generate a forecast. Furthermore, the focus of machine learning researchers with regards to financial forecasting has been to a large extent on next day forecasting of stock indices, as opposed to individual stocks.

To address this lacuna, this paper presents a set of experiments which compares the performance of models using Technical, Fundamental indicators, and their combination when forecasting change in the stock price of individual companies over a 126 days and 252 days horizon. The outcome is an analysis of the benefits of using Technical and Fundamental analysis-based indicators together when forecasting stock prices with machine learning models.

The remainder of this paper is organized as follows: Section II reviews trading and investment analysis approaches and related machine learning techniques; Section III describes the experimental setup; Section IV discusses results; finally, Section V presents conclusions.

II. BACKGROUND

A. *Technical versus Fundamental Analysis*

Technical analysis uses the historical stock prices of a company and trading volume information in both deciding what the stock price will be and making a trading decision [1,7]. Fundamental analysis calculates the expected stock price based on a detailed study of the underlying business drivers (profitability, operational efficiencies, managerial expertise, etc.) related to the company, its products, its industry and the general economy [1,9]. Although, from a philosophical perspective, "Technical analysts and Fundamental analysts are diametrically opposed to one another", these approaches can be complementary [6-9]. Finance researchers have investigated whether Technical, Fundamental or a Combined approach was more effective. Work in [15] compared predictive performance in one day ahead forecasting in the Egyptian stock market of Technical indicators (lagged prices) and Fundamental indicators (Book Value per share (BVPS) and Earnings per Share (EPS)). When the one day price was being forecast Technical indicators outperformed (RMSE of 69.9 vs. 82.5) Fundamental indicators, however, when one day ahead return was being forecast, Fundamental indicators outperformed (1.30 vs. 1.38) Technical ones. Work in [16] showed that using Fundamental indicators (components making up the FSCORE which is a ranking system using numerous financial ratios to indicate the financial strength of the company) to complement Technical indicators has outperformed (information ratio of 0.1845 versus 0.1335) a momentum strategy using only Technical indicators, when the investment horizon is 6 months. Similarly, work in [14] tested whether combining Fundamental and Technical analysis gave statistically significant better prediction for stock values compared to using only

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DOI 10.1109/HPCC/SmartCity/DSS.2018.00262

Fundamental analysis factors (Book value and Earnings Per Share) or Technical analysis indicators (momentum strategies) in isolation. The tests found that Fundamental analysis (Adjusted r-square of 0.7629) and Technical analysis (Adjusted r-square of 0.7546) were effective methods of share price valuation and that the combination (Adjusted r-square of 0.7686) was the best predictor of the three approaches. Furthermore, as pointed out in [14], there have been many documented cases in the foreign exchange (Forex) market of the combined use of indicators by market participants [17-18]. This suggests that both approaches can coexist and furthermore that their combination may be valuable – this paper seeks to exhaustively evaluate this suggestion.

B. *Machine learning methods in stock price forecasting*

1) *Inputs*

The type of inputs used in forecasting stock prices are, to a large extent, dependent on the underlying investment analysis approach: Fundamental or Technical Analysis. Historically, work using machine learning methods has shown clear preference towards using Technical indicators as inputs [10-13]. This trend of over-reliance on using Technical indicators as inputs is attributed to the fact that machine learning approaches depend on large volumes of data and that Technical indicators were more available and easily accessible, especially on a daily basis, whereas Fundamental indicators became available on a less frequent basis (quarterly or yearly) and as such were much less preferred. Most studies reviewed in the surveys [10-13] used Technical indicators only, a few used Fundamental indicators only, and a handful looked at combining the two to an extent. Work in [19] used Technical Indicators, Fundamental indicators and their combination as inputs for forecasting the stock direction for companies in the Indian stock market. Bothe standard and enhanced (optimized through Genetic Algorithms (GA)) Neural Networks (NN) and Support Vector Regression (SVR) models were used to generate the forecasts. Results indicated that the enhanced ANN model using a Combined indicator set achieved the highest accuracy rate (80.51%) followed by the plain SVM model with Technical indicators with an accuracy rate of 79.4%. The study included only 25 companies from an emerging market and did not necessarily provide a review of the results on a company level. In predicting the direction of Apple's stock price for the next day forecasting models (ANN, SVR, Decision Trees (DT)) using various data sources were utilized by [20]. The data sources included Market data (Financial time series data and P/E ratio), technical indicators, Wikipedia Traffic, and Google news counts. The performance of the models using each data source individually and in a combined manner were compared. The best performing model used all the data sources and achieved a hit ratio of 85% with an Area Under the Curve (AUC) of 0.874. Though the study aimed to predict the one day ahead direction change in the stock price of only one company, it showed that utilizing a number of data sources improved prediction accuracy. In addition to over-reliance on solely Technical indicators, the survey papers [10-13] show that most studies considered one, or only a few days ahead forecasting, and focused on stock market index forecasting over individual company forecasting.

2) *Supervised Machine Learning Methods:*

In terms of a broad categorization, the majority of machine learning approaches using labeled data and supervised learning methods tend to fall into three main groups [10]: models that use a single machine learning technique, models that use a hybrid combination of machine learning techniques with optimization techniques, and models that are an ensemble of various single models. ANN and SVR are listed as successfully deployed machine learning methods [10-13, 21].

C. *Research Questions*

Section II suggests a requirement to study individual stock price forecasting using supervised machine learning methods with forecasting horizons longer than next day, and which investigates impact on forecasting performance of using Technical, Fundamental input sets and their combination. This analysis seeks to answer the following questions:

- Are Fundamental or Technical analysis-based indicators more relevant when forecasting a stock's price with a horizon of six-months or a year using machine learning based methods?
- Does forecasting performance improve if both types of indicators are used together?

III. EXPERIMENT SETUP

Experiments were setup to predict the percentage change in a selected company's stock price in the future (252 and 126 trading days out), using ANN and SVR forecasting models exposed to Technical indicators, Fundamental indicators and their combination. For the forecasts generated, RMSE was calculated and captured by comparing against the actuals. The experiments were implemented using R [22] and the open source data mining tool WEKA [23] and involved 140 companies selected out of the S&P 500 index[1], which represents 80% of US equities market by capital. Companies were selected based on having sufficient data available for a period of time (identified as January 1996-December 2015) which ensured incorporation of times where the stock market exhibited a variety states (turbulences, ups and downs, etc.).

A. *Input Data:*

For each company two sets of financial data, Technical and Fundamental, were collected and a daily financial timeseries data was created. Finally, these two sets were merged by using the dates to create a combined data set.

1) *Technical Indicators:*

For each company in the study end of day stock price data (Open, High, Low, Close, Volume) was retrieved from Quandl[2] and TTR package [24] was used to generate the 10 technical indicators. To address the issue of any missing data, the average of the data from the closest available trading days was

[1] List retrieved from https://us.spindices.com/indices/equity/sp-500
[2] Price data retrieved from Quandl (https://www.quandl.com/product/WIKIP/WIKI/PRICES-Quandl-End-Of-Day-Stocks-Info)

used, as in [25]. Table I gives the list of technical indicators picked based on the coverage of Technical analysis in [1] and [26] and the parameters used (mainly defaults in [24]) in generating them where relevant.

TABLE I. TECHNICAL INDICATORS

Average True Range (ATR) over a period of 14 days.
Moving Average Convergence Divergence (MACD) with simple moving average method and 26 days & 12 days for the slow and fast periods respectively.
Money Flow Index (MFI) over a period of 14 days.
FastK and FastD values of Stochastic Oscillator using 14,3, and 3 days for FastK, FastD, SlowD respectively.
Directional Movement Index (DMI) using 14 days
Commodity Channel Index (CCI) using 20 days, and 0.015 as the constant to apply to the mean deviation.
Relative Strenght Index (RSI) using 14 days and weighted moving average.
Price Rate of Change (ROC) over 252 or 126 trading days.
The Chaikin Accumulation / Distribution (AD) line.

2) Fundamental Indicators:

Following [9], the fundamental indicators used in the experiments can be categorized into groups as follows: those relating to the performance of the company in question, those related to direct competitors, those related to the industry to which the company belongs, and macroeconomic indicators. The top two direct competitors of each company were identified based on market capitalization and picked out of the list generated by the Thomson One[3] database. The IBES[4] database contains the monthly forward looking forecasts by financial analysts on companies as well as their recommendations on buying/holding/selling the stock. The median of the monthly estimates by financial analysts for Earnings per share (EPS) 1 year and 2 years out, as well as long-term expected growth percentage in EPS, were retrieved for each company and their competitors. Missing values were dealt with by using "the last observation carry forward" method [25]. As these estimates were only available on a monthly basis, their frequency was converted to daily by dividing it by the prior day's stock closing price data.

The industry designation for the company was determined using the classification available on the Yahoo Finance website[5]. The daily index price data for each corresponding industry was retrieved from the MSCI[6] website which were transformed into moving average convergence and divergence (MACD) indicators for short term (with 26 days and 12 days) and medium term (with 126 days and 12 days). Apart from these company-related data, macroeconomic indicators[7] which were the same for all companies in the study were used. One such indicator was based on the foreign currency data, where the daily value of "Trade Weighted U.S. Dollar Index against Major Currencies" was transformed with MACD (126 days and 12 days). Another macroeconomic indicator used is the "S&P 500 futures data" whose daily value was transformed further using MACD (26 days and 12 days). The final macroeconomic indicator used was derived from the ratio of 10 year to 2 year constant maturity rate which was transformed using MACD (26 days and 12 days). Table II gives the list of fundamental indicators used.

TABLE II. FUNDAMENTAL INDICATORS

Earnings Per Share (EPS) 1 year out for the company / Price
(Earnings Per Share (EPS) 2 years out) / (Earnings Per Share (EPS) 1 year out)
EPS long term growth rate percentage
Earnings Per Share (EPS) 1 year out for competitor 1 / Price for competitor 1
Earnings Per Share (EPS) 1 year out for competitor 2 / Price for competitor 2
Daily MSCI industry index prices (MACD, 252 days, 12 days)
Daily MSCI industry index prices (MACD, 26 days, 12 days)
S&P 500 Futures prices (MACD, 252 days, 12 days)
Daily Trade Weighted U.S. Dollar Index against Major Currencies (MACD, 252 days, 12 days)
10 year to 2 year constant maturity rate (MACD, 26 days, 12 days)

The experiments use two different forecasting horizons: 126 days (i.e. 6 trading months) and 252 days (i.e. 1 trading year). The input sets used for the different horizons were adjusted to ensure that the inputs stayed relevant. For example, the Price Rate of Change (ROC) of the technical indicators is calculated for 252/126 days depending on the forecasting horizon. Similarly, Fundamental indicators would be adjusted where the formulae for industry and macroeconomic indicators would match the forecasting horizon.

B. *Additional experiment details*

Following [27], the data was split into 80% training data and 20% testing data. A standard way to ensure robustness is to use K-fold cross validation [28]. However, as K-fold cross validation requires random sampling to form the test and training sets, it is unsuited for financial time-series forecasting, in which it is important to separate testing data from training data such that the chronological order of the data is preserved [29]. This ensures that the model is not prematurely exposed to information in the training phase (look ahead bias), potentially producing unrealistically good performance. Therefore, during simulations testing data was used chronologically after training data. Following [29], to ensure robustness 10 random starting points were generated, and from each starting point available data was split into training and test sets. Each random starting point resulted in 1892 training set observations and 473 test set observations. Fig. 1 overlays the 10 random points against the overall stock market performance; it can be seen that some test

[3] Thomson One, Retrieved from Wharton Research Data Service, 2016

[4] I/B/E/S, Retrieved from Wharton Research Data Service, 2016

[5] Yahoo Finance, available at: https://finance.yahoo.com/ [Accessed September 2016]

[6] MSCI USA IMI SECTOR INDEXES, available at: https://www.msci.com/msci-usa-imi-sector-indexes [Accessed September 2016]

[7] Retrieved from Federal Reserve Economic Database (FRED), available: https://fred.stlouisfed.org/series/DTWEXM [September 2016]

start points (marked in x) occur during market up swings, and others occur during market down turns.

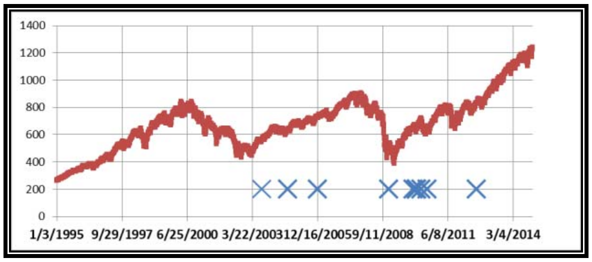

Fig. 1. Random Test points generated against backdrop of overall market

For the experiments, NN and SVR models were used as both have been successfully applied to similar problems [10-13]. To determine the parameters of the models, the training sets were further split into training and validation sets (again using the 80-20 split and preserving chronological order) and the model parameters which yielded the lowest forecasting error rate (RMSE) on the validation sets were set aside. To configure the NN model, the ideal number of hidden neurons, the learning rate and momentum rate were decided based on several tests. Work in [30] determined the number of hidden neurons by starting from a small number (the square root of the number of features) and incrementing until the performance of the model no longer improved. In determining the architecture, the scenarios shown in Table III have been run:

TABLE III. ANN PARAMETERS

# of Hidden Layers	3,5,7
Learning Rate	0.05, 0.3, 0.6
Momentum	0.1, 0.3,0.7

For the SVR, the C and gamma values have been tested over a number of different scenarios, as shown in Table IV, to determine the optimum model calibration:

TABLE IV. SVR PARAMETERS

C Values	0.125, 0.5 , 2
Gamma Value	0.01953, 0.125 ,0.5 , 1

To serve as a base case scenario, the Random Walk method has been implemented as described in [5].

IV. RESULTS

A. Experiment 1: Technical versus Fundamental

Experiment 1 compared the relative effectiveness of Technical analysis to Fundamental analysis from a machine learning lens. The forecasting performance (RMSE) of NN and SVR models using Technical and Fundamental data sets were evaluated using the test data and compared for each company in the study. Fig. 2 displays the average RMSE per industry when using different inputs for 126 days forecasting.

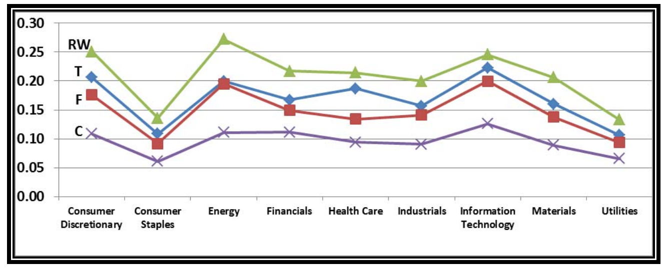

Fig. 2. Average RMSE of models using Technical (T), Fundamental (F), and Combined (C) inputs for 126 days forecasting

Comparison of Fundamental (F) and Technical (T) indicator-based models show that on average Fundamental analysis-based models (overall RMSE of 0.1464) outperform Technical analysis-based ones (overall RMSE of 0.1693) ones regardless of the company's sector. The gap between the forecasting performances of models using Technical and Fundamental indicators is narrower for firms in sectors such as Financials and Energy, whilst the gap is wider for Health Care. Fig. 3 displays the average RMSE per industry when using different inputs for 252 days forecasting, where similar trends as in the 126 days forecasting can be observed.

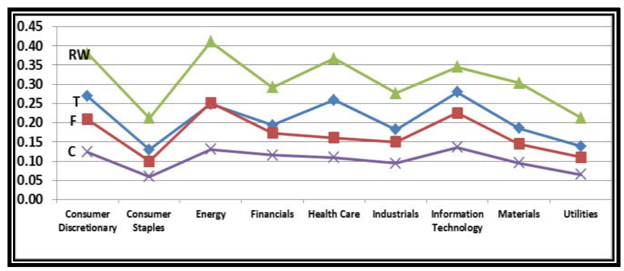

Fig. 3. Average RMSE of models using Technical (T), Fundamental (F), and Combined (C) inputs for 252 days forecasting

Regardless of whether the forecasting horizon is 126 days or 252 days, on average the Fundamental (F) indicator-based models outperform Technical (T) ones; in certain industries such as Health Care this outperformance is more pronounced. Furthermore, the machine learning models, regardless of the forecasting horizon or input used, outperform the Random Walk method. Table V shows the percentage of cases where the models using Technical (T) or Fundamental (F)-indicators were better, broken down by forecasting horizon and machine learning method (NN vs. SVR). In the majority of cases (with the exception of the NN models applied to companies in the Energy sector), regardless of the forecasting horizon and machine learning method used, models using Fundamental indicators perform better than those using Technical indicators. This outperformance is more evident when SVR is being used. When NN-based models are considered, the percentage of cases where models using Fundamental indicators outperform those using Technical indicators increases when the investment horizon increases from 126 to 252 days.

TABLE V. PERCENTAGE OF CASES WHERE FUNDAMENTAL OR TECHNICAL INDICATOR BASED MODELS WERE THE BETTER OF THE TWO

Sector	# of Comp.	126 Days				252 Days			
		ANN		*SVR*		*ANN*		*SVR*	
		T	*F*	*T*	*F*	*T*	*F*	*T*	*F*
Consumer Discretionar.	19	32	68	5	95	26	74	16	84
Consumer Staples	15	40	60	13	87	7	93	13	87
Energy	12	50	50	33	67	58	42	50	50
Financials	14	43	57	14	86	43	57	14	86
Health Care	18	11	89	-	100	-	100	-	100
Industrials	27	37	63	22	78	26	74	7	93
Information Technology	13	45	55	-	100	36	64	-	100
Materials	11	45	55	9	91	9	91	18	82
Overall	**140**	36	64	14	86	24	76	14	86

Table V indicates that forecasting models of companies in the Health Care and Information Technology sectors have a strong preference towards use of Fundamental indicators regardless of the Machine Learning method being used or the investment horizon. Performing statistical significance tests (p-value 0.05) confirmed that in all the cases where Fundamental indicator-based models outperformed the Technical indicator-based ones, the results were not observed due to chance.

To assess whether NN or SVR is better at forecasting with the given variables, the models' performances were compared. Table VI shows the percentage of cases where NN (average RMSE of 0.180) or SVR (average RMSE of 0.117) performed best. SVR dominated NN regardless of forecasting horizon or company industry, and especially when Fundamentals indicators were being used this outperformance peaked.

TABLE VI. ANN VS SVR (% OF CASES BEST)

Sector	# of Comp.	126 Days				252 Days			
		Techn.		*Fundam.*		*Techn.*		*Fundam.*	
		ANN	*SVR*	*ANN*	*SVR*	*ANN*	*SVR*	*ANN*	*SVR*
Consumer Discretionar.	19	11	89	0	100	5	95	0	100
Consumer Staples	15	13	87	0	100	7	93	0	100
Energy	12	33	67	0	100	0	100	8	92
Financials	14	21	79	0	100	14	86	0	100
Health Care	18	11	89	0	100	0	100	0	100
Industrials	27	7	93	0	100	0	100	0	100
Information Technology	13	8	92	0	100	8	92	0	100
Materials	11	9	91	0	100	0	100	0	100
Overall	**140**	0	100	0	100	0	100	0	100

Furthermore, as Fig. 4 indicates, on average the RMSE performance of the SVR models were clearly better regardless of forecasting horizon, company sector, or the input type.

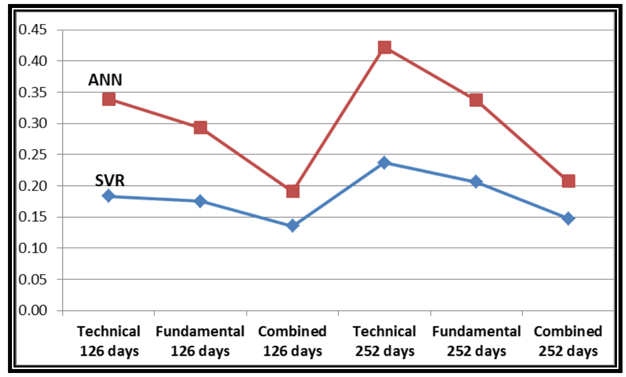

Fig. 4. RMSE of ANN versus SVR for forecasting tasks with various horizons and using Technical, Fundamental and Combined input sets

B. *Experiment 2: Combined versus Technical or Fundamental*

Another issue was whether using a combination of Technical and Fundamental analysis-based indicators would yield a better result than using either in isolation. Fig.2 and Fig.3 both show that models using the combined set outperformed (lower RMSE) models using Fundamental or Technical indicators, regardless of the forecasting horizon or business sector of the company. Performing statistical significance tests (p-value 0.05) confirmed that in 95% of all cases using NN-based models and in 98% of all cases using SVR models, using a Combined set of indicators achieved a lower RMSE than Fundamental and Technical indicator-based models, with results not observed due to chance.

In order to analyse the improvement achieved by using a combined indicator set, conditional random forest trees were applied [31-32], to generate the relative importance of features from the combined indicator set. Fig. 5 shows the average ranking of the 20 features across the 140 companies for forecasting horizon of 126 days. The ranking remained unchanged for the forecasting horizon of 252 days.

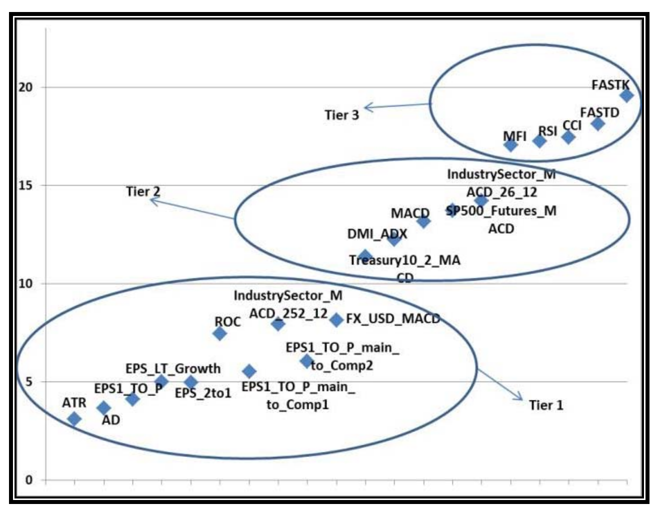

Fig. 5. Average ranking of relative importance (1 most important, 20 least important) of Combined indicators

There were 10 indicators which ranked as more important (indicated with a lower ranking) consistently for all companies; these indicators are grouped as Tier 1 in Fig. 5. From the Technical indicators, AD, ATR, and ROC are part of this group, and from the Fundamental indicators, the company-related information, competitor-related data and longer-term portion of the industry-related data, as well as the US FX rate were part of it. The fact that this group contains elements from both Technical and Fundamental input sets is indicative of the synergistic relationship that may be achieved by using both analyses together rather than separately. Furthermore, the features which ranked as least important consistently (Tier 3 on Fig. 5) were all Technical indicators, which explains why the performance of the models using Fundamental indicators outperformed those using Technical indicators. This reinforces that using only one set of indicators is not ideal and using them together yields better forecasting performance.

V. CONCLUSION

Machine learning methods have been successfully applied to learn from past movements of a company's stock price and generate future forecasts. Finance practitioners have argued there may be benefits to using Technical and Fundamental indicators together, whereas the focus of machine learning-based forecasting research has largely involved only Technical indicators.

Our experiments involving 140 companies from S&P 500 have shown that when forecasting the stock price change in 126 or 252 days, the models using Fundamental indicators (average RMSE of 0.1464 and 0.1685 respectively) outperform those using Technical indicators (average RMSE of 0.1693 and 0.2110 respectively). Experiments have also revealed that changes in stock price of companies in the Health Care and Information Technology sectors are better captured by Fundamental indicators than Technical indicators. Yet, in the case of Financial and Energy companies the better forecasting performance generated from using Fundamental indicators is less pronounced. Combining the indicators resulted in improved forecasting performance (statistically significant, p value 0.05) in over 95% of the cases. These results indicate that when possible Technical and Fundamental analysis-based indicators should be used together when forecasting stock prices using machine learning-based models.

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