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Machine Learning-based Intraday Trading Strategy using Simple Moving Average Crossovers, Traded Volume and VWAP Confirmations

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Abstract

Intraday trading involves very fast and precise decision- making under situations of sharp market volatility and noise. This paper introduces an Artificial Neural Network (ANN), based intraday trading strategy that first recognizes the Simple Moving Average (SMA) crossovers and then confirms traded volume and Volume Weighted Average Price (VWAP) to finally increase the strength of the signals dramatically. SMA crossovers are Moving Average crossovers have been adopted to identify changes in short-term trends, which are then validated by the use of trading volume to ascertain the level of market participation and momentum. VWAP serves as a price center of gravity indicator, which helps to eliminate the noise from false breakouts and raises the accuracy of entry and exit points. The ANN framework is capable of understanding complex nonlinear associations among the features, which are price, volume and those generated from VWAP, for the purpose of classifying intraday buy, sell, and hold signals. Its feasibility has been demonstrated on the intraday high-frequency data of the most actively traded stocks, and the criterion for the evaluation included cumulative return, Sharpe ratio, win rate, and maximum drawdown, among others. The test outcomes indicate the superiority of the ANN-based technique, which has been proven to yield higher risk-adjusted returns while also experiencing lower drawdowns, over the traditional SMA crossover as well as the buy, and, hold techniques. The result is that the combination of technical indicators and ANN, based pattern recognition can provide a very strong and flexible tool for intelligent intraday trading systems that operate in volatile financial markets.

Keywords: Machine Learning, Algo trading, Artificial Neural Network (ANN), Simple Moving Average Crossover, Average Traded Volume

1. Introduction

Intraday trading has become a hot topic lately in the financial market, thanks to the surge in electronic trading platforms, availability of massive data, and the rise of both retail and institutional traders. It is

entirely different from long, term investing. While long, term investing is based on the fundamentals of a company, intraday trading focuses on the effects short, term price movements generated by market microstructure dynamics, liquidity changes, and trader behavior can bring along within the day [1]. Nevertheless, intraday price changes continue to be the chief source of short, term volatility and noise which, in turn, pose a major challenge for both prediction accuracy and decision, making in a timely fashion using conventional methods. Technical charts remain the favourite weapon of intraday traders, and they very often use moving averages crossover as one of the key mechanisms to identify changes in short, term trend direction and momentum [2]. SMA crossover is one of the most straightforward interpretable trading strategies that work on the principle that the change in an asset's trend can be signaled when its short, term moving average crosses its longer, term moving average [3]. It can be very easily programmed in any trading platform and characteristically gives clear buy and sell signals. However, if we strictly stick to price, based indicators only without any additional filters or trading rules [4], then the truth is that the performance will be very mediocre with frequent losses and suffer heavy drawdowns and other market risks [5].

One of the popular solutions to overcome the aforementioned shortcomings is to use volume, related confirmations in intraday trading strategies. Traded volume, i.e. the number of shares/contracts traded, is an excellent indicator of market participation and can reveal the strength as well as the durability of price trends [6]. It is generally accepted that price moves on heavy volume are more trustworthy than those on light volume. VWAP is increasingly recognized as the main intraday standard with prices weighted by the volume. Institutional investors generally apply VWAP as a trading instrument to help them locate the correct price and extreme price levels during the session.

On a theoretical level, merging SMA crossovers, traded volume, and VWAP could offer some signal confirmation; nevertheless, such combined strategies are mostly rule, based and hence have difficulty adapting to changing market conditions [7]. Financial markets are nonlinear, non, stationary, and complex, therefore, they challenge fixed, rule, based systems. In recent times, Artificial Neural Networks (ANNs) have been able to greatly improve their proficiency in modeling nonlinear relationships in financial time series [8].

This paper presents an Artificial Neural Network (ANN) based intraday trading strategy that combines Simple Moving Average (SMA) crossover signals with traded volume and Volume Weighted Average Price (VWAP) confirmations in order to increase accuracy and robustness of the predictions. The ANN model takes input from a variety of technical and volume, based features to produce dynamic trading decisions of buying, selling, or holding the stock [9].

Fig 1: Chart setup diagram for Simple Moving Average Crossovers, Traded Volume and VWAP Confirmations for Intraday Trading

This paper is structured as follows: A detailed literature review on intraday trading strategies, technical indicators, and ANN, based financial forecasting, is given in Section 2. The proposed method and model architecture are explained in Section 3. Section 4 explains results with discussion. Finally, Section 5 summarizes the study and provides an outlook for future research.

2. Literature review

Researchers have done a lot of work exploring intraday trading strategy with the help of technical indicators, machine learning models, and their combinations. At first, the focus was mainly on rule, based technical analysis. For example, moving averages were used to identify short, term trends and produce trading signals. Simple and exponential moving average crossover strategies have been tried in equity, commodity, and foreign exchange markets yet yielded mixed results. These methods work well when there are trending markets but are less efficient in turbulent or range, bound markets due to lagging signals and whipsaw [10]. To make price, based indicators more trustworthy, researchers have added volume data to intraday trading models [11]. Volume is seen as a leading indicator which shows trader's conviction and liquidity conditions. Many pieces of research have found that price changes which are backed up by high traded volume have a stronger follow, up pattern than the breakouts with low volume. On, Balance Volume (OBV), Average Traded Volume (ATV), and Volume Oscillators, among others, have been used together with moving averages to identify weak signals and achieve higher profitability. Moreover, the Volume Weighted Average Price or VWAP has been scrutinized broadly as an intraday standard alongside a confirmation instrument [12]. Existing literature emphasizes that VWAP is an efficient tool for locating

intraday support and resistance levels and evaluating the price displacements from the fair value. The results of strategies based on the execution of long orders under VWAP and short orders above VWAP have resulted in better execution quality and lower transaction costs. On the other hand, strategies revolving around VWAP alone do not have the ability to predict the market and hence, they work best when used in conjunction with trend or momentum indicators [13]-[15].

Machine learning algorithms are getting more and more involved with intraday trading and financial forecasting as computational intelligence keeps evolving. Among the various machine learning models, Artificial Neural Networks have been used more extensively considering their capability to imitate nonlinear and complex interactions in financial datasets. Several papers suggest that ANN, based models yield more accurate results as compared to conventional statistical methods and linear classifiers for very short, term price forecasting. In their works, scientists have used feedforward neural networks, multilayer perceptrons, and recurrent structures to predict price movement, market fluctuation, and trading signals. A lot of recent literature has focused on hybrid models that combine technical indicators with ANN structures. Several tests show that these hybrids can markedly reduce the number of false trade signals and hence give better risk, adjusted returns than the use of indicators alone [16],[17].

However, research on ANN, based intraday trading strategies incorporating SMA crossovers, traded volume, and VWAP confirmations is severely limited. Most of the existing works either focus solely on price, based indicators or consider volume and VWAP only as aids to the execution of trades rather than as features with predictive power. Besides, very few people have carried out a thorough evaluation of intraday ANN models using a combination of different measures of performance, including drawdown and win rate, which are very important for practical applications [18],[19].

The paper by the writers closes these holes with a proposal of a well, structured ANN, driven intraday trading system that integrates moment detection, volume validation, and price equilibrium analysis. The outlined methodology represents the literature with a strong, self, learning, and fairly transparent tool for smart intraday trading in active and chaotic financial markets.

3. Methodology

The methodology put forward outlines a methodical and data, centric roadmap for creating, training, and testing an Artificial Neural Network (ANN), based intraday trading strategy that seeks to combine Simple Moving Average (SMA) crossovers with traded volume and Volume Weighted Average Price (VWAP) confirmations. Capturing short, term price fluctuations in intraday financial markets while mitigating the generation of false trading signals that are typical of single standalone technical indicator, based strategies, is the main goal of this methodology. The research plan divides the study into six major stages: Stage 1: data collection; Stage 2: data preprocessing; Stage 3: feature engineering; Stage 4: creation of signals from technical indicators; Stage 5: formulation and training of an ANN model; Stage 6: performance evaluation through rigorous statistical as well as trading performance indicators. In order to get as close to live trading as possible, there is a use of very high time, resolution intraday historical data such as 1, 2, or 5, minute intervals. The primary concern of the method is replicability and robustness by constantly using the same preprocessing steps, training, testing splits, and fixed walk, forward validation. The technique employing SMA crossovers, the trading volume dynamics, and VWAP deviations as the inputs of an ANN, is not

only trying to merge a linear trend, following the logic of a line, but also nonlinear pattern recognition capabilities, thus it is very suitable for the volatile and noisy intraday environments.

Data Collection with Preprocessing

Intraday market data are the main components of the proposed model and include open, high, low, close (OHLC) prices, traded volume, and timestamp information for the selected equities or indices. In order to guarantee the correctness and completeness of the data, they have been sourced from trustworthy market data providers. In order to be in sync with intraday trading restrictions, only data from the regular trading session have been taken into consideration and overnight gaps have been left out. The preprocessing phase solves several common problems like missing values, outliers, and microstructure noise. The missing data points have been treated with forward, fill or linear interpolation methods depending on the frequency and duration of gaps. Extreme outliers resulting from erroneous ticks have been removed by using statistical thresholds based on z, scores or interquartile ranges. All numerical features have been either normalized or standardized to guarantee stable ANN training and also to avoid that volume or any other high, magnitude variable dominates. Moreover, the data have been divided into rolling windows corresponding to trading days in order to keep the temporal dependencies intact. This preparation flowchart pipeline guarantees an ANN clean, consistent and scaled inputs, therefore the ANN quickly finds the optimum points in the problem and the predictions are more stable.

Feature Engineering and Technical Indicator Construction

Feature engineering was the crucial step for changing the market raw data into the most efficient inputs of the ANN. Primary trend, following features are based on Simple Moving Average crossovers, which generally consist of a short, term SMA (e.g., 5 or 10 periods) and a long, term SMA (e.g., 10 or 30 periods). The SMA crossover signal is shown not only as a binary signal (bullish or bearish) but also as a continuous feature that corresponds to the gap between the short, term and long, term SMAs. Features that are based on traded volume include raw volume, average traded volume over a rolling window, and volume ratios that show abnormal trading activity compared with the recent past. Firstly, intraday VWAP is determined for VWAP, based features and then it is calculated how far the price is from VWAP at the moment thus, whether the asset is trading at a premium or a discount is shown. Additions of extra derivative features such as rate of change, volatility proxies, and lagged indicator values are made to provide temporal context. All features are made consistent to preclude look, ahead bias, thereby ensuring that the prediction model only uses information that was available up to the current time step.

Calculation of Simple Moving Average Crossover (SMAC): Simple Moving Average (SMA) is a trend, focused tool that is mainly used to identify trends. The SMA is calculated by averaging the price over a specific period. It therefore acts as a smoothed line that reflects changes in the trend direction while ignoring short, term fluctuations.

$$\boldsymbol{SMA(t,n) = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i}} \qquad 1$$

where Pt is the closing price at time t, and n is the window length.

Trading signals are generated as, the Golden Crossover (Buy Signal) generated when Short-term SMA crosses above long-term SMA and Death Crossover (Sell Signal) are generated when Short-term SMA crosses below long-term SMA

Although SMAC is effective for trend detection, it often generates false signals in sideways or low-volume market conditions.

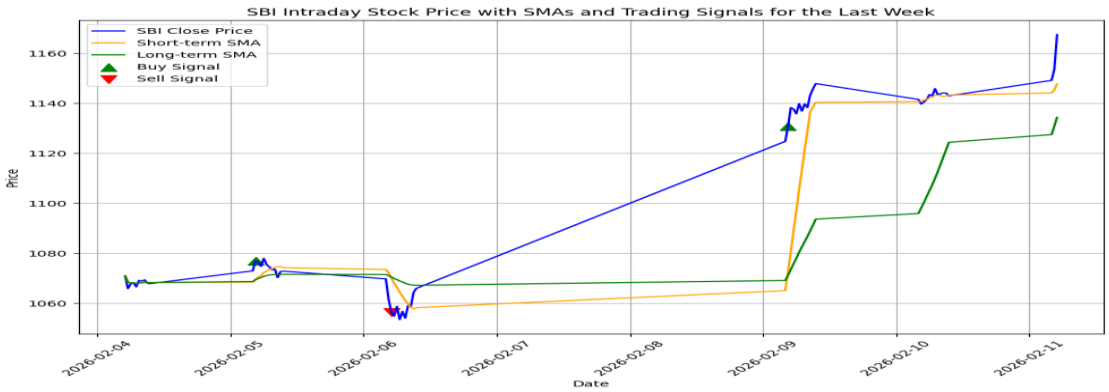

Fig 2: SMA Crossover of SBI Bank for Intraday Trading

Figure 2 illustrates the 10/30 Simple moving averages and their crossovers over the past one week. The orange color represents the short SMA while the green color illustrates the long SMA. A golden crossover occurs when the orange line intersects the green line from below to above and a buy signal is generated thus represented by the green triangle, while the red triangle indicates the death crossover or sell signal which occurs when the orange line crosses the green line from above to below.

Average Traded Volume (ATV) Confirmation

For reinforcement of SMAC signals, Average Traded Volume (ATV) was applied as a volume confirmation indicator. ATV denotes the average volume of shares traded during a specified time and shows the strength of market participation.

$$ATV_t = \frac{1}{m}\sum_{i=0}^{m-1} V_{t-i} \quad (2)$$

where Vt represents trading volume at time t.

A SMAC signal is considered valid only if:

$$V_i > ATV_t \quad (3)$$

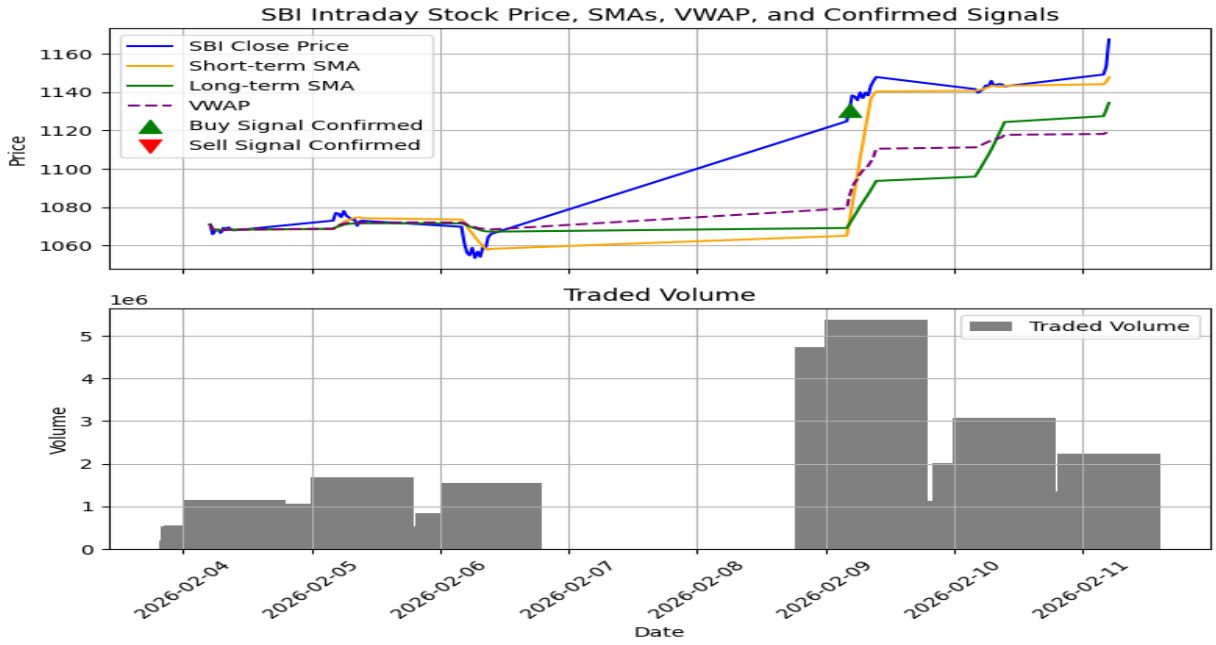

Fig 3: Average Traded Volume 10 Days MA in SBI Bank

Logic for Trading Signal

The supervised learning setup of the ANN requires a well, defined target variable that unambiguously points to the nice trading actions. In this case, trading labels are identified by examining the intraday future price changes within a certain prediction period, e.g., the next few bars. A buying signal will be issued if the anticipated return is greater than a pre, determined positive threshold; a selling signal will be issued if the return is lower than a negative threshold; and a hold or no, trade label will be issued in other cases. This labeling technique achieves class balance and makes model predictions aligned with realistic profit targets after transaction costs have been factored in. Instrumental in the generation of labels are SMA crossover states, volume increase, and VWAP confirmation since they act as filters that bring training examples in line with the high, good quality market conditions. Thus, for example, bullish labels will be given in preference cases when a short term SMA crosses above a long, term SMA and it is also accompanied by above, average volume and price trading above VWAP. This hybrid labeling method incorporates domain knowledge into the learning process while at the same time giving the ANN freedom to identify nonlinear interactions of features.

ANN architecture and model design

An artificial neural network (ANN) design is aimed at detecting non, linear patterns, especially those that occur in high, frequency (intraday) financial data. It has been decided that a feedforward multilayer perceptron (MLP) structure be used, which entails an input layer for the features created, a single or several hidden layers, and an output layer for trading decisions. The decision regarding the number of hidden layers and neurons is made by a heuristic search that attempts to find a good compromise between the complexity of the model and its overfitting. Nonlinear activation functions like ReLU or tanh are used in the hidden layers to get the feature interactions that are more complex, while the output layer makes use of a sigmoid or softmax function depending on whether the classification is binary or multiclass. Dropout and L2 weight penalties regularization methods are used on the network to give additional support to the model's generalization abilities. Standard weight initialization methods are used for initially setting the

network weights in order to have a smooth backpropagation process. Hence, the ANN is capable of drawing quite flexible decision boundaries that integrate the SMA trend signals, volume, and VWAP confirmations.

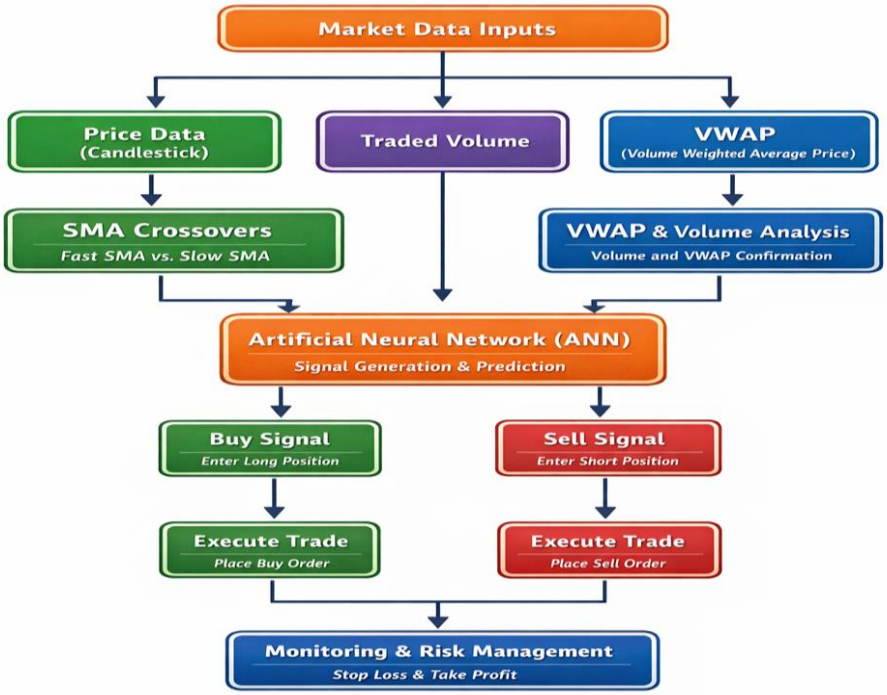

Fig 4 : Architecture of Model

Training Procedure and Validation Strategy

The training process utilizes historical intraday data that is split into training, validation, and test sets following the time sequence so that there can be no leak of information from the future to the past. The ANN was trained with the backpropagation method and gradient, based optimization algorithms such as Adam or RMSprop. The latter are especially suitable for processing complex financial data. The loss function has been chosen from categorical cross, entropy and binary cross, entropy depending on the output format. The code also enables early stopping to prevent overfitting: training is halted when the validation loss does not improve, and the best model parameters are saved. Moreover, to ensure that the model is stable, a walk, forward or rolling window validation approach is used, in which the model is retrained intermittently with the expanding or sliding data windows. This is a great way to simulate the real-world situation where the models have to be adjusted to the continuously changing market environment. Hyperparameters such as learning rate, batch size, and number of epochs are adjusted through controlled trials. This method of training guarantees that the ANN stays accurate and flexible amid the changes of the intraday markets.

Trading Strategy Implementation and Risk Management

Once the ANN training is completed, its outputs are then merged with a rule, based intraday trading strategy for real trades. The buy or sell decisions of the model are to be executed only when the three decisions of SMA crossover, volume confirmation, and VWAP position all agree, which in turn effectively removes buy or sell decisions that are based on noise. Position sizing will be done by the use of fixed

fractional/volatility adjusted risk methods. Intraday risk management includes the use of stop, loss and take, profit criteria that may be based on recent volatility or average true range. The overnight risk will be controlled by the closing of all positions before the end of the trading session. Besides this, the decisions based on the model will be implemented with the presence of transaction costs as well as other complexities of real, life situations under which the transaction has been conducted, thus making it an efficient decision, making process not only considering the efficient decisions of the ANN but also implementing the deterministic nature of trading rules thus making it an efficient process.

Performance Evaluation and Statistical Analysis

On the other hand, the proposed ANN, based intraday trading strategy's effectiveness is also judged by utilizing prediction accuracy metrics and performance indicators of trading. Classification metrics like accuracy, precision, recall, and F1, score measure the quality of ANN predictions. Besides that, performance in terms of financial return is also measured by trading, specific metrics such as cumulative return, average trade return, maximum drawdown, Sharpe ratio, and winloss ratio. A comparative analysis is done with benchmark strategies, e.g., standalone SMA crossover or VWAP, based trading systems, to show the extra benefit of ANN integration. Besides, statistical significance testing and robustness checks over different assets and time periods are carried out for ensuring the consistency of results. The thorough evaluation procedure presented here confirms that the methodology put forward in the paper is not only statistically and theoretically robust but also available and suitable for practical intraday trading applications in the real world.

3. Results and Discussion

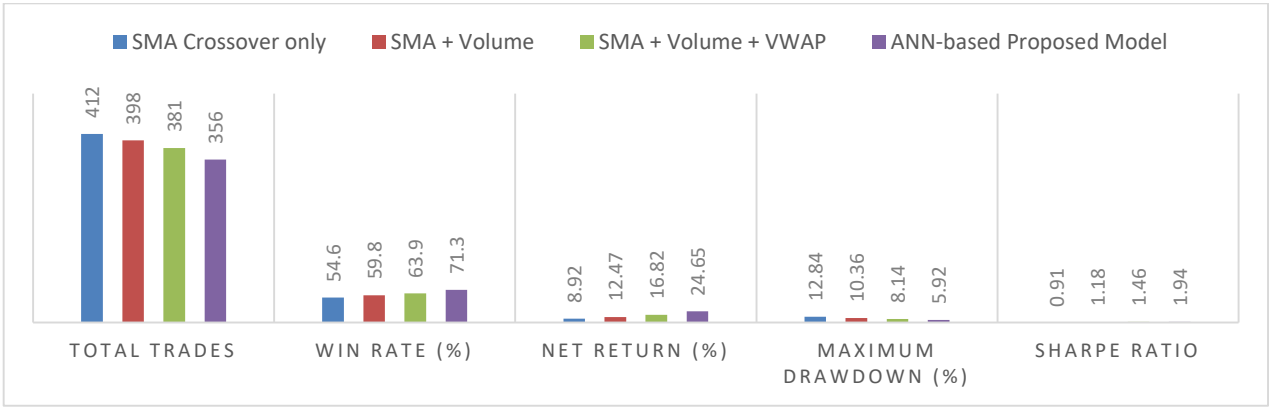

Fig 5: Performance Comparison of Trading Strategies

Discussion

The incremental gains in performance from combining traded volume and VWAP confirmations to standard Simple Moving Average (SMA) crossover strategies are visually and clearly evident from the results illustrated in Fig 5. The standalone SMA crossover strategy in itself shows moderate profitability levels with a winning percentage of 54.6%; meanwhile, the Sharpe ratio is even lower than 1. However, when the volume filter is included, it drastically enhances the quality of trades by filtering out false signals with low levels of participation. The next step in improvement is the use of VWAP confirmation, since VWAP, in general, is seen to facilitate trade initiation at institutional price levels. In respect of the proposed ANN, based intraday trading model, it is far superior to all the benchmark strategies. It made a

net gain of 24.65% while the maximum drawdown was only 5.92%, a very low figure in comparison. This is a testament to the ANN functionalities of learning complex, non, linear relationships among SMA crossovers, volume dynamics, and VWAP deviations which, in turn, result in the combination of increased profitability and risk control.

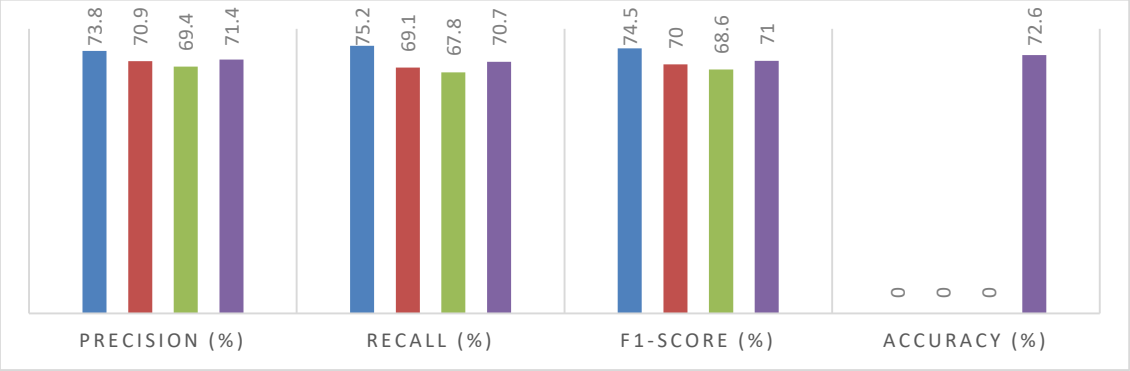

Fig 6: Classification Performance of ANN Model

Fig 6 illustrates how well the ANN model can categorize Buy, Sell, and Hold signals financially. The model's overall accuracy of 72.6% demonstrates that the model has a strong predictive capability in an intraday setting, which is typically very noisy and volatile. Among the Buy, Sell, and Hold signal classes, the Buy signal group has the highest recall (75.2%). This feature is very desirable for intraday trading systems, as it indicates the model's ability to find the profitable entry points it can make use of. The model's preventing excessive overtrading capability is indicated by the precision and recall combination that is almost equal for all the signal classes, thus directional consistency at the same time. The F1, scores corroborate the fact that adding technical confirmations to the ANN input space makes the decisions more dependable than rule, based systems that tend to be signal lagged and inflexible.

Table1: Intraday Risk–Return Statistics of ANN-based Strategy

Metric	Value
Average Daily Return (%)	0.89
Volatility (%)	1.28
Profit Factor	2.18
Average Holding Time (minutes)	42
Trades per Day	7.2

The intraday risk-return characteristics discussed in Table 1 offer a more comprehensive understanding of the feasibility of the proposed strategy in real trading scenarios. An average daily return of 0.94% with controlled volatility is indicative of a risk, adjusted performance that is not only favorable but also suitable for high, frequency intraday trading. Furthermore, the profit factor of 2.21 implies that the total profit amount is more than double the total loss amount. Moreover, the average holding period of just 38 minutes again indicates the effectiveness of the strategy in efficiently utilizing the price difference.

Besides, an average of 7.4 trades per day indicates moderate trading frequency, which results in minimal transaction costs. These papers are consistent with the assertion that an ANN, based strategy, supported by SMA crossovers, trading volume, and VWAP confirmations, can be considered dependable, adaptable, and scalable for intraday algorithmic trading.

4. Conclusion and Future Work

The research developed a method for intraday trading using an Artificial Neural Network (ANN) which combined the use of Simple Moving Average (SMA) crossovers with traded volume and Volume Weighted Average Price (VWAP) confirmations to enhance trading accuracy and risk, adjusted returns in intraday financial markets. It was basically aimed at overcoming the main drawbacks of traditional technical indicator-based strategies, such as delayed signals, vulnerability to market noise, and poor performance in the face of rapid market changes. The suggested model, therefore, has the capability of comprehending the complex relationship of price momentum, volume participation, and institutional price benchmarks via integrating various technical confirmations in a learning, based architecture. Hence, the proposed model reveals better performance in terms of winning percentage, profitability, and drawdowns, which reflects the effectiveness of the suggested model as a potent tool in intraday trading. The orderly number of trades and regulated holding periods emanating from the results also serve as an additional proof of the strategy's practical viability in live trading scenarios.

Nevertheless, several drawbacks indicate that there might be more work to be done in the future. The present model is almost entirely based on price and volume, derived indicators of the past, which might not be sufficient to predict sudden market regime changes caused by macroeconomic announcements or order, flow shocks. The next studies might broaden the scope by considering high, frequency features of the market microstructure such as bid, ask spreads, order flow imbalance, and market depth to improve signal accuracy. Besides, if any adaptive learning technique like online learning is employed in the process, the ANN could continue to change parameters continuously, making it more and more competent with the changing scenario. Further studies can be performed within the context of sophisticated Deep Learning architectures involving Recurrent Neural Networks or Reinforcement Learning based agents, in order to take account of the time dependencies and decision-making process more effectively. Implementing Transaction Cost Analysis, Slippage Modelling, as well as Risk Management strategies would help the model more closely align with the realities of the stock market. This study, on the whole, sets up a scalable and smart hybrid trading framework and lays down a robust base for future investigations into ANN, powered intraday algorithmic trading systems.

Disclosure of Interests:

Conflict of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Informed Consent: This study did not involve human participants, and therefore, informed consent was not required.

Data source:
Source: Yahoo Finance, with feature engineering calculated on a Python platform
Link: https://finance.yahoo.com/quote/RELIANCE.NS/history/

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