International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

# Swing Trading Strategy using Simple Moving Average Crossovers, Traded Volume and Super Trend Confirmations Integrated in Machine Learning

**Arup Kadia[1], Kamal Narayan [2], Prashansa Bharti[3], Bidya Bharti[4]**

[1]Assistant Professor, Faculty of Information Technology & Engineering, Gopal Narayan Singh University, India,

[2, 3,4] Student, BCA, Faculty of Information Technology & Engineering, Gopal Narayan Singh University, India, Email: kamaln297@gmail.com

**Abstract**

Different swing trading strategies emphasize making gains through measuring trend directions and patterns, utilizing technical indicators to achieve the greatest profits, and leveraging market trends. Therefore, swing trading is a highly appealing strategy for buyers and sellers, particularly for those who are financially very active. With regard to overcoming some of the challenges inherent in current rule-based swing trading strategies, such as delayed and false breakout risks, there is a vast opportunity for employing the Artificial Neural Network technique in conjunction with technical indicators making more reliable decisions and providing them more flexibility. The authors of the paper outline a method to use a neural network-based swing trading strategy where buy and sell decisions are based on different parameters, e.g. a simple moving average, volume, flow, as well as a super trend indicator confirmation strategy. Moving averages help fulfill swing trading goals by figuring out the prevailing trend, whereas volume helps make the trading more trust worthy. The super trend indicator also serves as a guide to picking up the right moment for buying and selling, which is especially helpful when you use the output values of the ANN model as swing trading inputs.

**Keywords:** Traded Volume Analysis, Algorithmic Trading Strategy, Simple Moving Average Crossover, Swing Trading, Super Trend Indicator, Technical Analysis,

## 1. Introduction

Swing trading strategies involve gaining profits through tracking trend movements and patterns in the market, incorporating the application of a series of technical indicators for the highest profit, and using the power of the market's momentum [1]. Therefore, swing trading is a highly appealing strategy for buyers and sellers, particularly for those who are financially very active. With regard to overcoming some of the challenges inherent in current rules, based swing trading strategies, such as delayed and false breakout risks, there is a vast opportunity for employing Artificial Neural Network techniques in conjunction with technical indicators, making more reliable decisions and providing them more flexibility

[2]. The authors of the paper outline a method to use a neural, network-based swing trading strategy where buy and sell decisions are based on different parameters, e.g. a simple moving average, volume, and super trend indicator confirmation strategy [3]. Moving averages help fulfil swing trading goals by figuring out the prevailing trend, whereas volume helps make the trading more trustworthy. The super trend indicator also serves as a guide to picking up the right moment for buying and selling, which is especially helpful when you use the output values of the ANN model as swing trading inputs [4].

Besides the use of moving averages and volume, the Super Trend indicator has also been a favorite of traders as it can change its levels depending on the volatility and thus, it is better capable of detecting reversals in the trend [5]. The Super Trend indicator, which is based on the Average True Range (ATR), eliminates minor price fluctuations and thus, it is capable of giving clearer trend, following signals. Nevertheless, even if combined, strict rule-based interpretations of SMA crossovers, volume, and Super Trend indicators are still quite limited in capturing the complex, nonlinear relationships present in financial time series data [6].

Artificial Neural Networks (ANNs), which are a copy of the human brain's way of learning, have been very successful in recognizing nonlinear patterns, dealing with noisy data and adapting to changing market conditions [7]. Over the last few years, ANN, driven models have become very popular in stock market prediction and algorithmic trading because they can uncover the hidden relationships among several technical indicators. When an ANN model is made part of the technical indicators, the way in which it is selected is no longer constrained by a rule-based, logically driven, approach but becomes a data-driven selection approach [8].

The study produces an artificial neural network-based swing trading strategy that involves the use of intersectional signals from the SMA lines, trade volume, and the Super Trend to create optimized buy and sell decisions [9]. The changes in SMAs are utilized to reveal the direction of the dominant trend, the traded volume acts as a verification of the strength of the price fluctuation, and the Super Trend indicator increases the confidence of the signal by confirming the continuation or reversal of the trend. All these are combined and fed into an ANN model that is capable of learning the nonlinear relationships among the different indicators and thus predicting favorable trading decisions [10].


**Fig 1: Swing Trade Setup in Reliance Industries**

The main goal of this study is to improve the performance of swing trading by diminishing the occurrence of false signals, refining the timing accuracy, and raising the level of profitable trades. The suggested approach is intended to deliver a sturdy, adaptable, and systematic decision, support trading system that can be effectively applied to the markets of real, world equities [11]. The findings of this work should be able to add to the existing literature on intelligent trading systems and justify the use of a blend of conventional technical indicators and artificial intelligence for swing trading purposes.

## 2. Literature review

The use of technical analysis in stock market trading has been a very popular topic over the years. Among the different methods that rely on moving averages, Simple Moving Average (SMA) crossover strategies remain the most popular ones. While there are many studies that have confirmed the ability of SMA crossover strategies to produce abnormal profits in trending markets, their results still significantly drop if there is a range, bound or a very volatile environment due to lagging signals and frequent whipsaws [12]. So, researchers have highlighted that moving average strategies can be made more reliable if additional confirmation mechanisms are used. Volume traded in a market has for a long time been acknowledged as one of the most important elements for market analysis [13]. The primary empirical studies documented a close connection between price changes and volume resulting in the interpretation of volume as a gauge of the agreement of market players. Many researchers have combined volume indicators with moving averages to get rid of the noise and thus enhance the effectiveness of trades. It has been demonstrated that volume, confirmed breakouts result in performances that are better than those of price, only strategies especially in swing and positional trading situations [14].

However, volume, based instructions are usually of a heuristic kind and therefore, they might not be able to adjust effectively to the changing market condition. The Super Trend indicator was introduced as a more advanced volatility-based trend-following tool derived from the Average True Range. Comparing Super Trend against classic indicators such as MACD and RSI reveals that Super Trend produces more concrete entry and exit points with less noise in volatile markets. As it comes with a volatility-adjusted framework, it tends to respond much better against reversals in trends, hence becoming an ideal pick for any strategy based on swing trading. Nevertheless, similar to other technical tools, Super Trend is still vulnerable and without using it with other tools, or if used with fixed rule, based thresholds only, it will give poor results [15]-[17].

With the progress in computational intelligence, machine learning techniques have been highly attractive for financial market forecasting. Artificial Neural Networks (ANNs) are considered one of the most popular models due to their very high approximation capability and flexibility. Initial experiments showed that models based on ANN give better results than linear statistical models in forecasting stock prices and returns [18]. Afterwards, researchers have taken ANN further and utilized it for generating trading signals based on combinations of technical indicators. Recent literature highlights the importance of the effectiveness of various hybrid structures, such as technical indicators-integrated models, as well as ANN models. Recent examples of successful applications of the ANN system in the domain of finance were proven to increase considerably not only profitability but also the resulting risk-adjusted returns. The main advantage of such models lies in their ability to capture nonlinear interactions among trading signals which are very difficult to represent by rules alone [19].

Certainly, there are only a few research works that have directly addressed ANN, powered swing trading strategies integrating simultaneously SMA crossovers, traded volume, and Super Trend confirmations. Generally, most of them either concentrate on intraday trading or use a very limited set of indicators. This study fills the void in the literature by developing a full, fledged ANN, based swing trading system that utilizes the combined effect of a trend, following indicator, volume strength signal, and a volatility, based confirmation one. The proposed approach aims to seek improvement not only in the consistencies of the trading signals but is also meant as a step toward smart swing trading systems, integrating knowledge of technical analysis with sophisticated machine learning models.

## 3. Methodology and model specifications

### 3.1 Research Framework and System Architecture

The research work proposed is based on the quantitative and experimental research approaches to create and test an Artificial Neural Network (ANN)based swing trading strategy. The complete framework leverages the integration of the conventional technical indicators with a data, driven machine learning model to increase the accuracy of decision, making. The system architecture is made up of four major parts: data acquisition and cleaning, technical indicator calculation, ANN model creation, and trading signal generation along with the performance evaluation. The first step involves the collection and cleaning of historical price and volume data to ensure that there are no inconsistencies, missing values, or outliers. The technical indicators Simple Moving Average (SMA) crossovers, traded volume, and Super Trend are calculated and then converted into well, organized input features. These features are the inputs for the ANN which is developed to decide or forecast the best trading actions (buy, sell, or hold). The last section assesses the effectiveness of the suggested strategy through the use of typical trading and risk measures. This flexible framework allows for the system to be scalable, adaptable, and practically applicable in real, world swing trading scenarios.

### 3.2 Data Collection with Preprocessing

Historical market data are the main ingredients of the proposed trading strategy. The dataset contains daily open, high, low, close (OHLC) prices and traded volume of the selected equity stocks for the period of several years in order to cover the different phases of the market. Daily frequency data are selected to be coherent with the swing trading time frame, which usually lasts from several days to weeks. Data preprocessing consists of a series of operations aimed at making the data dependable and consistent. First, missing values resulting from holidays or wholesale errors in the data feed are dealt with by means of forward, fill or interpolation methods. Second, irregular prices or volume are checked and eliminated, since they should not be reflected in the calculation of the proposed indicator. Third, normalization of numerical data features is done through min-max scaling for the purpose of range equality for the ANN structure. Normalization helps to accelerate convergence and also avoids the problem of features with larger numerical ranges over shadowing the others in the learning process.

Besides that, the data is split into train, validation, and test sets with a chronological split to eliminate the possibility of look, ahead bias. The train set is employed to fit the model parameters, the validation set is used for the model selection, and the test set is used as a final out, of, sample evaluation, thus the proposed model is ensured to be robust and generalizable. Financial time-series data can be incomplete because of market off days, or temporary stoppages of trading. Missing values are filled through the forward-fill method to keep the continuity. The dataset is from the beginning to the end to keep the time order which is necessary for the time-series learning process. The unnecessary attributes are eliminated, and only the necessary features for indicator calculation and model training are kept.

### 3.3 SMA Crossover Feature Extraction

Simple Moving Averages (SMAs) help to reveal the overall trend direction and strength in the market. Here, closing prices are used to calculate the two SMAs a short one and a long one. The short, term SMA tracks the latest price changes, while the long, term SMA is a measure of the overall market trend. When the short, term SMA goes above the long, term SMA, this is a buy (bullish) signal as it shows the possibility of the price going up. On the other hand, if the short, term SMA goes below the long, term SMA, this is a sell (bearish) signal. Rather than using these crossover signs to make trading decisions, the signals are being encoded here to be the ANN model's inputs. Hence, it will be up to the model to figure out how significant the event is under changing conditions. Other derivatives made this way are, among others, the "gap" between different short and long, term SMAs and the "line angles" of the MAs. These features, which show trends in the data and are useful for the ANN to recognize market momentum at a very nuanced level, are inevitably significant to swing trading strategies. Simple Moving Average (SMA) is a tool that helps to identify market trends. It finds the average prices over a set period, thus removing the impact of short, term fluctuations and pointing to the overall nature of the market.

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

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

Two SMA values are computed, these are Short-term SMA and Long-term SMA
Trading signals are generated as:
Golden Cross (Buy Signal) generated when Short-term SMA crosses above long-term SMA and Death Cross (Sell Signal) are generated when Short-term SMA crosses below long-term SMA. Although effective in detecting trend classes, SMAC mostly tends to give false signals during sideways or low-volume market conditions.

### 3.4 Traded Volume Analysis and Confirmation Mechanism

It is well known that the traded volume has a big importance in the validation of price changes and is used as main strength indicator of price changes. Here, volume is used as a confirmation signal only and not as a separate source of trading signals. The raw volume data is first averaged by a moving average to reduce the noise and make the main participation trend stand out. From volume, derived features are volume moving average ratios, volume breakout indicators, and relative measures of volume. A price movement with the help of volume above the average is considered a more reliable one since it reflects a stronger market consensus. These volume features along with SMA-based inputs are fed into the ANN, thus enabling the model to recognize the differences between strong and weak trend signals. Using the volume data, the system proposed in this paper helps the model to be less likely to mistake a false breakout or low, liquidity situation for a real breakout. The ANN understands the relationship between price trends and volume so that it can use volume confirmation flexibly and historically instead of using fixed heuristic rules. 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.

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

where Vt represents trading volume at time t.

A SMAC signal is considered valid only if:

$$V_i > ATV_t \qquad 3$$

### 3.5 Super Trend Indicator Computation

The Super Trend indicator has been added as a component that provides trend confirmation that is adjusted for volatility. It is derived from the Average True Range (ATR), a measure of volatility in the market that looks at the range of price changes over a given period. The Super Trend changes its level thresholds according to the volatility; thus, it is good at ignoring the small price movements. This paper represents the Super Trend signals as both categorical and numerical features, such as the trend direction (up or down), the distance between the price and Super Trend line, and the duration of the trend. These features point towards the trend's strength and stability, which are the very elements for making swing trade decisions. Adding Super Trend goes hand, in, hand with SMA crossovers to fix their problem of being lagging. While the SMAs indicate the direction of the trend, the Super Trend enhances the signal's reliability by checking whether the trend is strong enough or profitable enough to enter a swing trade. By equipping the ANN with this feature, the best combinations are identified based on the trend and volatility situations.


**Fig 2: SMA crossover-based trading with volume and super trend confirmations**

### 3.6 Artificial Neural Network Model Design

The main focus of the proposed technique would be the Artificial Neural Network model. The reason for choosing the model would be its proficiency in dealing with non-linear patterns. A feedforward multilayer perceptron would be the best choice for the proposed model. There would be the input layer in the network comprising the features such as the crossovers of the SMA, traded volume, and the Super trend indicators. It may comprise one or more hidden layers through the application of non-linear activation functions. The layer at the end of the network produces the trading outputs that can be either trading decisions framed as classification outputs (buy, sell, hold) or probability scores of each action. The network uses a supervised learning method to train itself, which means that it is provided with a set of input, output mappings to learn from, where the outputs are labels based on future price movements within the defined swing trading period. The training technique includes the propagation of the error signal in the backward direction through the layers of the network. It uses the optimization technique to modify the weights. It uses a specific set of loss functions for both classification and regression to measure the degree of difference between the predicted and actual values. It tries to achieve the minimum possible error. It uses regularization approaches such as dropout and early stopping to increase the capacity of the network.

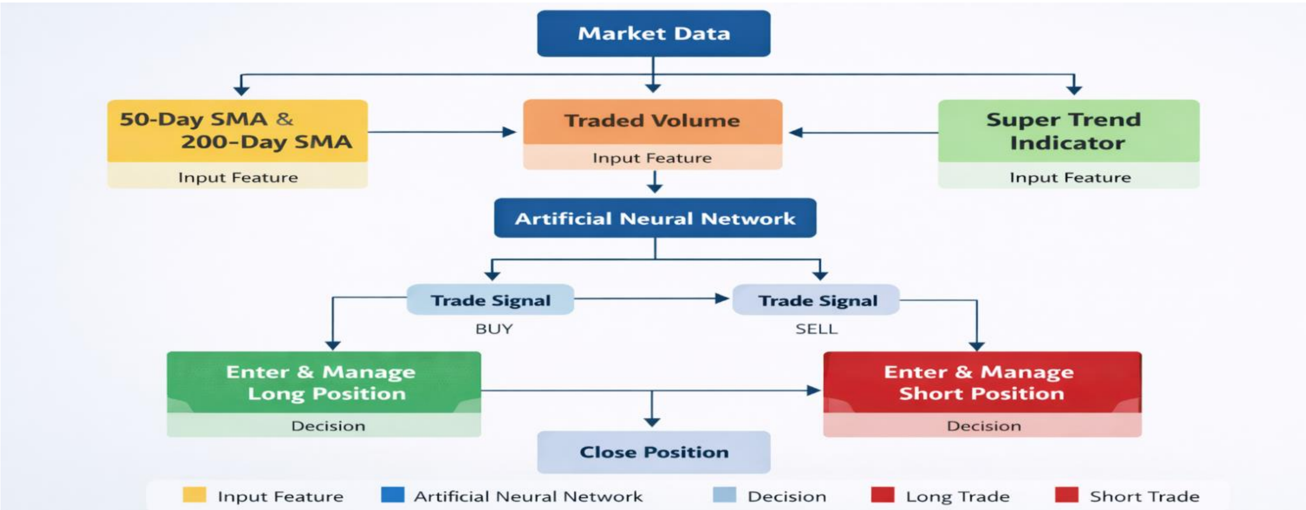


**Fig 3: Block diagram for swing trading Strategy**

### 3.7 Trading Signal Generation and Risk Management Rules

Once the ANN has been trained, the model will produce trading signals on the basis of the input features which may be either from real, time or historical data. A buy signal will be initiated if the model indicates a very high possibility of price going up and this prediction is further supported by trend and volume confirmations. In the case of identification of bearish conditions, a sell signal will also be generated. Hold signals are introduced to refrain from making any trades during uncertain or low, confidence situations. To make sure the strategy is not only theoretically sound, but is also practically applicable, some basic risk management rules are embedded into the review. These rules comprise of preset stop, loss and take, profit points derived from the price volatility or the ATR figures. The rules of position sizing are also enforced to limit the risk exposure and the possible loss. These restrictions keep the strategy realistic and in line with the professional trading standards. The combination of the signal generation from ANN and risk management based on rules results in a well, balanced system that uses the power of artificial intelligence on the one hand and, on the other hand, trading discipline is retained through the implementation of trading controls.

### 3.8 Performance Evaluation Metrics

Financial as well as statistical performance metrics are utilized to evaluate the effectiveness of the proposed ANN, based swing trading strategy. Cumulative returns, annualized returns, win rate, maximum drawdown, and risk, adjusted measures like the Sharpe ratio are the key trading metrics. These metrics help to give a full account of the profitability and the level of risk exposure. Besides trading metrics, the measures of predictive performance like accuracy, precision, recall, and F1, score are the ANN classification performance evaluation tools. Benchmark strategies including traditional SMA crossover systems and rule, based indicator combinations are used for the comparative analysis. Out, of, sample testing is done to confirm that the performance observed is not an effect of overfitting. Performance improvement validation can be done through statistical significance tests. The study, through this thorough evaluation framework, evaluates the robustness, reliability, and business value of the proposed ANN, based swing trading strategy.

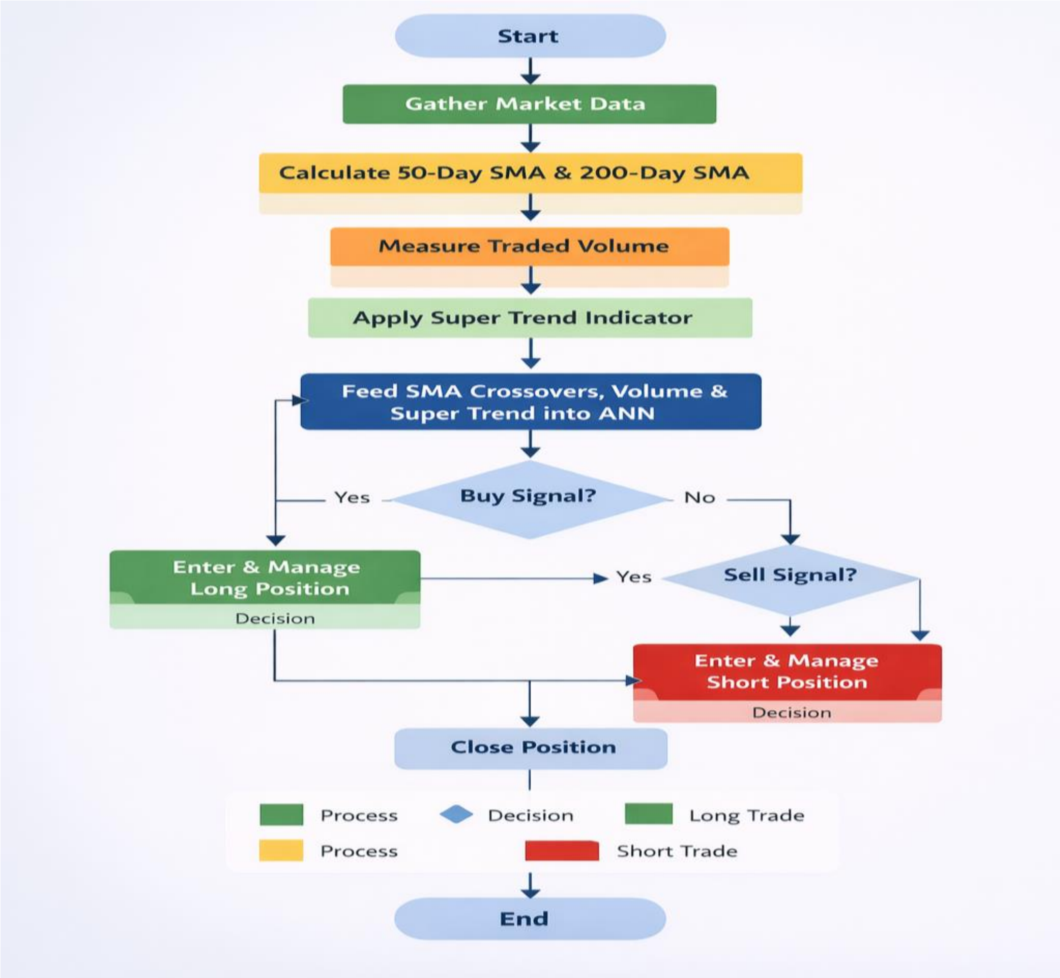


**Fig 4: Architecture of the Model**

Concerning this caveat, price movements are purported to have significant backing in the form of trading activity.

## 4. Empirical Result

The effectiveness of the suggested artificial neural network (ANN) based swing trading strategy, which merges Simple Moving Average (SMA) crossover, traded volume and Super Trend confirmations, is tested on daily price data from the past. The findings are contrasted with the baseline strategies in order to evaluate profit, risk exposure and forecasting accuracy. The assessment centers on an out, of, sample testing approach so as to guarantee the model stability and to avoid a look, ahead bias.

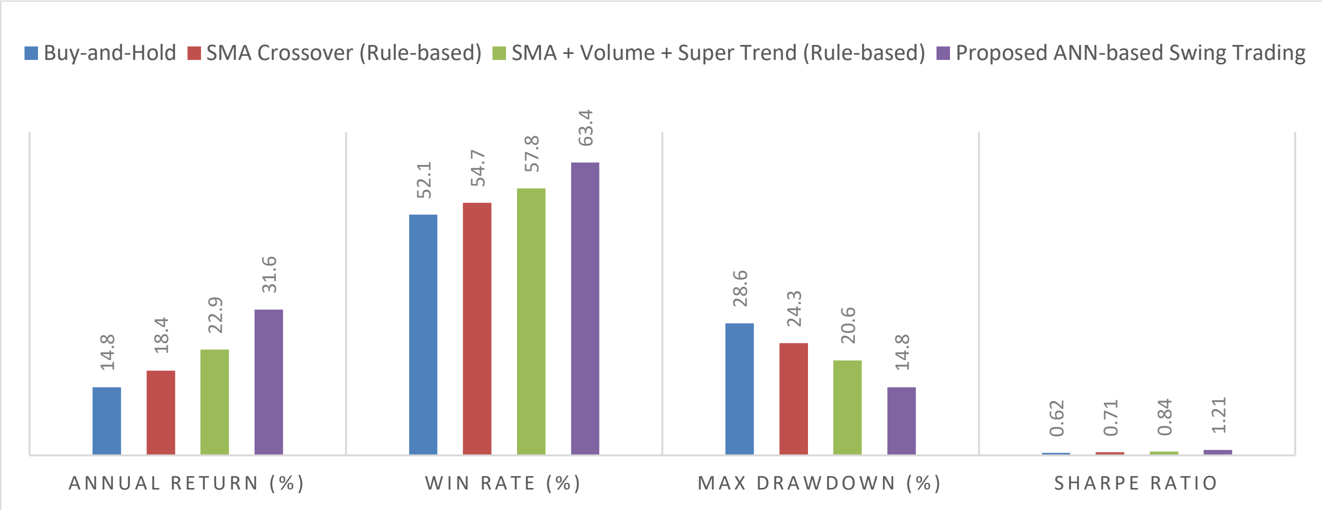


**Fig 5: Trading Performance Comparison**

As seen in Fig 5, various trading strategies have been compared based on their performance metrics. The classic buy, and, hold approach delivers average returns but is exposed to very high drawdown, which means that it is very risky during the down phases of the market. The rule, based SMA crossover strategy slightly raises the annual returns; nevertheless, its drawdown is still quite high due to frequent false signals in the sideways markets.

Adding traded volume and Super Trend confirmations in the rule, based system results in a better performance, which is reflected in higher returns and lower drawdown. This is, thus, the role of multi, indicator confirmation in swing trading. However, the ANN, based strategy significantly outperforms all the benchmark methods. It attained the highest annual return of 31.6% and a winning percentage of more than 63%, while its maximum drawdown was also the lowest. The Sharpe ratio of 1.21 shows that the ANN is very efficient in managing risks. It is also able to make the best entry and exit decisions by understanding the complex relationships between the indicators.

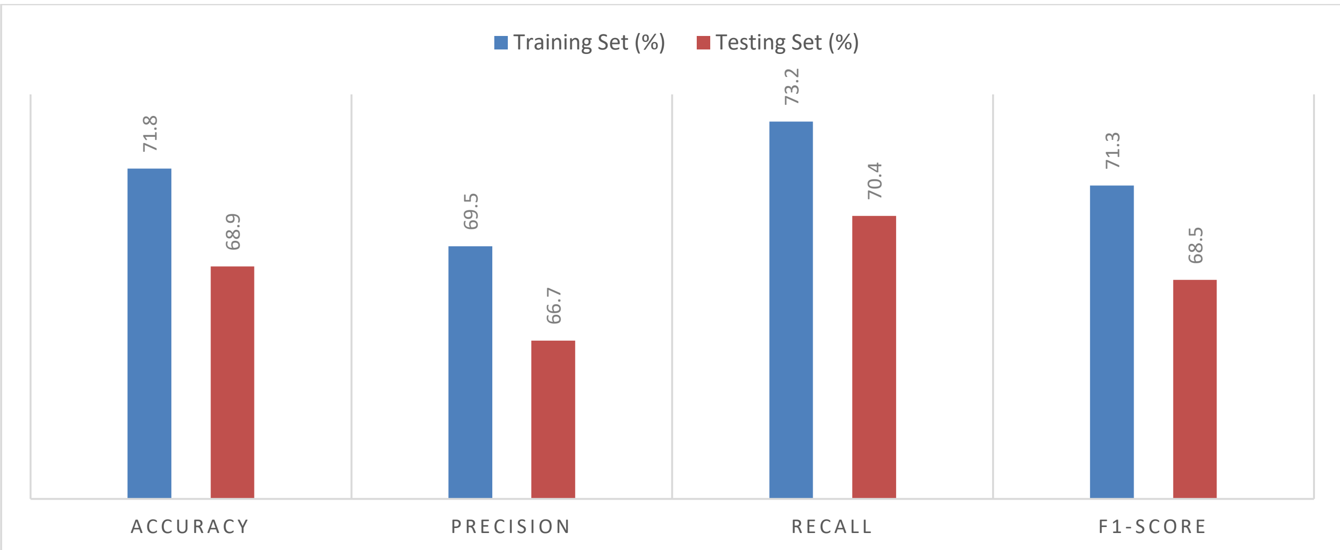


**Fig 6: Predictive Performance of ANN Model**

Fig 6 shows a comparison of the prediction accuracy of the ANN model on the training and the testing datasets. The small difference in performance of the model for training and testing suggests that the model generalizes well and has little overfitting. The 68.9% testing accuracy indicates that the model is able to classify swing trading opportunities correctly even in market situations it has not seen before.

As recall is higher than precision, it means that the ANN model can successfully find most of the profitable trading opportunities, which is very important in a swing trading environment as missing out on a strong trend can lead to significant losses. Moreover, the balanced F1, score is another measure confirming the consistent performance of the model. In sum, these findings underscore that the ANN model is capable of effectively representing the complex interplay of variables such as SMA crossovers, volume changes, and volatility, adjusted Super Trend signals.

**Overall Discussion**

The joint analysis of the two tables corroborates that the use of artificial intelligence in swing trading strategies significantly enhances the performance of the strategies compared to the traditional rule, based systems. Even though single technical indicators can help, their set thresholds and the assumption of linearity are limitations in the sense that they reduce their capacity to adapt to different situations. An ANN, based framework can thus be considered a solution to the mentioned issues as it can change the weights of the input indicators depending on the historical data and the current market situation.

A decrease in drawdown coupled with better profitability is a sign of improved risk management, thus the suggested strategy can be used in real trading. To sum up, the results publish the decision to use the model of an ANN for the multi, indicator system integration for swing trading and add to the pool of data supporting the development of intelligent trading systems.

**Conclusion and Future Work**

The paper has developed an Artificial Neural Network (ANN)based swing trading strategy which uses Simple Moving Average (SMA) crossovers, traded volume, and Super Trend confirmations to decide on the most accurate and robust trades. The system aimed at tackling the inherent drawbacks of the conventional rule, based swing trading systems like the signal lag, frequent whipsaws, and the low level of adaptability to changing market conditions. The strategy, through an ANN model that combines trend identification, volume, based validation, and volatility, adjusted confirmation, successfully picks up the complicated nonlinear relationships in financial time series data.

Compared to core benchmark approaches mainly buy, and, hold, and rule, based indicator strategies, the ANN, based swing trading strategy put forward here is shown to be spectacularly better on the ground of annual returns, winning percentage, and risk, adjusted performance, with a notably less maximum drawdown being experienced. This confirms the models ability to accomplish higher profits and better risk management through dynamically optimizing the points of market entry and exit based on patterns learned from the market, rather than fixed heuristic rules. Besides, using traded volume and Super Trend indicators double up the signal as reliable ones by eliminating weak trends and false breakouts, which are the main problems in swing trading.

The proposed framework, albeit very effective, still has room for improvements and extensions in multiple directions. One of the possible research directions is the exploration of the usage of advanced deep learning architectures such as Long Short, Term Memory (LSTM) or Gated Recurrent Units (GRU) to better understand and anticipate the complexities of time series in price movements. Besides that, adding more technical indicators, macroeconomic variables, or sentiment, based features extracted from the news and social media may result in a more accurate prediction. In addition, adaptive risk management mechanisms and dynamic position sizing strategies could be utilized to further capital efficiency.

Further studies might also be concerned with examining the applicability of the proposed model in different asset classes, such as commodities, forex, and cryptocurrencies, in order to test its universal suitability. Besides that, real, time implementation and transaction cost modeling would give a better picture of the practical usage. All in all, the present study is an addition to the continuously evolving area of intelligent trading systems and shows the promise of ANN, based multi, indicator frameworks for strong and adaptive swing trading strategies in today's financial markets.

**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/

**References**

1. Kumar, S., Kadia, A., Sharma A., Kumar, R., (2026) "Proximal Policy Optimization (PPO)–Driven Reinforcement Learning Model for Automatic Stock Trading using the combination of Trend–Volume–Volatility Integration". International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110103 1-15 DOI: 10.71097/IJSAT.v17.i1.10103
2. Kumar, A., Kumar, G., Alam, K., Kadia, A., (2026) "**Smart Money Detection with Simple Moving Average and Traded Volume Confirmation Integrated in Machine Learning".** International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110343 1-11 https://doi.org/10.71097/IJSAT.v17.i1.10343
3. Kadia, A., Alam, K., Kumar, G., Kumar, G., (2026) " Machine Learning–Driven Stock Price Breakout Identification with Simple Moving Average and Traded Volume Confirmation" International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110341 1-11 https://doi.org/10.71097/IJSAT.v17.i1.10341

4. Adhikary, S., Kadia A., (2025), "Algorithmic Trading with a Combination of Advanced Technical Indicators – An Automation", International Journal on Science and Technology (IJSAT). 16(3) IJSAT25037777 1-20, 2025, https://doi.org/10.71097/IJSAT.v16.i3.7777
5. Kumar, S., Kadia, A., Sharma A., Kumar, R., (2026) "Algorithm Trading Platform using Simple Moving Average Crossover (SMAC) and On-Balanced Volume (OBV) Integrated in Reinforcement Learning" International Journal of Engineering Development and Research. 14(1), ISSN: 2321-9939 , IJEDR2601221 758-767 Available :https://rjwave.org/IJEDR/papers/IJEDR2601221.pdf
6. Kadia, A., (2026) "Machine Learning based Stock Trading Strategies using Simple Moving Average with Average Traded Volume Crossover Confirmation" Published in: 2025 IEEE Silchar Subsection Conference (SILCON), DOI: 10.1109/SILCON67893.2025.11327015
7. Kumar, R., Kadia, A., Kumar, S., Sharma A., (2026) "Capture Market Trends through Multi-Indicator Confirmations using Reinforcement Learning Models". International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110080 1-15 DOI: 10.71097/IJSAT.v17.i1.10096
8. Kadia, A., Adhikary, S., Dey, R., Kar, A. (2025). "Deep Learning Based Stock Trading Strategies Using Leading Multi-Indicator Confirmations". International Journal on Science and Technology (IJSAT). 16(3) IJSAT25037682 1-15. https://doi.org/10.71097/IJSAT.v16.i3.7682
9. Sharma A., Kadia, A., Kumar, S., Kumar, R., (2026) "Super Stock Trading: Automation in Reinforcement Learning with Advanced Multi-Indicator Confirmations". International Journal on Science and Technology (IJSAT). 17(1) IJSAT260110096 1-16 DOI: 10.71097/IJSAT.v17.i1.10080
10. Kadia, A., Dey, R., Kar, A. (2025). "Smart Stock Trading using an Advanced Combination of Technical Indicators with Volume Confirmation Integrated in Reinforcement Learning". International Journal on Science and Technology (IJSAT). 16(3) IJSAT25037453 1-20. https://doi.org/10.71097/IJSAT.v16.i3.7453
11. Kadia, A., Kumar, S., Qureshi, W., Sharma A., Kumar, R., (2026) "Simple Moving Average Crossover and Support Resistance Zone-based Stock Trading using Reinforcement Learning", International Journal of Engineering Development and Research. 14(1), ISSN: 2321-9939 , IJEDR2601260 35-45 Available at https://rjwave.org/IJEDR/papers/IJEDR2601260.pdf
12. Kumar, R., Kadia, A., Kumar, S., Sharma A., Qureshi, W., (2026) "Reinforcement Learning Algorithm-based Equity Trading with Candlestick-Pattern", Journal of Advance and Future Research . 14(1), ISSN: 2984-889X, JAAFR2601581 281-286 available at: https://rjwave.org/jaafr/papers/JAAFR2601581.pdf
13. Qureshi, W., Kadia, A., Kumar, S., Sharma A., Kumar, R., (2026) "Autonomous Trading Across Bull, Bear, and Sideways Markets with Reinforcement Learning Algorithm", International Journal of Engineering Development and Research. 14(1), ISSN: 2321-9939, IJEDR2601261 46-55 Available at https://rjwave.org/IJEDR/papers/IJEDR2601261.pdf
14. Dey, R., Kassim, S., Maurya, S., Mahajan, R. A., Kadia, A., & Singh, M. (2024) "Machine Learning Based Automated Trading Strategies for Indian Stock Market", Journal of Electrical Systems, ISSN:1112-5209, 20(2s):747-758, DOI: https://doi.org/10.52783/jes.1572

15. Dey, R., Kassim, S., Maurya, S., Mahajan, R. A., Kadia, A., & Singh, M. (2024) "Machine Learning based Financial Stock Market Trading Strategies with Moving Average, Stochastic Relative Strength Index and Price Volume Actions for Indian and Malaysian Stock Market", Journal of Electrical Systems, ISSN:1112-5209, 20-2s (2024): 759-767, DOI: https://doi.org/10.52783/jes.1576
16. Atsalakis, G. S., & Valavanis, K. P. (2009). Surveying stock market forecasting techniques – Part II: Soft computing methods. *Expert Systems with Applications, 36*(3), 5932–5941. https://doi.org/10.1016/j.eswa.2008.07.006
17. Chen, A. S., Leung, M. T., & Daouk, H. (2003). Application of neural networks to an emerging financial market: Forecasting and trading the Taiwan Stock Index. *Computers & Operations Research, 30*(6), 901–923. https://doi.org/10.1016/S0305-0548(02)00037-0
18. Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010
19. Kara, Y., Boyacioglu, M. A., & Baykan, Ö. K. (2011). Predicting direction of stock price index movement using artificial neural networks and support vector machines. *Expert Systems with Applications, 38*(5), 5311–5319. https://doi.org/10.1016/j.eswa.2010.10.027