Ensemble of Neural Networks to Forecast Stock Price by Analysis of Three Short Timeframes

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Abstract: Financial markets are known for complexity and volatility, and predicting the direction of price movement of financial instruments is essential for financial market participants. This paper aims to use neural networks to predict the direction of Apple's share price movement. Historical stock price data on three Intraday timeframes and technical indicators selected for each timeframe are used to develop and evaluate the performance of various neural network models, including Multilayer Perceptron and Convolutional Neural Networks. This research also highlights the importance of selecting appropriate technical indicators for different timeframes to optimise the performance of the selected neural network models. It showcases the use of neural networks within an ensemble architecture that tracks the directional movement of Apple Inc. share prices by combining upward and downward predictions from the three short timeframes. This approach generates a trading system with buy and sell signals for intraday trading.

1 INTRODUCTION

Historically, price movement predictions have relied on statistical and mathematical methods, including but not limited to Relative Strength Index (RSI) (Singh and Patel, 2021), Fibonacci retracement (Chen and Zhang, 2022) and moving averages (Gupta and Sharma, 2023). The use of analysis methods using technical indicators was widespread until the 2010s, when advancements in computer power made it possible to manipulate market participants' opinion using false signals on popular technical indicators. Following this, neural network based systems for analysing financial markets began to emerge. However, they require significant computer power when analysing raw transaction data for intraday trading (Lee and Chen, 2023).

Therefore, there is a need for more accurate, and less labour-intensive methods of predicting price trends, especially as financial markets face large increases in data and transaction volume due to the advances in telecommunications technology as well as market institutionalisation (Fabozzi et al., 2013). Machine learning methods are widely used for their ability to handle large datasets and non-linearities in data (Ogulcan E. Orsel, 2022).

This paper focuses specifically on predicting the directional movements of prices for Apple Inc. (AAPL) across multiple Intraday Trading (IT) timeframes. Each timeframe is characterized by a different intraday trading frequency and employs a distinct Neural Network (NN) architecture. The goal is to develop a system that uses combined analyses from different timeframes to determine the accuracy of optimal buy or sell decisions on an intraday basis. This strategy aims to make use of volatility, thus increasing the probability of compounding small profits from minor price changes but many times. The approach of multiple timeframes is inspired by the Alexander Elder trading strategy, also known as the triple-screen trading system. This strategy monitors three timeframes of the same price trend data, differing in frequency, using appropriate technical indicators to observe long, medium, and short-term trends (Elder, 1993), thereby creating a more robust overall trading strategy. The choice of using AAPL was made because Apple Inc. is one of the most recognizable and heavily traded securities on the stock market, providing an excellent use case for futures price movement forecasting using neural networks. Also, Apple

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Inc. has been a publicly traded security for a long period, hence historical price data spanning several years is publicly available. The availability of data makes AAPL ideal for developing and testing neural network models for predicting price movements. Finally, the high liquidity and volatility of AAPL shares represent opportunities for intraday trading, making it a suitable subject for high-frequency trading strategies. By focusing on AAPL, this study aims to provide insights that can be generalized to other securities and commodities in the futures market, thereby contributing to the broader field of financial forecasting and trading.

To achieve this aim, the following objectives have been established:

- Develop and evaluate classification models in a parallel ensemble architecture, utilizing historical intraday data from the AAPL ticker across three different timeframes.
- Explore the impact of different technical indicators on the accuracy of the predictions.
- Demonstrate the use of the triple screen trading philosophy of Dr. Alexander Elder (Elder, 1993) using new capabilities provided by machine learning and neural networks.
- Combine the predictions from the parallel ensemble architecture to calculate the final accuracy of the trading system.

The rest of this paper is organised as follows: Section 2 investigates the literature and state-of-the-art studies on the topic; Section 3 describes the dataset, the technical indicators and the Neural Networks employed for this research; Section 4 outlines the results; Section 5 provides discussion about the results and experiments; finally the conclusions are drawn in Section 6.

2 LITERATURE REVIEW

Traditional methods of financial market analysis depend heavily on statistical analysis of historical stock price data and other variables known as economic or technical indicators and sentiment indicators (Bollen et al., 2011). Methods such as time series analysis and the concept of moving averages have regularly been used in stock price forecasting and are still widely used for short-term forecasting (Smith and Williams, 2022). Autoregressive Integrated Moving Average (ARIMA) models' level out fluctuations in pricing to identify trends present in the data (Patel and Verma, 2024), economic technical indicators like Relative Strength Index (RSI) present perceptions of market movements which include upward and downward trends (Garcia and Rodriguez, 2022). The major problem, however, is traditional methods have difficulty in interpreting nonlinear movements, and this makes them sensitive to market fluctuations (Lee and Chen, 2023). To this end, the use of machine learning methods has been employed extensively over the years with the aim of accounting for such fluctuations and achieving better predictive accuracy(Dhruhi Sheth, 2022). Neural networks are more effective than Traditional statistical methods in handling nonlinear financial data (Shah and Kumar, 2022).

In (Manickavasagam et al., 2020), the authors explored hybrid modelling techniques to forecast the future prices of WTI (West Texas Intermediate) and Brent crude oil with the primary objective of improving the accuracy of crude oil price forecasting. The experiments demonstrated that hybrid models combined with certain model optimization techniques like IPSO (Improved Particle Swarm Optimisation) and FPA (Flower Pollination Algorithm) significantly improve the accuracy of crude oil price forecasts. The idea of deriving technical indicators from historical price data and using them as inputs or features for training was particularly useful and was adopted for the purpose of our research.

Forecasting directional movements of stock prices for intraday trading using Long Short-Term Memory (LSTM) and Random Forests is presented in (Ghosh et al., 2022). The authors' goal was to outperforming traditional market benchmarks by leveraging advanced machine learning techniques. The experiment demonstrated that incorporating multiple features, including opening prices and intraday returns, into the ML models improved the prediction accuracy and trading performance. Both LSTM networks and Random Forests were effective in forecasting stock price movements, with LSTM networks showing a slight edge in performance. We found the concept of using historical stock price data for the prediction of directional movements of stock prices to be valuable for our research purposes.

Another interesting approach for forecasting stock index futures intraday returns is presented in (Fu et al., 2020). The authors have used a functional time series model in combination with the Block Moving (BM) technique that provided superior dynamic forecasting for stock index futures compared to traditional point prediction methods. This approach better captures intraday volatility and market microstructure, enhancing forecasting accuracy. The paper emphasizes the advantages of functional data analysis in financial forecasting, particularly in high-frequency trading environments, where traditional methods may fall short. The dynamic nature of the model allowed for more accurate and real-time predictions, crucial for financial decision-making.

The potential of neural networks in forecasting financial market volatility is also demonstrated in (Hamid and Iqbal, 2004). The importance of data pre-processing, variable selection and proper network training in achieving accurate predictions are well highlighted in the paper.

Despite many papers on forecasting financial instrument prices, there is a significant gap in simultaneous chronometer analysis of several time-frame sets using neural networks. Solving this issue is the principal scientific novelty of this paper.

3 METHODS

This section covers various aspects of this research, including the dataset, the technical indicators used in each timeframe, the labelling algorithm, and the neural networks employed.

3.1 Dataset

The dataset for this research consists of Apple Inc (AAPL) data across the following three intraday timeframes:

- 5-minute timeframe : 47,350 rows (70% of data)
- 15-minute timeframe: 15,963 rows (24% of data)
- 60-minute timeframe : 3,994 rows (6% of data)

The total number of rows is 68,307 with raw data features including open, high, low, close and volume. The data was accessed and downloaded from Alpha Vantagethrough their API, selected for several reasons, with the primary one being the ease of access it offers, allowing for straightforward retrieval of data through API calls.

The technical indicators were extracted from the raw dataset and used as derived features. In this research, the following technical indicators are also included in the input data: momentum, volume, moving averages, and directional indicators. These technical indicators are distributed across three time frames.

Short-Term Timeframe (5 Minutes)
This timeframe is used for analysing charts that focus on shorter-term movements, typically on an intraday or very high-frequency basis, such as hourly or every couple of minutes (Achuthan and Hurst, 2021). The aim of these charts is largely for determining the most precise entry and exit points form the trends. Price action (i.e. logic) is usually tested on the short-term timeframe for the timing of trades (especially on an intraday basis). For the purpose of this research, the technical indicators On-Balance volume, parabolic stop and reverse (parabolic SAR) and Williams Percent Range (Williams%R) of the closing prices were chosen for the short-term timeframe.

Medium-Term Timeframe (15 Minutes)
This timeframe is used for analysing charts that are typically medium-term (i.e. daily charts) (Achuthan and Hurst, 2021). The aim of these charts is largely for determining the potential entry points based on long-term trends seen in the longer term charts. For the purpose of this research, the technical indicators Exponential Moving Average, Alligator, Average Directional Index and Stochastic Oscillator of the closing prices were chosen for the medium-term timeframe.

Long-Term Timeframe (60 Minutes)
As the name implies, this timeframe is used for analysing charts that are typically longer term (i.e., weekly or monthly charts). The purpose of these charts is largely to determine the long-term trends (Achuthan and Hurst, 2021). For the purpose of this research, the technical indicators Moving Average Convergence Divergence, Relative Strength Index, Bollinger Bands and On-Balance-Volume of the closing prices were chosen for the long-term time frame.

The choice of these sets of technical indicators for each of the above timeframes was determined by the analysis of numerous empirical experiments that are not of significant value to this paper.

3.2 Labelling Algorithm

The labelling algorithm is defined to classify the movements of closing prices at each time interval and for each timeframe into three categories: upward (up), no action (wait) and downward (down) movements. In order to achieve an accurate labelling algorithm for the closing prices of each interval, there are a number of inputs, with the first being the take profit and stop loss levels denoted as **take_profit** and **stop_loss**. In addition to these inputs, we include the **Returns**, **std_deviation** of asset returns (interpreted as **typical_volatility**(σ)), the **Multiplier** (a function of individual risk appetite) and **future_returns** (the price change between the current closing price and the closing price of the immediate future interval). The multipliers are usually determined by the risk appetite of the individual investor and are used to arrive at the take-profit or stop-loss figure as a multiple of the volatility.

Equations 1 - 4 are the mathematical interpretations of the labelling algorithm:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1}$$

where R_t is the Return at time t, t is the time of the current interval, $t-1$ is the time at the previous interval, and P is the price of the asset at t.

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(R_i - \bar{R})^2} \tag{2}$$

where σ denotes the Volatility, R_i is the Return at the current interval, $\bar{R}$ is the mean of the returns and N is the number of returns or the number of intervals per timeframe. Thus volatility in this context refers to the degree of variation of trading price from the mean over time.

$$FC_t = Close_{t+1} \tag{3}$$

FC_t is the Future Close Price, t is the time at the current interval and $t+1$ is the time at the immediate following interval.

$$PC_t = \frac{FC_t - Close_t}{Close_t} \tag{4}$$

where PC_t denotes the Price Change at time t, t is the time at the current interval.

The aim of this labelling approach is to hit as many take-profit points as possible within the trading day while minimising the probability of loss. To achieve this, different multipliers are used for take-profit and stop-loss points, indicating a higher risk associated with stop-loss compared to take-profit.A greater number of take-profit points reflects the objective of maximising profit settlements, whilst fewer stop-loss points suggest a willingness to take on more losses but less frequently. Thus:

$$stoploss = -multiplier * volatility(\sigma) \tag{5}$$

and

$$takeprofit = multiplier * volatility(\sigma) \tag{6}$$

For the purpose of this research, stop-loss value is a magnitude of 2 higher (as a number and not in value) than take-profit.

Finally, in differentiating the upward and downward signals, we define certain rules in the code as it can be seen in the pseudo-code 1

After the labels are created, they are further classified in two 'attention' and 'wait' categories where

while $PC_t > takeprofit$ **do**
  signal = UP;
  if $PC_t <= stoploss$ **then**
    signal = DOWN;
  else
    Signal = WAIT;
  end
end

Algorithm 1: Labelling Algorithm.

attention consists of the upward and downward signals. These are then used in the first phase of training and testing as two classes. Figure 1 represents the results on closing prices after the labelling Algorithm 1 is applied.

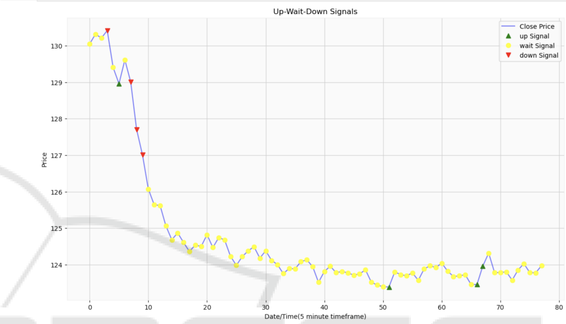

Figure 1: Result of Labelling algorithm on closing price as interval (5 minute interval).

In the second phase of training and testing, only the attention class from the previous phase is considered. This class is further split into up and down classes which are then trained and tested on a set of three neural networks, each corresponding to a different timeframe.

3.3 Neural Network Architecture

The neural network models used in this research include Multi-Layer Perceptrons (MLP) and Convolution Neural Networks (CNN). Table 1 shows the neural networks used in this research and some of their properties.

Table 1: First and second phase Neural Network characteristics.

Timeframe	Model	Num of Features	Resampling Method	Loss Function
5 min	CNN	5	SMOTE	Binary cross-entropy
15 min	MLP	6	SMOTE	Binary cross-entropy
60 min	CNN	6	SMOTE	Binary cross-entropy

The authors conducted several experiments with different sets of hyperparameters for each of the neural network architectures used. The combinations of hyperparameters that showed the highest results are described below.

Multi-Layer Perceptrons (MLP)
The MLP models used are feed-forward neural networks consisting of three dense layers with 64 neurons each, and the Rectified Linear Unit (ReLU) as the activation function. The Keras API with TensorFlow backend was used for implementation with a binary cross-entropy loss function. Dropout layers set 20% of the neurons to 0 during training to prevent overfitting. MLP models were used in the 15-minute timeframe.
Convolutional Neural Networks (CNN)
The CNN's layers include convolutional, pooling, flattening, dense and dropout layers as described below.
Convolutional Layers: These layers extract features from the input data using filters. The first convolutional layer has 64 filters and a kernel size of 1. Subsequent layers use 128 filters and apply the ReLU activation function for non-linear feature extraction.
Pooling Layers: Two pooling layers with a pool size of 2 are used to reduce the dimensionality of the feature maps, allowing the network to focus on the most significant features.
Flatten Layer: Converts the pooled feature maps into a one-dimensional vector, which is fed into the dense layers. *Dense Layers*: These fully connected layers consist of 64 neurons that use the ReLU activation function and perform the final classification tasks. *Dropout Layer*: A dropout layer with 50% dropout is applied to prevent overfitting by randomly disabling half of the neurons during each training iteration. *Output Layer*: The final layer uses a sigmoid activation function for binary classification tasks, producing a probability for each class.

4 RESULTS

4.1 First Phase Results (Attention & Wait Signals)

In the first phase, each individual model's ability to precisely detect Attention and Wait signals is tested. Since the original dataset after the labelling process is unbalanced, precision (see equation 7) the primary metric used for evaluation.

$$precision = \frac{(TP)}{(TP+FP)} \tag{7}$$

The precision values of each Attention and Wait classes in the ensemble architecture as well as the overall precision values for each neural network were recorded. When Attention values are matched across all three timeframes, the Attention output from the first stage was accepted. This led to a significantly reduced input for analysis in the second stage, which no longer contained imbalance, which is more prevalent in the Attention and Wait datasets, resulting in a more realistic outcome (Jin et al., 2022).

Tables 2, 3, 4, and 5 show the results of performance metrics from the training (60%) and test(40%) sets of the Attention (0) and Wait(1) phases, as well as the overall results for the training and test sets. Figure 2 represents the visualisation of the precision scores on the test sets.

Table 2: Class performance of models in the Attention and Wait classification training sets.

Class (timeframe)	Model	Precision %	Recall %	F-score %
0 Attention (5-min)	CNN	72	78	75
1 Wait (5-min)	CNN	76	70	73
0 Attention (15-min)	MLP	52	55	54
1 Wait (15-min)	MLP	52	49	50
0 Attention (60-min)	CNN	50	61	55
1 Wait (60-min)	CNN	47	37	41

Table 3: Class performance of models in the Attention and Wait classification test sets.

Class (timeframe)	Model	Precision %	Recall %	F-score %
0 Attention (5-min)	CNN	72	77	74
1 Wait (5-min)	CNN	76	70	73
0 Attention (15-min)	MLP	57	52	54
1 Wait (15-min)	MLP	56	61	59
0 Attention (60-min)	CNN	69	58	63
1 Wait (60-min)	CNN	64	74	69

Table 4: Overall performance of models in the Attention and Wait classification training sets.

Model (timeframe)	Precision %	Recall %	F-score %	Accuracy %
CNN (5-min)	74	74	74	74
MLP (15-min)	52	52	52	52
CNN (60-min)	49	49	48	49

Table 5: Overall performance of models in the Attention and Wait classification test sets.

Model (timeframe)	Precision %	Recall %	F-score %	Accuracy %
CNN (5-min)	73	73	73	73
MLP (15-min)	55	54	54	54
CNN (60-min)	66	66	66	66

As it can be seen from Tables 3 and5 and Figure 2, the highest precision of recognition of Attention and Wait signals is demonstrated on 5-minute and 60-minute time frames during validation on test sets.

4.2 Second Phase Results (Upward & Downward Signals)

The training and testing evaluation metric measured for the NNs in this phase is accuracy (see equation 8).

$$accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{8}$$

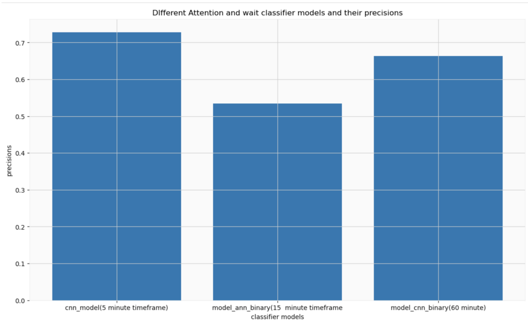

Figure 2: Precision values on Test sets of Attention and Wait classification NNs.

The accuracy values of each Up and Down class in the ensemble architecture of the second phase, as well as the precision and recall values for each neural network were recorded. Macro average values were selected for the overall values recorded, as they account equally for each class in the classification task. This approach is appropriate since the imbalance in the Up and Down datasets is far lower than in the Attention and Wait datasets. (Jin et al., 2022). Tables 6, 7, 8, and 9 represent the results of performance metrics achieved for the training(60%) and test(40%) sets of the Up(0) and Down(1) phase as well as the overall results for the training and test sets.

Table 6: Class performance of models in the Up and Down classification training sets.

Class (timeframe)	Model	Precision %	Recall %	F-score %
1 Up (5-min)	CNN	61	50	55
0 Down (5-min)	CNN	59	70	64
1 Up (15-min)	MLP	56	61	59
0 Down (15-min)	MLP	58	53	56
1 Up (60-min)	CNN	64	68	66
0 Down (60-min)	CNN	68	64	66

Table 7: Class performance of models in the Up and Down classification test sets.

Class (timeframe)	Model	Precision %	Recall %	F-score %
1 Up (5-min)	CNN	60	43	50
0 Down (5-min)	CNN	53	70	61
1 Up (15-min)	MLP	56	61	59
0 Down (15-min)	MLP	57	52	54
1 Up (60-min)	CNN	64	61	62
0 Down (60-min)	CNN	62	61	62

Table 8: Overall performance of models in the Up and Down classification training sets.

Model (timeframe)	Accuracy %	Recall %	F-score %	Precision %
CNN (5-min)	60	60	60	60
MLP (15-min)	52	52	52	52
CNN (60-min)	66	66	66	66

Figure 3 represents the visualisation of the accuracy metric on the test sets for each timeframe in the second (Up & Down) phase.

Table 9: Overall performance of models in the Up and Down classification test sets.

Model (timeframe)	Accuracy %	Recall %	F-score %	Precision %
CNN (5-min)	53	56	56	57
MLP (15-min)	52	57	56	57
CNN (60-min)	56	63	63	63

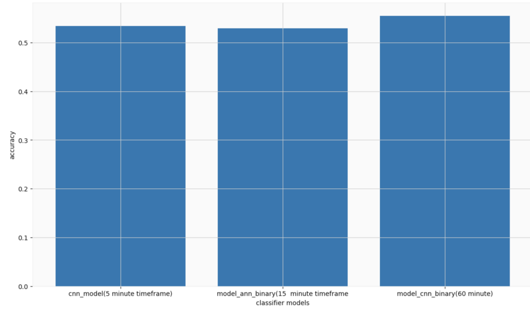

Figure 3: Visualization of the accuracy values for test sets of Up and Down classification neural networks.

As seen from the Tables 7, 9 and Figure 3, the overall accuracy on test sets is reduced; however, combining the predictions using ensemble of the triple timeframe increases final accuracy significantly.

4.3 Final Phase Results (Overall Upward & Downward Prediction)

Finally, the total accuracy of the triple timeframe system (5-min, 15-min and 60-min) is calculated by synchronising the predictions in each timeframe and dividing the final number of upward signals by the total number of signals on a given trading day, and converting the answer to a percentage. Upward signals on a given trading day are correct responses, considering the predictions of the triple timeframe system up during this day. Figure 4 represents the visualisation of the final up and down data points from which final accuracy is determined.

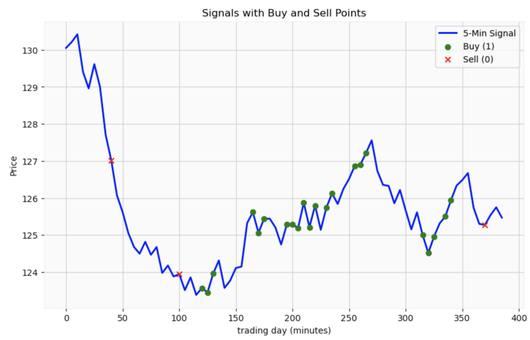

Figure 4: Visualisation of buy and sell signals for 1st trading day.

Figure 4 show a total of 25 (22 Buy (green dots) and 3 Sell (red crosses)) signals for the given trading day. The accuracy of the system on this trading day is 88%, as calculated in equation 9.

$$Accuracy = \frac{22}{25} * 100 = 88\% \quad (9)$$

Using a single time frame as input usually demonstrates lower levels of accuracy; for example, 61% accuracy was shown in (Qin, 2024) to predict the AAPL stock trend.

5 DISCUSSION

This section outlines the rationale behind key decisions made regarding the overall research direction. It covers several aspects including the use of technical indicators, historical stock price data for deriving technical indicators and the multiple timeframe ensemble architecture which was modelled after the triple screen trading strategy of Dr. Alexander Elder (Elder, 1993).

5.1 Triple Timeframe Predictive Ensemble Model

Technical indicators are used in addition to price data in training different neural networks across three different timeframes and two phases of training. The first phase classifies signals into classes suggesting action (Attention) and inaction (Wait), whilst the second phase focuses on classifying the attention signals into two classes predicting upward or downward price movement. This approach is novel, as although previous studies have employed the triple screen trading strategy of (Elder, 1993), which inspired the use of three timeframes, the combination of multiple training phases for different specific purposes and the use of technical indicators as features, has not been explored. Additionally, it is worth mentioning that the signals, which were used for the labelling of the upward and downward movement of the prices, were entirely derived from the closing price volatility, making another unique aspect of this research. Typically, volatility is determined using concepts such as bid-ask spread (Milke, 2023), Average True Range (ATR) and True Range (TR) (Team, 2022).

5.2 Final Accuracy

The approach explored in this research involves analysing the predictions made by each neural network model across different timeframes in a time-synchronised manner. Following this, a decision is made by determining whether the predictions at each time step in each timeframe coincide with those on the other two timeframes. If the answer is yes, then the uniformity suggests a 'Buy' signal (final "1") or a 'Sell' signal (final "0"). If the answer is no, the lack of uniformity across the timeframes indicates inaction. Thus, the final accuracy is calculated by dividing the number of 'buy' signals by the total number of signals and the result is the probability of accuracy.

This ensemble approach to making a final decision allows for an increase in the forecast accuracy of the direction of the future movement of the stock and, therefore, reduces the risk of an incorrect decision. Focusing on many small profits accelerates the capital increase, just as small daily interest payments increase capital many times over due to the compound interest formula.

6 CONCLUSIONS

This paper explores the use of neural networks to predict the directional movement of stock prices on intraday trading using an Apple Inc. case study. The paper describes the integration of multiple timeframes of intraday data, using technical indicators as features for several neural networks, such as CNN and MLP, within an ensemble architecture. The use of stock price data to predict the directional movement of futures introduces some limitations, as futures market data have distinct properties that are not captured in stock price data. As such, further refinements are needed, in line with future work, to optimize performance for practical trading applications. Overall, this paper offers novel findings into the use of neural networks for financial forecasting in intraday trading.

A potential future direction for this research is scalability across other securities and using a more robust measure of volatility, such as Average True Range (ATR) or True Range (TR) in order to account for the full range of price volatility. The exploring of price movement patterns can be done with Japanese candlesticks (Milke, 2023). This approach cold be also applied to futures contracts as well as other financial instruments other than stocks, thus accounting for the difference in structure of futures data and other financial instruments.

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