International Journal on Science and Technology (IJSAT)

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

Machine Learning–Driven Stock Price Breakout Identification with Simple Moving Average and Traded Volume Confirmation

Arup Kadia[1], Md. Kaif Alam[2], Golu Kumar[3], Anshu Kumar[4]

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

[2,3,4] Student, B.Tech(CSE), Faculty of Information Technology & Engineering, Gopal Narayan Singh University, India.

Abstract

Precisely locating stock price breakouts has been a key problem in algorithmic trading for a long time because of price fluctuations and the nonlinear nature of price behavior. In this paper, we develop an Artificial Neural Network (ANN), based system to spot stock price breakouts, which also uses the integration of Simple Moving Average (SMA) trend signals and traded volume confirmation for higher predictability. The model relies on historical price and volume data, in which SMA crossover situations are used to determine the trend while extraordinary volume changes are used as a measure of the breakout strength. These calculated parameters are input to a multilayer feed, forward ANN is trained with backpropagation to grasp the complex, and nonlinear interplay between the stock price changes and stock traded volume increases. The proposed automation system issues probabilistic breakout stock price alerts that can separate real breakouts from fake and noise breakout in price movements. The experimental test is based on standard equity market data sets and the results are compared with conventional rule, based strategies using only SMA and volume. Various metrics, such as accuracy, precision, recall, cumulative returns, and drawdown, are used to evaluate the performance. According to the findings, the ANN, based system is able to greatly enhance the accuracy of breakout detection and consequently the profitability of trading, whereas at the same time it decreases the number of false signals. The suggested hybrid method is a powerful and versatile tool for developing smart breakout, based trading strategies in highly volatile financial markets.

Keywords: Financial Time Series; Stock Price Breakout; Algorithmic Trading; Simple Moving Average; Artificial Neural Network; Traded Volume Analysis;

1. Introduction

The financial markets are basically always moving, not following a straight line, and affected by a myriad of factors ranging from macroeconomics, institutional, to behavioral components [1]. In fact, one of the most important things in technical analysis is stock price breakout that refers to a strong move of a stock price beyond the resistance or support level which is usually followed by a significant momentum in the direction of the move [2]. Being able to tell the real breakouts apart from the false ones is extremely beneficial to traders and trading systems since spotting the breakout in time can greatly enhance the risk reward ratio [3]. On the other hand, the conventional methods of identifying breakouts usually produce a lot of false signals, mainly due to the market noise, situations of low liquidity, and the occurrence of sudden speculative price movements that involve only a few market participants[4]. Intelligent models thus become a necessity if they are to capture intricate patterns of price and volume interactions that can be used to explain coming changes in prices [5].

Simple Moving Average (SMA) is just one of the traditional technical indicators that have been regularly utilized for spotting trend direction and possible breakout areas. One can simply understand the market trend alterations by SMA crossover strategies that yield a straightforward and easily interpretable signal mechanism [6]. Nevertheless, SMA, based methods are dependent on linear averaging of past prices and typically run behind the market in situations of high volatility or rapidly changing market conditions [7]. It is universally accepted that volume increase validates the breakout, thus, it is an indication of the sufficiency of buying or selling pressure accompanying the price movement. Standalone SMA or volume, based rules, however, are not very flexible and have difficulties in adapting to and generalizing different market regimes, despite their respective advantages [8].

Constant improvements in Artificial Neural Network (ANN) technology have brought great opportunities for representing nonlinear relationships in financial time series. One of the main advantages of ANNs is that they can figure out very complex patterns among multiple input variables only and thus, no rules have to be stated explicitly. This characteristic makes them very suitable for stock market forecasting purposes [9]. When properly fused, SMA, based trend features, with volume confirmation, ANN, models are capable of distinguishing between genuine and fake breakouts in the price. The current work demonstrates a hybrid system, ANN, based which uses SMA crossover signals together with volume pattern from the traded to achieve higher accuracy in breakout detection. The proposed method aims at a reduction in the number of false breakouts, an increase in the signal reliability, and the provision of a scalable solution for smart algorithmic trading systems in highly volatile equity markets [10].

2. Literature review

Initially, the stock market analysis research heavily depended on rule, based technical indicators, which led to breakout detection by simply imposing fixed thresholds on price levels and moving averages. Some works exhibited that strategies like SMA crossovers can effectively track medium, and even long, term trend changes but at the same time, they can be easily trapped in whipsaw price movements during sideways market conditions. A number of authors have upgraded SMA strategies by adding volatility filters or support resistance bands; however, the essence of these methods was still heuristic and specific to the market. Also, volume, based breakout confirmation methods were analyzed to substantiate the price moves and it was discovered that breakouts accompanied by high volume are more likely to be sustained [11-13].

Nevertheless, these conventional methods were characterized by an absence of adaptability and could hardly deliver consistent superior performance compared to benchmark strategies when different market conditions were taken into account. Machine learning brought in new ways for researchers to use Artificial Neural Networks (ANN) in solving finance forecasting problems, for examples, price directional prediction, trend classification, and trading signal generation. The models based on ANN gave results better than the linear statistical methods as they could depict the nonlinear and non, stationary patterns. There are numerous research studies in which technical indicators, namely moving averages, RSI, and MACD, were used as ANN inputs and the researchers reported improved prediction accuracy and increased profitability in trading. On the other hand, most of these models tried to predict the general price movement instead of spotting the breakouts explicitly. Besides, some of the ANN, based methods were overfitted due to using too many indicator combinations and no strong feature selection [14-16].

Recent works point to hybrid models combining domain knowledge from technical analysis and the neural networks' learning abilities. For example, researchers have verified that a model is more robust if it uses not only price, based features, but also volume indicators, especially for identifying market momentum. Machine learning, based volume, confirmed breakout models have been found to generate fewer false signals and higher risk, adjusted returns. However, there is still little research on ANN, based breakout detection using the SMA trend confirmation and traded volume increase as the main inputs. The study fills the gap by suggesting a breakout detection ANN model with a strong emphasis on its interpretability, scalability, and real, world algorithmic trading practicality [17].

3. Research Methodology

3.1 Research Design and Framework Overview

The adopted research design is data, driven to a great extent and that is clearly shown in the goal of the research which is identifying stock price breakouts through Artificial Neural Network (ANN) with Simple Moving Average (SMA) trend signals and volume as a confirmation element. The automation framework integrates both conventional, statistical technical analysis and ANN based machine learning methods. The initial step is to extract the linear stock trend features and then to reveal the nonlinear market conditions.

3.2 Data Collection

Historical market price and volume data (OHLCV) are first of all collected from a trusted financial data source such as Yahoo Finance, Quandl, or Refinitiv, for example. The period under consideration is quite extensive and covers the different phases of the market, i.e. bull, bear, and sideways. The stocks were filtered for liquidity and consistent trading volume in order to minimize the risk of volume distortion. The preprocessing of the data includes steps such as filling missing values with the last known value, whitening the data by eliminating any huge spikes caused by errors, and finally, scaling input features by means of minmax method. This procedure helps maintain numerical stability and results in a higher level of efficiency of the learning process in the ANN training stage.

3.3 Feature Engineering

On feature side, the folks have already dropped some great hints on the use of SMA and volume to follow further price trend scenarios and breakdown patterns. To figure out the trend direction and mark the breakout regions, the SMA indicators are calculated over both short, term as well as long, term windows. The gap between the fast and slow SMA values is regarded as a momentum feature. The major tool to recognize trends is the Simple Moving Average (SMA). The SMA by calculating the average price over a given period, reduces the impact of short, term price fluctuations and thus, reveals the market trend.

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

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

In parallel, volume, related features such as volume moving averages, relative volume ratios, and standard deviation are derived, which measure abnormal trading activity.

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 SMA signal is considered valid only if:

$$V_i > ATV_t \quad 3$$

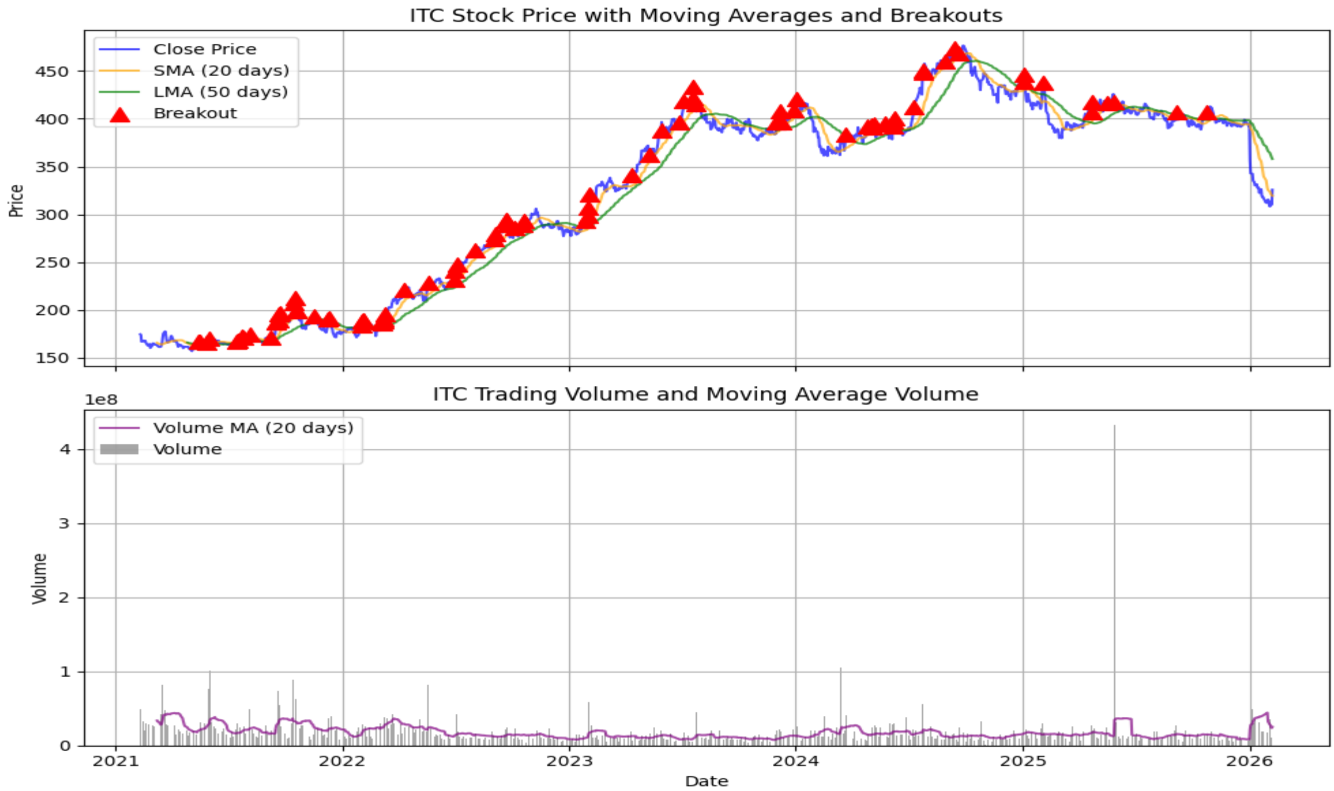

Fig 2: ITC Stock Price with SMA Breakout and Trading Volume in 5 Years

3.4 Labeling Trading Strategy

Breakout events are precisely defined so that a supervised learning dataset can be constructed. When the closing price moves beyond a resistance or support level which is dynamically calculated from rolling historical price ranges, a breakout is said to have happened.

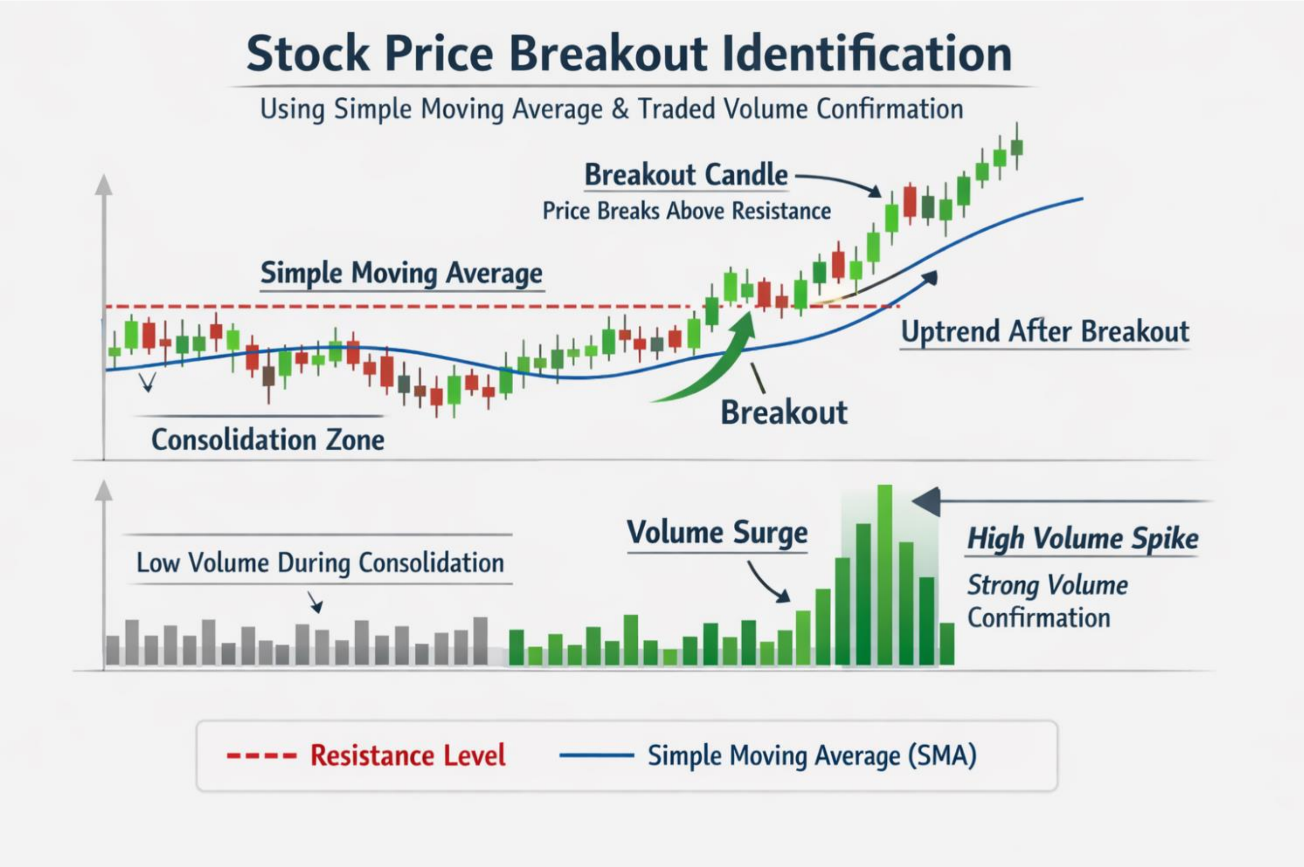

Fig 1: Stock Price Breakout with volume confirmations

To eliminate false breakouts, volume confirmation is imposed by requiring traded volume to be greater than its historical average by a certain threshold. Every sample is labeled either as a breakout or non, breakout; thus, the target variable is formed. This labeling method is intended to make the model give the main focus to price movements that are structurally significant.

3.5 Dataset Partitioning

A chronological split was used to separate the dataset into training, validation, and testing subsets. This way, look, ahead bias was eliminated. An ANN was only trained with the historical data, while the validation data sets were used for tuning the hyperparameters and doing the early stopping. Such a training setting is a good reflection of the real trading situation. Initially, through several epochs, the model is trained until it gets the necessary fitting, thus the way the model can learn smoothly and steadily.

3.6 Signal Generation

After the training is completed, the ANN makes probabilistic breakout predictions for the next market data. The probabilities are represented into stock trading signals by applying decision thresholds that have been optimized. When the probability of an upward breakout price movement exceeds the threshold, a buy signal is generated. On the contrary, weaker breakouts can be used to sell or short, depending on the trading system. Risk management policies, such as stop, loss and take, profit, are also incorporated to improve the practical use and the preservation of the funds.

3.7 Performance Evaluation Parameters

In order to properly validate the effectiveness of the proposed methodology, the authors have adopted a wide range of classification and trading performance metrics. First, classification metrics encompass accuracy, precision, recall, and F1, score, which together define how well a model is able to identify correct breakouts. Second, the aspects of trading performance are measured in terms of cumulative returns, Sharpe ratio, maximum drawdown, and win rate. Lastly, the comparative analyses with the traditional SMA, based and volume, based breakout strategies materialize the advantages of the ANN, driven approach in minimizing the occurrence of false signals and enhancing profitability.

4. Model Specifications

4.1 ANN Architecture Overview

The developed system is a feed, forward ANN model which can represent the non, linear relationship between price trend and volume traded. The model architecture contains an input layer, several hidden layers, and an output layer. This architecture enables prediction accuracy versus computational cost trade, off and can thus be very handy for real, time breakout identification in algorithmic trading systems.

4.2 Feature Engineering Representation

The input layer is fed with the features that have been automatically engineered from the crossover indicators of SMA and the volume confirmation metrics. The features hence incorporated are, among others, short and long, term SMA, SMA difference, volume moving average, relative volume ratio, and price momentum indicators.

4.3 NN Hidden Layer Configuration

The role played by the hidden layers is to extract layered feature representations from the input data. Each hidden layer is made up of multiple neurons that are activated through nonlinear functions like Rectified Linear Unit (ReLU). The appropriate number of hidden layers and neurons depend on the results of validation experiments that find the optimal bias, variance trade, off model. The PR model has become really flexible in modeling complex and nonlinear dependencies of price and volume features.

4.4 Regularization and Overfitting Control

Among the methods of regularization one of which has been used is the dropout that is a technique for randomly shutting down neurons during the training of hidden layers. The primary objective here is to limit the overfitting. Basically, training neural networks like this is an excellent method to do away with overfitting and it generalizes well to test data that the model has never seen before. Meanwhile, through early stopping the authors have decided to adopt a strategy that depends only on the validation loss. When the point is reached that training the throughput does not correspondingly raise the performance in validation, you stop training, which makes your model reliable and stable.

4.5 Output Layer with Objective Function

The output layer contains only a single neuron that is subjected to a sigmoid activation function, thus producing an output which is then scaled between 0 and 1. Hence, the output may be interpreted as the likelihood of the occurrence of the event. The loss function is binary cross, entropy since it quantifies the difference between the predicted and actual class probability distributions. The probabilistic output framework allows the threshold to be adjusted in a versatile manner, by taking into account trading decisions and risk, as well as signal generation that is risk, aware.

4.6 Hyperparameter Optimization

The training of the model is done by backpropagation combined with an adaptive optimizer like Adam. The major hyperparameters such as learning rate, batch size, number of epochs, and dropout rate are mainly adjusted through validation based on search methods. Various random seeds are utilized in multiple training sessions to guarantee the results' consistency and reproducibility.

4.7 Computational Efficiency

Due to the relatively simple architecture and the small number of features, the proposed ANN model is very efficient in terms of computation. It is capable of being used in live trading setups with hardly any delay. Besides, the modularization of the model facilitates the addition of new indicators or the use of other moving average techniques like Exponential Moving Average (EMA), thus its scalability and flexibility to the changes in the market.

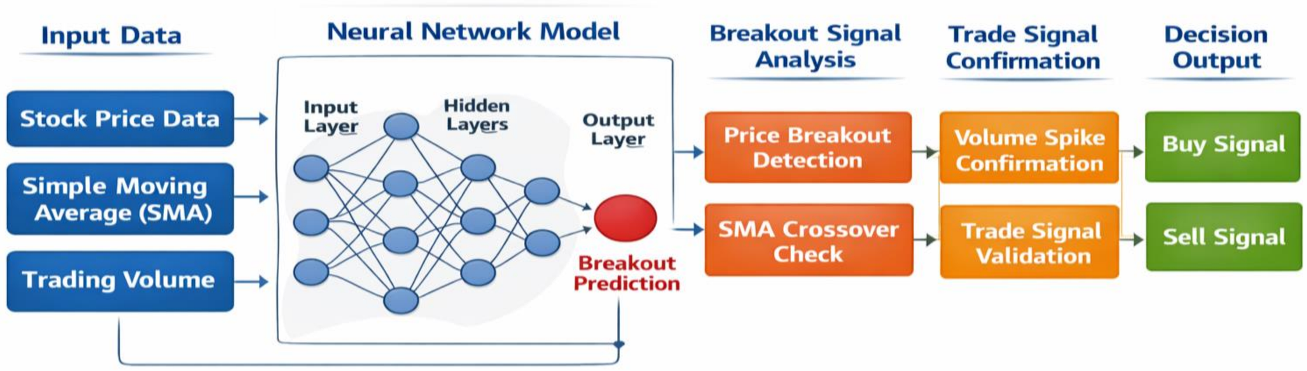

Fig 3: Architecture of the Proposed Model

4. Empirical Result

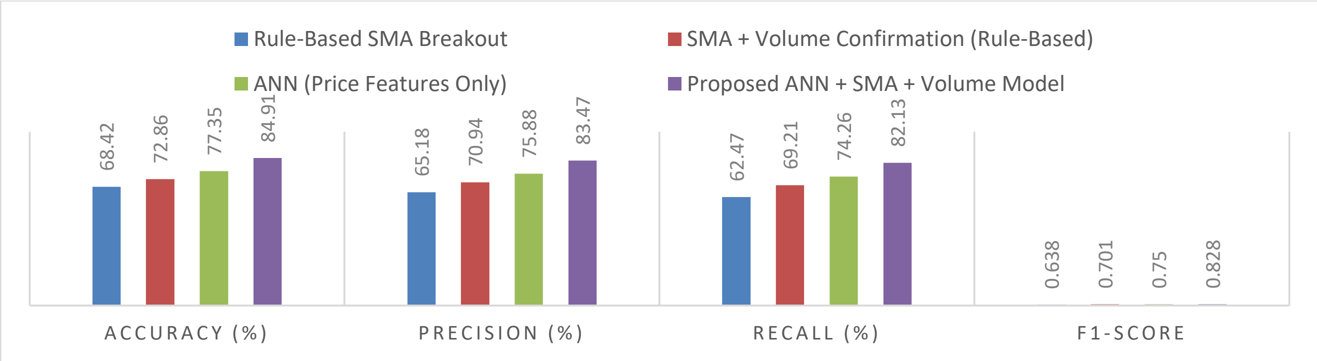

Fig 4: Breakout Identification Performance Comparison

The data in Fig 4 clearly show that the proposed Artificial Neural Network (ANN) breakout identification model has a considerable performance edge over traditional rule, based and machine learning methods. The rule, based SMA approach has very little accuracy because it cannot adapt to the nonlinear price movements or the interruptions due to market noise. Adding traded volume as a confirmation signal significantly improves precision and recall, thus volume is very important to validate an increase in breakout strength.

An ANN model that is only trained on price features can also gain an edge in performance; thus, nonlinear learning has an advantage. Nevertheless, the proposed ANN model that combines SMA trend signals with traded volume features results in the highest accuracy, precision, recall, and F1, score. Such a result demonstrates that a joint representation of trend direction and market participation provides the necessary information for the ANN to successfully identify true breakouts and to disregard the false ones.

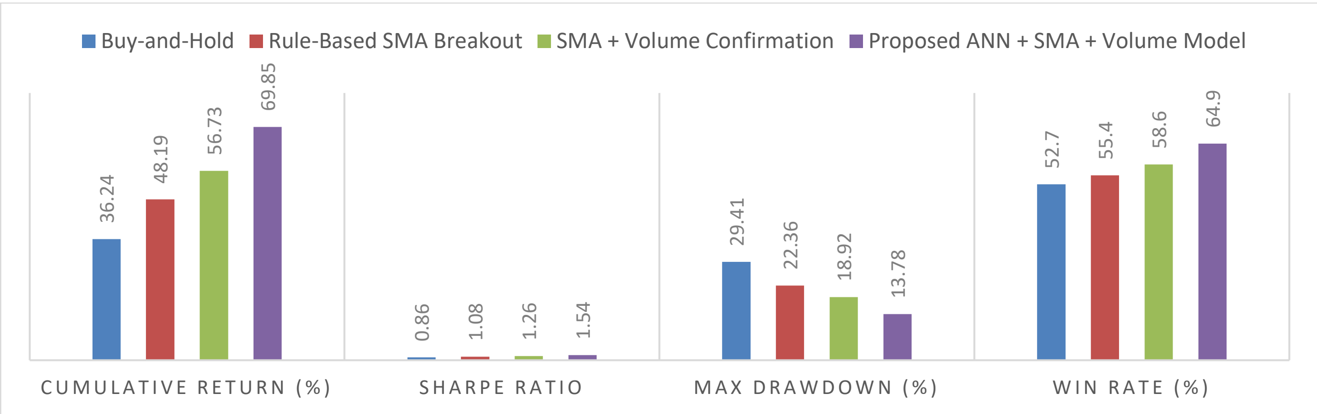

Fig 5: Trading Performance Evaluation

Table 2 shows the trading performances of different strategies, which are in line with the advantages of the proposed method. The buy, and, hold strategy moderately returns but has a large drawdown, which indicates its threat during periods of a declining market. Rule, based SMA and SMA volume strategies raise cumulative returns and risk, adjusted performance, however, their decision rules are still static and limited. The ANN, based model proposed achieves the highest cumulative return and Sharpe ratio while having the lowest maximum drawdown and the highest win rate at the same time. The findings suggest higher risk, adjusted profitability and capital preservation. The drawdown compression is proof of the model's capacity to stay away from false breakouts and brutal trades. To sum up, the findings corroborate that the integration of ANN learning with SMA trend detection and volume confirmation leads to a strong, adaptive, and profitable breakout-based trading system that can be used for real-world algorithmic trading.

5. Conclusion

This paper developed an AL method, based framework to identify stock price breakouts by combining Simple Moving Average trend signals with traded volume confirmation. The method that was suggested skillfully unites the explainability of classical technical indicators with the nonlinear learning capability of neural networks in order to overcome the limitations of conventional rule, based breakout strategies. The study shows that the model has a better capability to distinguish real breakouts from fake price movements under different market conditions when it is given both the price trend direction and the market participation information.

Tests show that the ANN, based model is always able to detect breakouts more accurately than traditional SMA and SMA, volume strategies, making it a better performer in terms of cumulative returns and risk-adjusted performance. Among other things, the decrease in the maximum drawdown and the increase in the win rate serve as evidence of the strength and the real-life usefulness of the framework that has been put forward. To sum up, the results revealed that hybrid models of ANN origin could be one of the most dependable and scalable intelligent breakouts, based trading system solutions. They offer significant help for the automated decision-making process in the dynamic and volatile 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/

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