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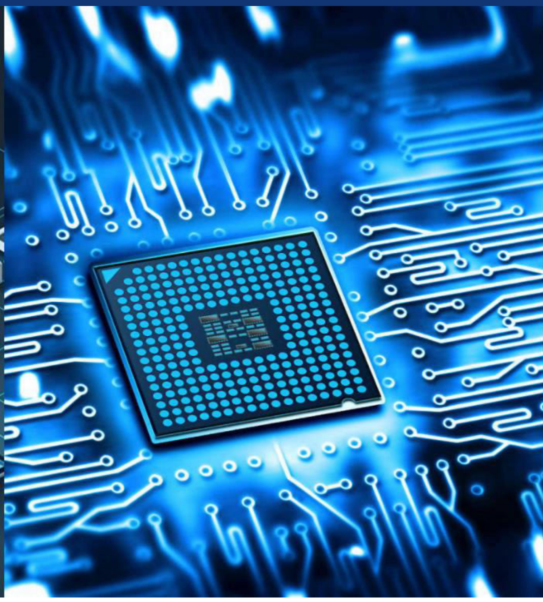


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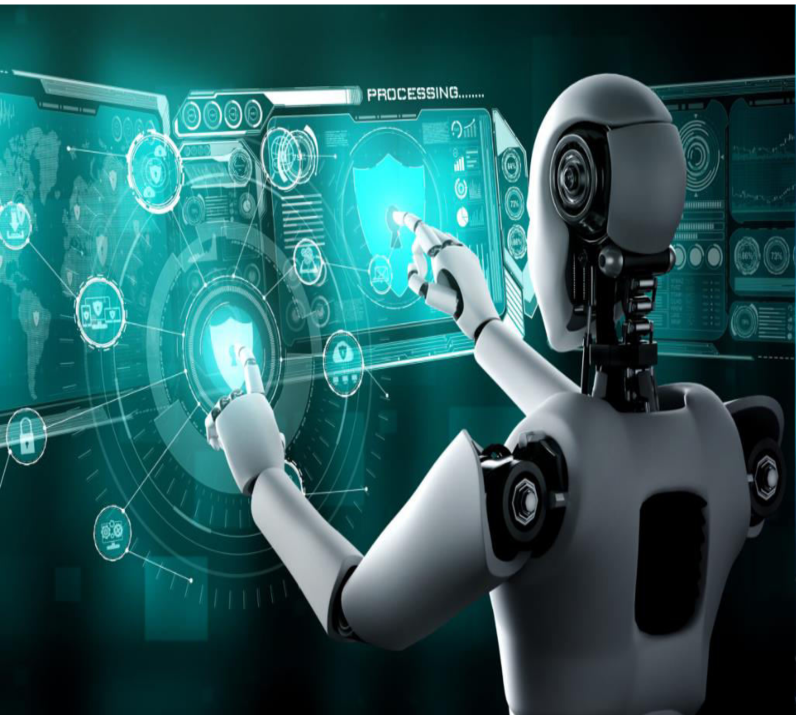

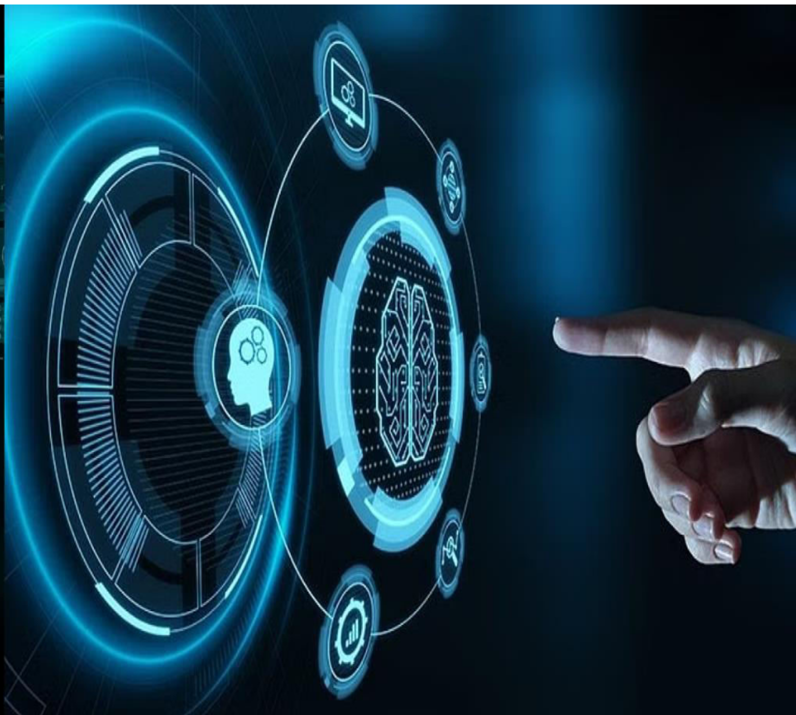

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AI – Driven Intraday Trading

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ABSTRACT: This project focuses on the development of an intraday trading bot designed to predict stock price movements and execute trades based on advanced machine learning algorithms. The bot utilizes a combination of ARIMA (Autoregressive Integrated Moving Average), Support Vector Regression (SVR), and Random Forest models to forecast short-term price trends. In addition, it incorporates technical indicators such as Simple Moving Averages (SMA) and Exponential Moving Averages (EMA) to enhance prediction accuracy. The model leverages historical stock data obtained from Yahoo Finance, using features like price, volume, and momentum indicators. The bot's architecture is structured with a base class for stock prediction, allowing for easy integration and extension of different models. The goal of this project is to automate intraday trading strategies by providing real-time, data-driven decision-making, with a focus on maximizing profit and minimizing risk

I. INTRODUCTION

The ability to precisely predict the price movement of stocks is the key to profitability in trading. Many investors spend time actively trading stocks in hope of outperforming the market, colloquially referred to as a passive investment. In light of the increasing availability of financial data, prediction of price movement in the financial market with machine learning has become a topic of interests for both investors and researchers alike. Insights about price movements from the models could help investors make more educated decisions. In this project, we aim to focus on making short term price movements prediction using the time series data of stock price, commonly used technical-analysis indicators, and trading volume. Such predictions will then be used to generate short-term trading strategies to capitalize on small price movements in highly liquid stocks.Intraday trading involves buying and selling financial instruments within the same trading day, aiming to capitalize on short-term price movements.

It requires quick decision-making and a solid understanding of market trends, making it a high-risk, high-reward strategy. Machine learning plays a crucial role in trading by analyzing vast amounts of data to identify patterns and predict future price movements. This technology enhances trading strategies, improves decision-making, and can lead to more profitable outcomes.The objectives of the project may include developing predictive models, optimizing trading strategies, and evaluating the effectiveness of machine learning algorithms in intraday trading. These goals aim to leverage data- driven insights for better trading performance.

The scope of the project encompasses the application of machine learning techniques to various financial instruments, including stocks, commodities, and currencies, focusing on intraday trading strategies. It may also involve models and analyzing their performance in real market conditions. Limitations of the project could include the challenges of data quality, the unpredictability of market behavior, and the potential for overfitting models to historical data. Additionally,

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external factors such as economic news and market sentiment can significantly impact trading outcomes, complicating the predictive process.

II. RELATED WORK

With the increase of available financial data investors can access to, as suggested by Hegazy, Osman, Soliman, Omar S. and Salam, Mustafa A (2013), machine learning techniques have been applied to create a powerful trading strategy that helps traders more likely make right decision in buying or selling the assets. As mentioned in Chen, Sheng and He, Hongxiang (2018), Neural Network models including both Long Short Term Memory (LSTM) and Convolutional Neural Network can successfully capture the micro-change of time-series data, resulting in accuracy higher than 70% across many different datasets. In addition to deep learning methods, a more traditional model as Support Vector Machine (SVM) is also effective to do the classification work, which predicts whether the price movement will be up or down.Despite numerous deep learning applications in stock price prediction, only few research focuses on actual profits generated by ML-driven trading. We decided to further explore how the accuracy of predictions from various machine learning models are correlated with the profits that we would obtain based on predicted results.Therefore, the main goal of this paper is not only assessing statistical performance of machine learning in forecasting future price movements but also effectively the evaluating the results in terms of actual profits.

III. DATASET AND FEATURES

The dataset is the the SPDR S&P 500 trust (NYSE: SPY) with 1-minute intervals from March 1st until May 24th 2019. The data is available on the IEX Trading website.
The features includes price and trading volume. We also used technical indicators including Simple Moving Average (SMA), Exponential Moving Average (EMA), Crossovers, consecutive price trends with 5, 10, 12, 20, 26, 50, 100, 200 days lookback window). These indicators represent volatility, momentum, and trending strength of price movement. Details of each technical indicator can be found in the appendix.

METHODS

Feature Selection

We used Lasso regularization method to select more statistically significant features by shrinking their corresponding coefficients towards zero. **Variables selected by Lasso includes:**

Original Features: Volume and Price.

Simple Moving Averages: SMA5, SMA15, SMA20, SMA200
Crossovers: SMA5Cross, SMA10Cross, SMA15Cross, SMA20Cros, SMA50Cross, SMA100Cross, SMA200Cross
Consecutive price trends: Up.Down10, Up.Down15, Up.Down50

MODELS

Since the goal of the project is to predict the next-minute price movement (binary classification), we use logistic regression as our baseline model. In order to evaluate how complicated the problem is as well as to understand the structures in the data, we explore the data set with the following models: BaselineModel:Webuiltlogistic Regressionwithandwithout regularization, as reference to the baseline models. Regularization used includes Ridge and Lasso methods.

Support Vector Machine

For the support vector machine model, we started off by exploring different kernels, including Linear, Polynomial (degree 3), Sigmoid, and Radial Basis Function kernel. After training our simple model, we adjust the model by varying the cost of constraint violation. Specifically, we adjust the "C" part of the optimization problem below.

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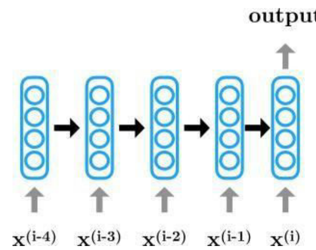
$$\min_{w,\xi,b} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi^{(i)}$$

such that $y^{(i)}\left(w^T x^{(i)} + b\right) \geq 1 - \xi^{(i)}; \quad \forall i \in \{1, \dots, n\}$

RNN models: We tested Single-layer LSTM, Multi-layer LSTM (Figure 1a),
and Multi-layer GRU (Figure 1b) with 128 hidden units in each layer with RELU activation function. We tested multiple lookback windows, and discovered that having a lookback window of 5 works best. Regularization includes early stopping and dropping out parameters.
Convolutional Neural Network model: Single layer CNN with a linear layer. The models has access to five data points, to match the RNN model. More complicated CNN models were considered, but was not completed due to time constraints.



Single Layer RNN (b) Multi Layer RNN Figure 1: RNN models

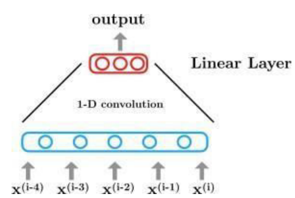
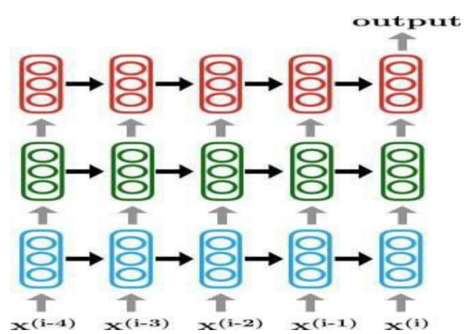


Figure 2: NN model



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As our task is a binary classification, we chose sigmoid activation function in the last layer of all Neural Network models (RNN and CNN). Accordingly, our loss function is binary cross-entropy loss.

$$l(\theta) = \frac{1}{n}\sum_{i=1}^{n}[y \log(p) + (1-y)\log(1-p)]$$

Neural Network Hyperparameter Tuning

Once all models were successfully implemented, we also tuned relevant parameters and hyperparameters to improve the model performance by using Grid Search method. Especially for Sequence models that incorporates historical information, we varied different values of lookback window (5, 10, 15, 30 days) and how they affect the statistical performance. Other relevant hyperparameters we tuned include learning rate (across log scale), batch size, number of hidden units, and number of epochs. The results of best hyperparameters are listed as following: Learning rate = 0.0001 Batch Size = 64 Number of hidden layers = 128 and number of epochs: 10 (low due to early stopping)

IV. EXPERIMENTS/RESULTS/DISCUSSION

Model	Accuracy (Training Set)	Accuracy (Test Set)	AUC (Test Set)	Profit/Hour (Test Set)
Baseline (Logistic)	0.4988	0.4899	0.4876	$-0.11
SVM (Linear)	0.5354	0.5341	0.5355	$0.68
SVM (Polynomial)	0.5452	0.5449	0.5449	$1.61
SVM (RBF)	0.5433	0.5384	0.5393	$0.79
SVM (Sigmoid)	0.5024	0.4983	0.5021	$-0.69
GRU	0.5141	0.5096	0.4928	$0.51
LSTM (Single-Layer)	0.5011	0.4983	0.4989	$-0.20
LSTM (Multi-Layer)	0.5127	0.5110	0.4817	$0.47
CNN	0.5130	0.4889	0.5000	$-0.46

Table 1: Statistical Performance and Cumulative Profits of all models.

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Statistical Performance :

According to Table 1, the accuracy of training set is generally higher than that of test set, as the models tend to more overfit to the training set. When generalized in the test set, the performance slightly dropped.
From all of the models, the support vector machine with polynomial kernel has the best performance in all metrics. Most of the SVM methods outperform the deep learning methods (LSTM, GRU and CNN) as we expected due to the size of our dataset (approximately 20,000 datapoints). All models except SVM (Sigmoid Kernel), Single-layer LSTM, and CNN models post positive profits.

Portfolio Performance :

The use of model with high statistical performance is not necessarily a successful trading strategy, as the predicted results are only directional, not reflective of actual profits. Therefore, we implemented another algorithms that incorporates directional prediction to generate portfolio value over time. In our case, we would long the asset if the predicted probability is above the upper threshold, short the asset if the probability is below lower threshold, and continue holding our position, if the predicted probability lies in between the two thresholds. The results shown in Table 1 correspond to the
0.48 -0.50 threshold range (lower - upper: 0.48 - 0.50).To compute the cumulative profits from our ML-based strategies, we execute trading in our test set under the condition where the principal amount of cash is $1000 with no leverage. Furthermore, in this project, every trade is fully long/short decision, which means that we would spend all cash buying as many shares as possible when we decide to long and short selling as many shares as possible when we decide to short. The results presented above show our profit in zero- transaction cost environment. The result was summarized in the form of how many dollars we can make per hour (as opposed to per minute) so as to illustrate the profit in reasonable unit.
In the real trading world, transaction cost is incurred in every execution order. To make our cumulative profits most realistic, we applied transaction cost in every minute the order was executed. Using transaction cost of 15 basis point, we found out that the transaction costs erode all of our profit, resulting in negative return for all strategies (models). This is primarily because transaction cost associated to a complete process of entering and exiting a position is 30 bps or 0.3%. However, as we are trading within minutes range, short-term price movements within a few minutes rarely goes above 0.3%. This means, even though we make correct predictions, we are still losing money. Here are a few limitations to our study. First we simplified our problem to a binary classification, which resulted in low profits as discussed earlier.
Second, we only tested our methods on the NYSE: SPY data set, which may not be representative of other stocks in the market. Considering other stocks would allow for a generation of a portfolio that better represent what investors do in real world.

V. CONCLUSION/FUTURE WORK

This paper explored the usage of multiple machine learning models to predict future prices of stocks. We first simplified our problem to a binary classification problem. Then we narrowed down our data, which consists of multiple indicators, to a smaller and more statistically significant subset. Finally we experimented with the different models and found out that SVM with polynomial kernel had the best performance on the dataset we have. Nevertheless, there are multiple limitations to this study, most notably the size of the dataset.
In the future we hope to modify our models to takes into account the magnitude of profit or loss. This includes multi-class classification that accounts for magnitude of price movements or even regression models predicting next-minute price. We also hope to expand our models to incorporate data from other stocks and gather more data to better train our deep learning models. We could also include portfolio optimization, weighing each assets based on predicted probability once we work with different stocks.
CONTRIBUTIONS

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Art Paspanthong: DataCollection, Data Preprocessing, Implemented SVM models, Evaluation Metrics (Trading Execution/Portfolio Generation/Profit Calculation), Report write-upWill Vithayapalert: Implemented Baseline, RNN models, Hyperparameter Tuning, Report write-upNick Tanivasadakarn: Neural Network, Data Processing, Creating framework, Report write- up

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