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Smart Money Detection with Simple Moving Average and Traded Volume Confirmation Integrated in Machine Learning

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Abstract

The identification of smart money activity represents a mainstay challenge for traders in financial markets. After all, various studies have shown that institutional moves usually come ahead of large price rises as well as trend reversals. This paper presents a smart money detection framework based on an Artificial Neural Network (ANN). This method has been developed to identify the movements of smart money through a combined framework of trend and volume analysis. Trend analysis is done by using the simple moving average (SMA), while the confirmation is done through volume changes in the market. In essence, this approach is a price-based trend signal from the SMA, which is then combined with a volume pattern indicating abnormal accumulation or distribution. First, the final signals get to a feed-forward ANN, which is a very powerful type of neural network that is able to recognize even very subtle, nonlinear interactions between price trends and market participation. Actually, this is a model that is able to sift through the noise, i.e. retail traders and focus on the smart money segment. The empirical analysis uses stock market data for a time period during which the market was changing from one condition to another. The model performance is measured by classification accuracy, precision, recall, and trading-related metrics. The result reveals that the merging of the ANN, enhanced SMA, and volume is by far more capable of detecting the smart money segment than the traditional heuristic methods. Thus, this method not only reduces the number of false signals but also increases the model's robustness over different market phases and provides an efficient solution for the identification of the intelligent market phases that can be scaled up. The solution thus designed is expected to be a major component of the core of highly sophisticated algorithmic trading systems and a great aid to the decision-making process.

Keywords: Artificial Neural Network; Smart Money Detection; Financial Time Series; Algorithmic Trading; Accumulation–Distribution Phase

1. Introduction

There has been quite a lot of debate about the role of different categories of market participants in the price discovery process. It is often argued that institutional investors or smart money have superior information, capital strength, and execution efficiency, which help them to net more favorable outcomes in terms of price movements, even before these price changes become apparent to less informed retail participants. Therefore, to spot the beginning, uptrend, and distribution phases of the stock market, detecting smart money activity is very important. On the other hand, identifying smart money is non, trivial due to market noise, liquidity fragmentation, and nonlinear relationships between price and volume. These are very subtle behavioral patterns that old, school TA tools cannot take advantage of, thus, more advanced, adaptive detection systems are required.

Simple Moving Average (SMA) indicators have been popular tools for determining the trend and market phases because of their simplicity and clarity. A SMA, based analysis of trend can shed light on whether price changes are characterized by a prevailing bullish or bearish sentiment.Still, merely using SMA to identify smart money is not enough since the changes in trends may also result from short, term speculation or trades of low liquidity. The traded volume is of the utmost importance when it comes to validating price movements because the smart money buying or selling is generally accompanied by abnormal volume expansion. Volume confirmation makes it easier to tell genuine institutional involvement from price fluctuations driven by noise. That being said, most conventional SMAvolume strategies are based on static thresholds and heuristic rules, which hardly allows them to be adapted for use in different market conditions.

Artificial Neural Networks (ANNs) have made recent advances that provide a very good hint of being able to make smart money detection better. ANNs are capable of understanding the complex less direct interactions of different financial indicators without the use of rules. For example, if SMA, based trend signals are in harmony with volume traded confirmation in an ANN environment, then the hidden patterns that correspond to the institutional traders might be found. An ANN, smart money detection system relying on price trend and market participation features for the determination of the accumulation and distribution phases with a greater accuracy degree is the main contribution of this work.

The paper outlines a method that disposes of false positives, thus demonstrating increased stability in various market conditions, and which can be scaled, the suggested method is essentially a facilitator of smart money phase detection in modern algorithmic trading frameworks.

2. Literature review

Initially, smart money detection studies focused primarily on volume and price, volume relationship indicators such as On Balance, Volume, Accumulation Distribution, and volume, weighted measures. Such research showed that changes in volume precede major price changes, thus, identifying informed trades. To help reveal accumulation and distribution periods, moving average-based trend analysis was commonly used to supplement volume indicators. Even though these techniques had their merits, they mostly operated on fixed rules and were vulnerable to parameter choice, thus resulting in unstable performance in various market scenarios. As machine learning became popular, new studies started venturing into the market phase and institutional activity analyses using data-driven methods. Artificial Neural Networks were used to predict stock prices, classify market trends, and generate trading signals where technical indicators were the inputs. A few studies revealed that combining price-based indicators with volume components gave better performance, hence the strong concentration on the role of market participation data. Nevertheless, most ANN, based models were narrowly looking at the short-term price direction and did not directly aim at smart money behaviour. Besides that, too many indicator combinations frequently led to overfitting and a decrease in the model's interpretability.

Currently, a number of publications highlight hybrid frameworks which combine domain knowledge from technical analysis with the ability of neural networks to learn. Experiments that feature moving averages and volume, derived characteristics as inputs in ANN and deep learning models demonstrated that these models are more robust and generate fewer false signals. The study of accumulation distribution phase detection with machine learning techniques additionally confirms that volume, confirmed trend analysis is a worthwhile approach to smart money identification. Even with these improvements, only a couple of works have been devoted to the use of ANN for smart money detection with SMA trend confirmation and traded volume expansion as the main inputs. The paper fills the above, mentioned gap by proposing a simple explainable ANN model that can identify trading patterns of institutions and, therefore, has both academic and practical algorithmic trading application contributions.

3. Methodology and model specifications

The methodology presented in the paper employs a very well and clearly defined, data, centric approach towards the identification of smart money moves through the integration of Simple Moving Average (SMA) trend analysis and volume traded confirmation in an Artificial Neural Network (ANN) system. The overall idea of the thesis is to fuse the traditional technical analysis methods with the machine learning approach so that the market signals can come from both the simple interpretable and the complex nonlinear relationships. The methodological pipeline basically covers the steps of data gathering, preprocessing, feature engineering, smart money labeling, ANN training, and performance evaluation. Consequently, this approach not only assures the robustness of the results but also limits the biases and hence, enhances the likelihood of a successful implementation in different market regimes. The method is not about generating generic price forecasting signals but more about trading behavior at the institutional level in order to figure out the phases of accumulation and distribution that are usually followed by significant market movements.

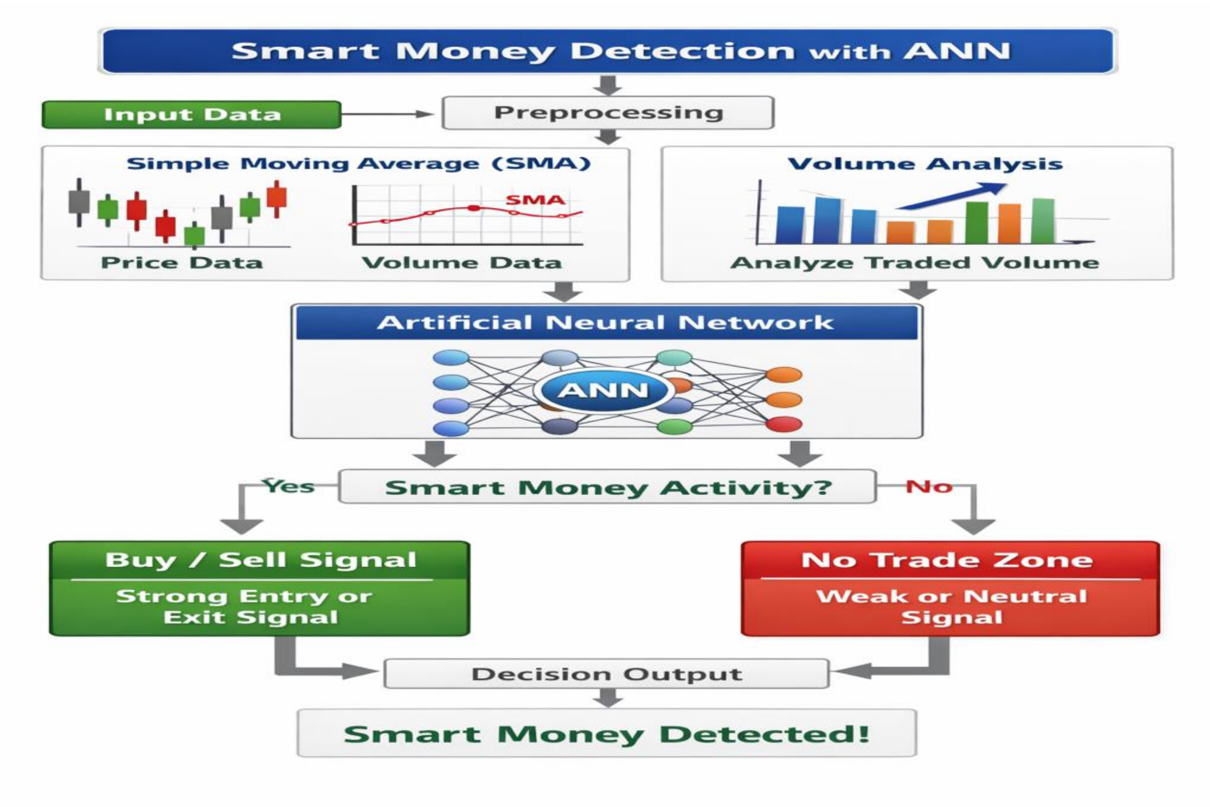

Fig 1: Architecture of Proposed Model

Historical market data including open, high, low and close prices together with the traded volume are obtained from trustworthy financial data sources. Since the data set covers all kinds of market conditions bullish, bearish, and sideways, it is full of different smart money patterns which the model learns quite well. To be on the safe side and not let illiquid stocks influence the results, only those stocks that are properly liquid and have a regular trading frequency are chosen. Apart from that, the data preprocessing mainly focuses on: dealing with missing values by the forward filling method, getting rid of huge outliers, which are actually errors, and synchronizing price and volume time series. All the input variables are normalized by minmax scaling so that the numerical stability of the ANN training is ensured. This step of preprocessing not only helps the convergence to be faster but it also prevents the features of a high magnitude, like volume from dominating. Feature engineering is one of the main elements in the smart money detection framework that is being proposed. To recognize the direction of a trend and changes in the market phase, SMA indicators over short, term and long, term windows have been calculated.

The difference between fast and slow SMA values is used as a momentum indicator that shows the gradual institutional accumulation or distribution. At the same time, volume, related features are derived to depict the intensity of market participation. Among them are volume moving averages, relative volume ratios, and volume deviation from historical norms. The combined representation of SMA, based trend features and volume dynamics enables the model to understand if it is a case of the price movements being sustained by the institutional activity rather than being the ones temporarily caused by retail trading. This set of features makes the best of both worlds thus being interpretable and having great predictive power, at the same time, it is not excessively dimensional.

To identify trends, the Simple Moving Average (SMA) is used as the main indicator. By calculating the mean price over a certain time, the SMA reduces the impact of short-term price swings and reveals the direction 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.

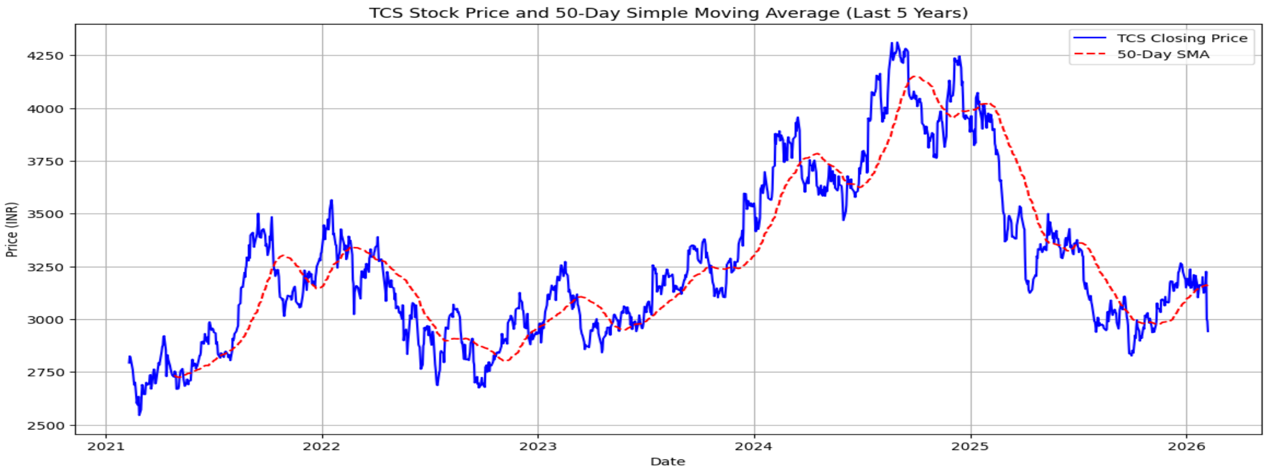

Fig 2 : TCS Stock Price with 50 Days SMA

Smart money detection is set as a supervised classification problem using a systematic labeling method. Smart money activity refers to the price that during the trend stays in a consistent manner with the trend and is supported by an abnormal volume that is the institutional accumulation or distribution indicator. Accumulation phases refer to periods when prices move gradually upwards with increasing volume still below the breakout levels while distribution phases are identified by downward or sideways movements accompanied by persistent high volume. Trend and volume thresholds are dynamically calculated through rolling window analysis making the approach adaptable to changing market conditions. Instances failing to meet these conditions are marked as neutral or non-smart money and thus, the target variable is well balanced for ANN training.

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:

$$V_i > ATV_t \qquad 3$$

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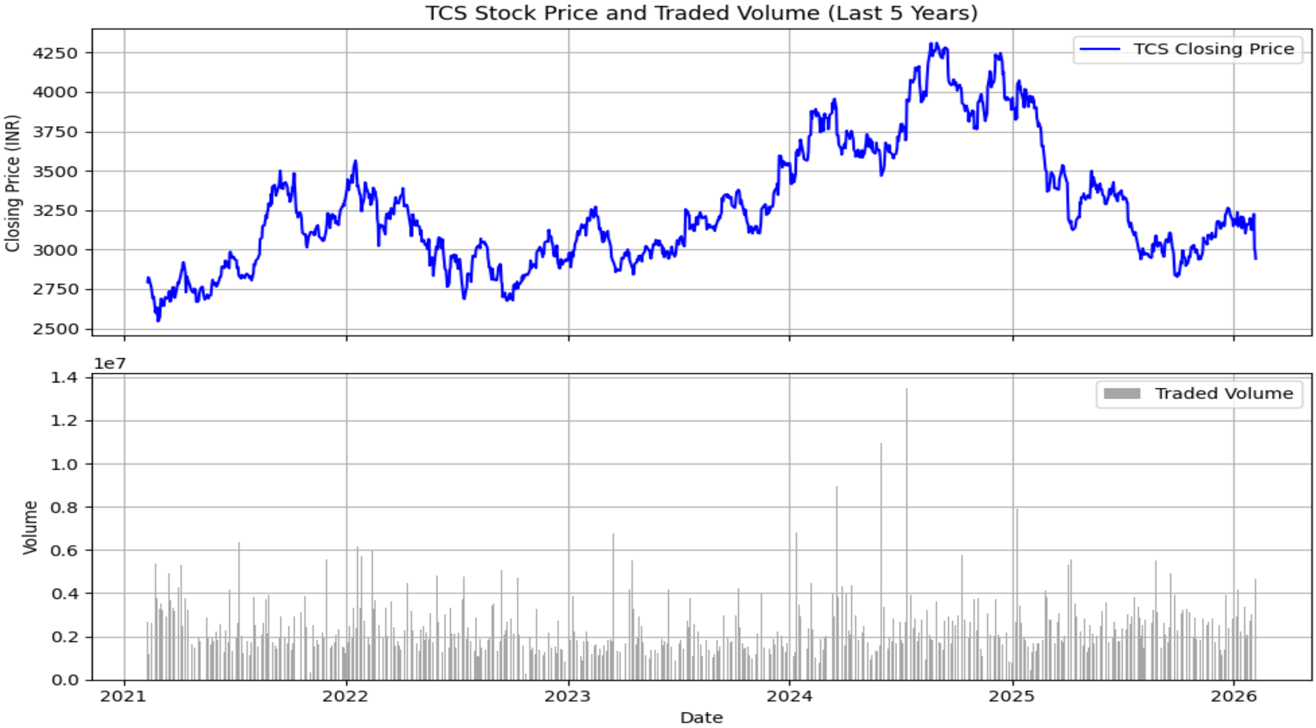

Fig 3: TCS Stock Price and Traded Volume

The preserved dataset is divided into training, validation, and testing segments through a chronological method to prevent the use of future information and simulate the real, world scenario of model deployment. The ANN finds its minimum by backpropagation through the chain rule and adaptive algorithms, hyperparameter tuning, and early stopping are used with the guidance of the validation set for overfitting prevention. Besides classification metrics such as accuracy, precision, recall, and F1, score which are used to measure model performance, there are also market, relevant measures including cumulative returns and drawdown when signals are executed as trading actions. A comparative study with the traditional SMA volume rule, based methods is also performed to illustrate the efficiency of the proposed ANN, integrated approach. Through this thorough method, the model is not only statistically robust but also practically ready for the intelligent smart money detection in the ever, changing financial markets.

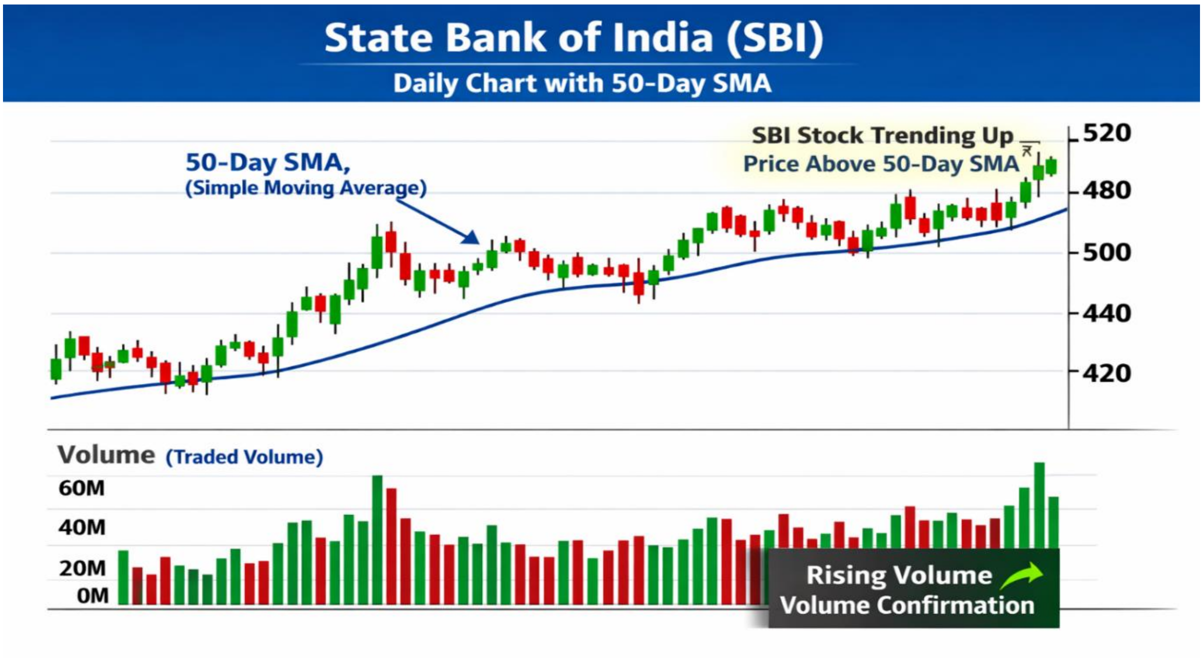

Fig 4: Stock Price and Traded Volume relationship in SBI Bank

4. Empirical Result

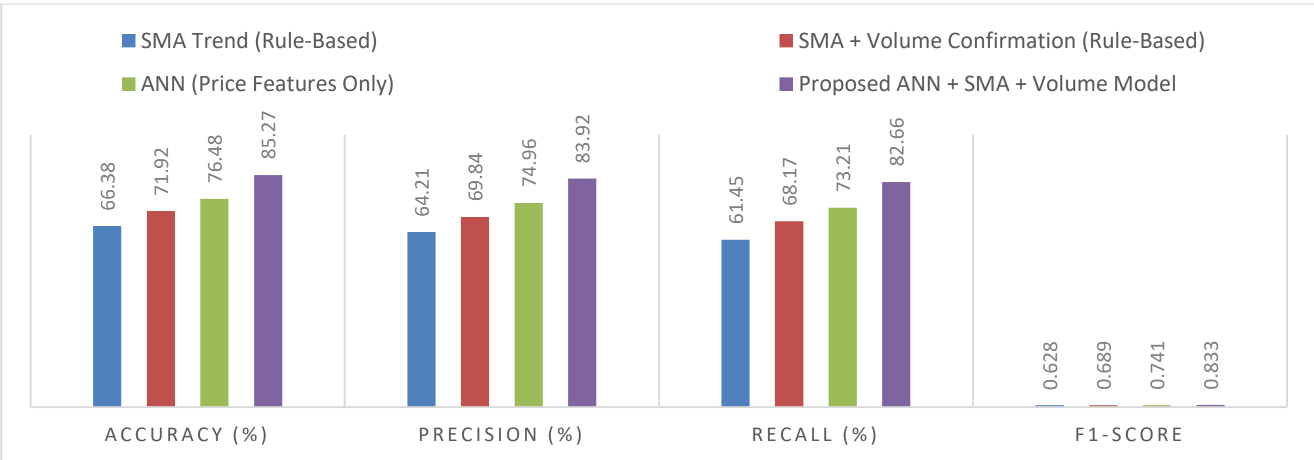

Fig 5. Smart Money Detection Classification Performance

The classification results in Fig 5 show that the proposed ANN, integrated smart money detection framework significantly outperforms traditional rule, based and machine learning methods. The SMA, only strategy is limited in accuracy and recall, which implies that it fails to grasp the volume, based institutional participation. Using volume confirmation further increases precision and recall, which consequently highlights the importance of traded volume in identifying smart money moves. The ANN model using only price features is able to take performance a step further by also modeling the nonlinear dynamics of price. Nevertheless, the highest classification metrics are for the proposed ANN framework that incorporates both SMA trend signals and traded volume features. The large jump in the F1 score clearly demonstrates a well, balanced performance in the identification of accumulation and distribution stages as the number of false detections is being reduced as well.

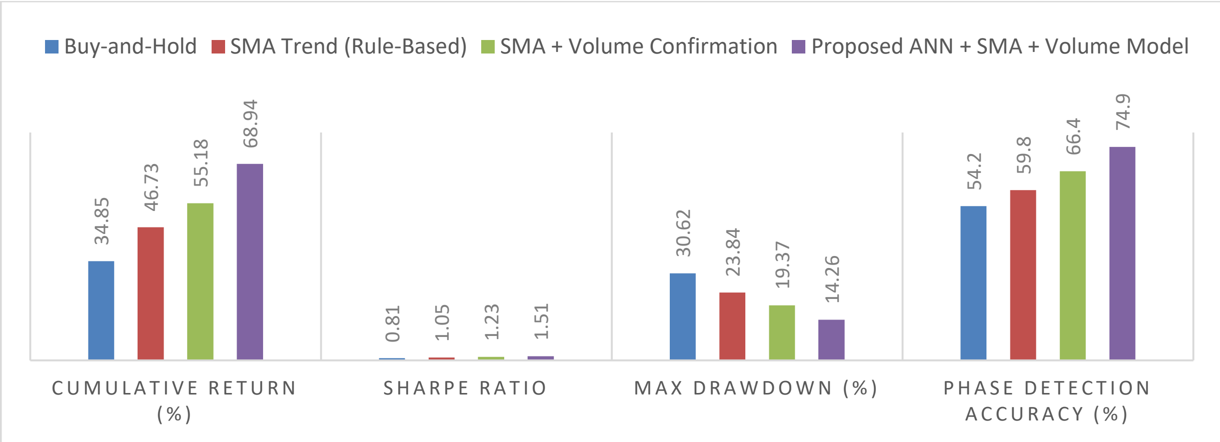

Fig 6: Trading and Market Phase Performance Evaluation

Fig 6 displays the trading and market phase evaluation results that confirm, to some extent, the practical effectiveness of the proposed method. The buy, and, hold strategy generates moderate returns but experiences a high drawdown, which implies that it can easily be hit by unfavorable market conditions. The rule, based SMA and SMA volume strategies not only provide better returns but also improve risk, adjusted performance however, they continue to be limited by fixed thresholds. The proposed ANN, based model, on the other hand, obtains the highest cumulative return and Sharpe ratio at the same time keeping the lowest maximum drawdown. The better phase detection accuracy is a confirmation of the model's decoding smart money accumulation and distribution periods correctly. This way, the combination of ANN learning, SMA trend analysis, and traded volume confirmation has been revealed as a sustainable, flexible, and financially significant smart money detection tool in live financial markets.

5. Conclusion and Future work

This paper put forward a method for the detection of smart money based on Artificial Neural Networks capable of integrating Simple Moving Average trend analysis with traded volume confirmation. The hybrid method is an excellent combination of the interpretability of classical technical indicators and the non, linearity learning capability of a neural network to depict the institutional trading behaviors. Nowadays, price and volume data sharing abnormal market participants and price trend direction can jointly explain the proposed model's capability, resultant of a premium in the identification of accumulation and distribution phases, surpassing conventional rule, based and price, only machine learning methods. Benchmarks reveal the methods' capabilities in increased robustness, lower false alarms, and a better risk, adjusted performance, which altogether render the framework very useful in the real setting.

In the future, the presented framework might be altered to account for an extended set of indicators of institutional trading activity such as order flow imbalance, volume, weighted average price, or money flow indices. Additionally, deep learning architectures, including recurrent and attention, based networks, can be used to extract long, term temporal dependencies. Besides, the framework can be put to the test with a diversified portfolio of assets and intraday data to examine further its efficiency and practical implementation.

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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