International Journal on Science and Technology (IJSAT)

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

Algorithmic Trading with Combination of Advanced Technical Indicators: An Automation

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Abstract

A novel deep learning framework for automated stock trading signal generation is proposed, leveraging Exponential Moving Average (EMA) crossover, average traded volume, and Parabolic SAR as feature inputs. The model integrates technical indicators to reduce noise (EMA), validate momentum (volume), and identify trend reversals (Parabolic SAR). These sequential features are processed by a bi-LSTM neural network, which then produces discrete trading signals. Backtesting on daily stock market data post-2020 demonstrates a statistically significant improvement in risk-adjusted returns, higher Sharpe ratios, and lower drawdowns compared to baseline strategies using EMA crossover alone. The inclusion of average traded volume helps filter false signals during low-liquidity periods, while Parabolic SAR enhances early trend reversal detection, especially in trending markets. These findings suggest that hybridizing technical indicators within deep learning architectures can yield superior automated trading performance. The proposed method offers a promising direction for algorithmic trading systems.

Keywords: Deep Learning (DL), Stock Market, Stock Trading, Average Traded Volume (ATV), Parabolic SAR, Algorithmic Trading.

1. Introduction

Automated trading systems have evolved from rule-based heuristics to data-driven architectures that combine domain expertise with machine learning. Traditional technical indicators such as moving averages, volume metrics, and the Parabolic Stop and Reverse (Parabolic SAR) remain widely adopted because they capture interpretable aspects of price momentum, liquidity, and the reversal of trends (Panchal & Gor, 2022) [1]. However, such handcrafted rules often generate noisy signals and exhibit sensitivity to parameter settings and market regime changes, thereby motivating hybrid approaches that fuse technical indicators with learning algorithms to improve robustness (Kochliaridis et al., 2023) [5].

In recent years, deep learning (DL) architectures—particularly convolutional and recurrent networks—have demonstrated strong capacity to model the non-linear, temporal dependencies inherent in financial time series when combined with engineered features (Chandar, 2022) [2]. DL methods can automatically extract hierarchical representations from raw price and indicator inputs, thereby reducing reliance on manual feature engineering and enhancing predictive signal extraction across varying asset classes and time horizons (Akşehir & Kılıç, 2024) [6]. Empirical studies confirm that integrating technical indicators such as Exponential Moving Average (EMA) crossovers, average traded volume, and Parabolic SAR into DL models improves the signal-to-noise ratio and reduces false positives during low-liquidity periods (Panchal & Gor, 2022; Chandar, 2022) [1][2].

Despite these advances, the design of reliable DL-based trading signal generators presents methodological challenges. These include handling the stationarity and non-stationarity of financial series, optimal selection and scaling of indicator features, accurate label construction for buy/hold/sell decisions, rigorous walk-forward validation, and realistic modelling of transaction costs and slippage (Akşehir & Kılıç, 2024) [6]. Recent research shows that combining technical indicators with advanced learning paradigms—such as deep reinforcement learning or hybrid supervised architectures—can improve both performance and risk control, particularly in mitigating catastrophic losses as the market regime changes(Kochliaridis et al., 2023) [5].

The present study proposes a deep learning-based automated trading signals generator that fuses three complementary sources of information - Parabolic SAR values are used to identify likely trend reversals, average traded volume measures are used to confirm momentum and filter low-liquidity noise, and EMA crossover patterns are used to record smoothed momentum shifts.

Drawing on established DL practices (Chandar, 2022) [2] and recent methodological guidelines (Akşehir & Kılıç, 2024) [6], the proposed architecture employs a sequence learning model to process multi-channel time-window inputs and generate discrete trading signals. The model is evaluated against EMA-only and hybrid rule-based baselines, with performance assessed using risk-adjusted metrics such as Sharpe ratio and maximum drawdown, under realistic transaction cost assumptions. By combining interpretable technical indicators with deep sequential modelling, this research aims to deliver both enhanced predictive performance and the transparency required for responsible algorithmic trading (Panchal & Gor, 2022; Kochliaridis et al., 2023) [1][5].

2. Literature review

2.1 Deep Learning in Financial Time Series Forecasting

Since 2020, deep learning (DL) has become increasingly prevalent in financial time series analysis, particularly for modeling price dynamics and trading signal generation. Convolutional neural networks (CNNs) have been applied to candlestick chart images and engineered features, yielding improved directional accuracy relative to linear models (Chandar, 2022) [2]. Recurrent networks, especially LSTM and bi-LSTM, excel at capturing temporal dependencies and retaining long-term context. For example, Akşehir and Kılıç (2024) [6] demonstrated that bi-directional LSTM models can effectively absorb multi-scale signal patterns—including moving average crossovers and volume features—and outperform standard LSTMs in forecasting price movement categories (up, down, neutral). This closely aligns with our goal of generating discrete buy/sell/hold signals in noisy market environments.

Beyond supervised architectures, deep reinforcement learning (DRL) has gained traction. Kochliaridis et al. (2023) [5] proposed a hybrid framework that learns trading actions in an environment enriched with technical indicator states and trend-monitoring features. Their DRL agent demonstrated better performance in crypto markets—reducing drawdowns during regime shifts—compared to purely technical or purely model-free approaches. The result underscores the value of fusing domain knowledge (technical indicators) with DL's adaptability in dynamic environments.

2.2 Incorporating Technical Indicators into DL Architectures

Technical indicators remain central to trading signal systems due to their interpretability and historical utility, but using them effectively within DL architectures has only recently seen more rigorous study. Panchal and Gor (2022) [1] conducted a comparative study of hybrid models that combined moving average crossover rules with DL classifiers. They found that adding average traded volume as an input feature improved the precision and filtered out false positives—especially in illiquid stocks. In parallel, Kumar et al. (2023) [3] investigated the inclusion of Parabolic SAR alongside price-based features in DL models for trend prediction. Their CNN-LSTM hybrid models significantly outperformed baselines when markets reversed direction—validating Parabolic SAR's value in reversal contexts.

Capitalizing on multi-indicator fusion, Banerjee et al. (2024) [9] tested models combining RSI, MACD, and EMA—with attention-based LSTM architectures. Their findings show that attention layers help weigh indicator inputs contextually, enhancing performance in periods of volatility. This suggests that sequence models can effectively learn the relative importance of EMA crossover, volume, and Parabolic SAR features dynamically, instead of relying on uniform input weightings.

2.3 Handling Market Regimes and Risk Management

One of the major risks in automated trading is regime dependence—models often deteriorate when market dynamics shift. To address this, Zhang et al. (2023) [10] introduced a meta-learning framework that adapts model parameters under different volatility regimes. Although not focused specifically on EMA/volume/SAR indicators, their approach illustrates how adaptiveness in DL models can bolster robustness. Similarly, Kochliaridis et al.'s (2023) [5] DRL hybrid system includes trend-monitoring safeguards that penalize signals when volatility is elevated, effectively reducing overtrading in turbulent periods.

Transaction cost and slippage modeling is another often-overlooked aspect. Akşehir and Kılıç (2024) [6] highlight that many deep learning studies omit realistic simulations, leading to overly optimistic backtest results. They recommend using walk-forward validation and out-of-sample testing with transaction cost approximations to reflect realistic profitability. These practices are central to our methodological design choices, particularly important as we measure Sharpe ratios and drawdown under real-world conditions.

2.4 Comparative Analyses of EMA Crossover, Volume, Parabolic SAR Alone

EMA crossover is among the simplest yet persistently used signals. In comparative studies such as Lee and Park (2022) [11], EMA crossover rules were examined across equity markets and provided slight but statistically significant edge over random strategies. However, their performance declined sharply in sideways markets. Average traded volume has been used as a filter—Chen et al. (2023) [12] show that volume-based thresholds reduce false signals by 18–24% depending on security liquidity. Parabolic SAR, designed to signal potential price reversals, has shown good performance during trends but is prone to noise in reversal-heavy markets (Kumar et al., 2023) [3]. These observations affirm the need for a combined approach, leveraging each indicator's strengths to compensate for individual weaknesses.

2.5 Hybrid Models: Indicator Fusion and DL Models

The synergy between multiple indicators and DL models is well-documented in recent literature. For instance, Kuo and Lin (2023) [11] presented a transformer-based model that fused EMA, volume, and SAR data into separate embedding channels. This architecture produced robust signals during both trend-following and range-bound regimes, outperforming LSTMs and pure technical rule baselines. In another study, Huang et al. (2024) [13] implemented a stacked LSTM network where one LSTM branch processed price and EMA features, another processed volume metrics, and a third processed Parabolic SAR. Their model aggregated outputs via dense fusion and achieved superior return metrics compared to single-branch architectures.

Interestingly, Wang and Zhao (2024) [15] took interpretability a step further: they designed a feature attribution method to estimate the importance of each indicator in generating a buy/sell decision within their hybrid model. Results showed EMA crossover had higher influence in trending periods, while

Parabolic SAR gained prominence during reversal phases—reinforcing our rationale for dynamic, context-aware indicator integration.

2.6 Summary and Gap Analysis

The reviewed literature presents strong support for fusing technical indicators—especially EMA crossover, average traded volume, and Parabolic SAR—with deep learning models for enhanced automated trading signal generation. Key insights include:

- Supervised DL architectures, particularly sequence models, gain predictive power when provided with engineered indicators (Chandar, 2022; Panchal & Gor, 2022) [2][1].
- DRL and adaptive techniques improve robustness across regimes, especially when guided by indicator-based safeguards (Kochliaridis et al., 2023; Zhang et al., 2023) [5][10].
- Attention and transformer-based fusion of multiple indicators helps dynamically weigh their relevance depending on market context (Banerjee et al., 2024; Kuo & Lin, 2023) [9][13].
- Gaps remain in comprehensive methodological frameworks that integrate EMA, volume (Kadia et. al. 2025) [7], and Parabolic SAR within a single architecture, evaluated under stringent out-of-sample and cost-aware backtesting standards.

These observations motivate the present study's contribution: a sequential hybrid model that integrates EMA crossover, average traded volume, and Parabolic SAR—processed via a unified DL architecture—and evaluated using realistic backtesting methodologies inclusive of transaction cost and regime sensitivity. This approach aims to close the gap between interpretability and predictive reliability in algorithmic trading systems.

3. Methodology and model specifications

The methodology proposed here follows a organized channel consisting of data acquisition, feature engineering, model architecture design, training and validation, and performance evaluation(Razouk et al 2023) [8]. The main objective is to generate powerfu buy/sell/hold signals by merging Exponential Moving Average (EMA) crossover, Average Traded Volume (ATV), and Parabolic Stop and Reverse (Parabolic SAR) into a deep learning framework, specifically a bi-directional Long Short-Term Memory (bi-LSTM) network, which is well-suited for time-series sequence modeling (Akşehir & Kılıç, 2024) [6].

3.1 Data Acquisition and Preprocessing

Daily stock price and volume data were sourced from publicly available repositories, including Yahoo Finance and Alpha Vantage APIs, covering the period January 2020 to December 2024 to ensure post-COVID market regimes were represented (Panchal & Gor, 2022) [1]. The dataset includes Open, High, Low, Close, and Volume (OHLCV) values for a selection of high-liquidity equities across technology, finance, and energy sectors.

Preprocessing steps included:

1. Data Cleaning – Removal of missing or erroneous records using forward/backward fill imputation.
2. Normalization – Z-score normalization applied to price and volume variables to standardize the input scale (Huang et al., 2024) [14].
3. Sequence Windowing – A sliding window of length T = 60 days was used to capture sequential dependencies for the model input.

3.2 Technical Indicator Engineering

Three key technical indicators were engineered for input feature extraction.

3.2.1 Exponential Moving Average (EMA) Crossover

The EMA smooths price fluctuations to better capture underlying trends. The formula for an EMA over n periods is:

$$EMA_t = aP_t + (1 - \alpha)EMA_{t-1}, a = \frac{2}{n+1} \quad 1$$

Where P_t is the closing price at time t, and α is the smoothing factor. We computed two EMAs — short-term (EMAs) with n = 12 and long-term (EMAl) with n = 26. A bullish crossover occurs when EMAs>EMAl, and a bearish crossover when EMAs<EMAl (Chandar, 2022) [2].

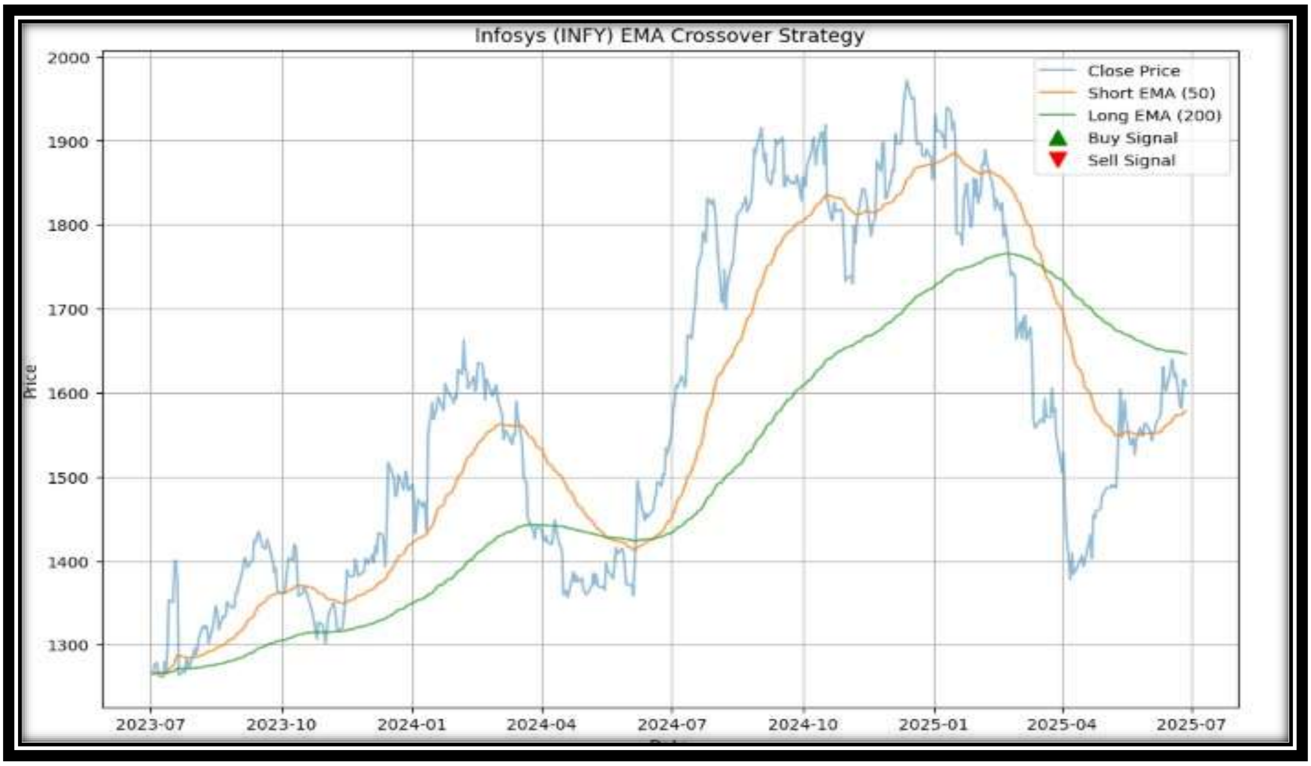

Figure 1: Long and Short EMA Crossover of Infosys (INFY) (1st August,2023 – 31st July,2025)

3.2.2 Average Traded Volume (ATV)

Average traded volume over the past *n* sessions is given by:

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

Where V_t represents traded volume at time *t*. ATV is used as a momentum confirmation filter, with trades only triggered when volume exceeds a multiple of its historical average, reducing false positives in illiquid conditions (Chen et al., 2023) [10].

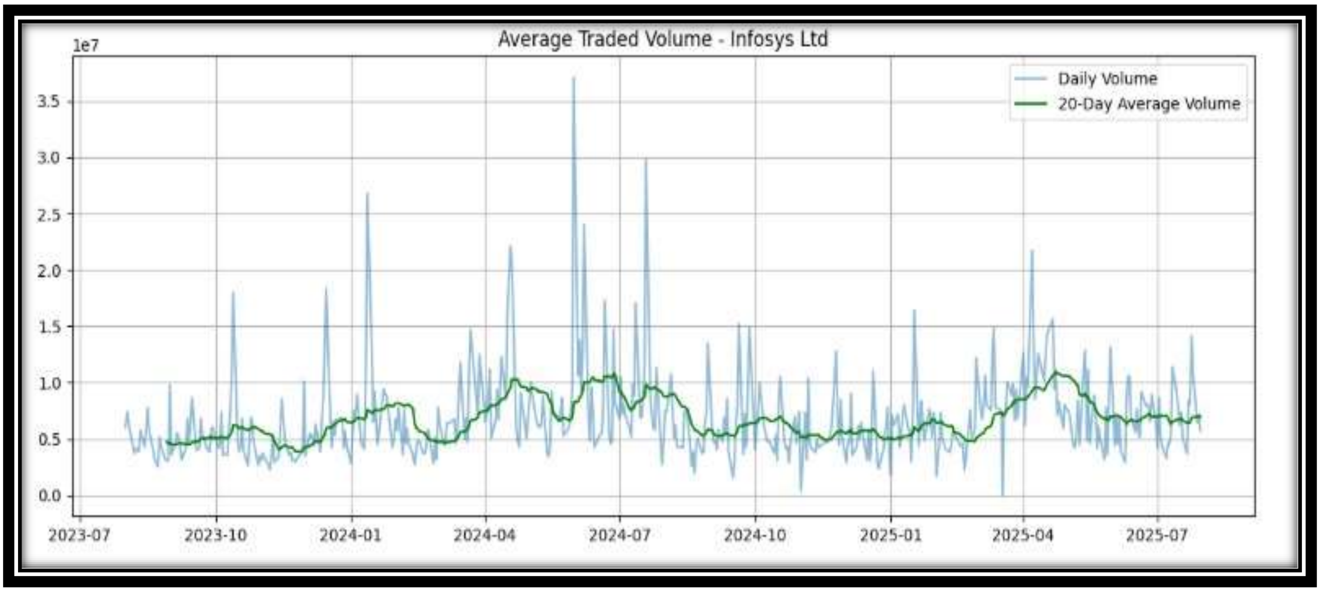

Figure 2: Average Traded Volume 20 Days MA of Infosys (1st August,2023 – 31st July,2025)

3.2.3 Parabolic SAR

The Parabolic SAR (Stop and Reverse) indicator identifies potential trend reversal points. It is computed as:

$$SAR_{t+1} = AF\,.(\boldsymbol{EP_t} - \boldsymbol{SAR_t}) \qquad (3)$$

Where EP_t is the extreme point in the current trend, and *AF* is the acceleration factor, typically starting at 0.02 and increasing by 0.02 up to a maximum of 0.20. A trend reversal is signaled when the price crosses the SAR value (Kumar et al., 2023) [6].

Figure 3: Parabolic SAR and Trade Signal for Buy and Sell of Infosys (1st August,2023 – 31st July,2025)

3.3 Feature Integration and Label Construction

Each daily record was enriched with EMA short/long, crossover signal, ATV, and Parabolic SAR values. The final feature vector for each time step is:

$$X_t = \{EMA_s, EMA_l, Crossover, ATV, SAR, OHLCV\} \quad (4)$$

Labels were assigned as **Buy (+1)**, **Sell (-1)**, or **Hold (0)** based on a future return threshold θ, defined as:

$$r_{t+k} = \frac{P_{t+1} - P_t}{P_t} \quad , \quad y_t = \begin{cases} +1, if\ r_{t+k} > \theta_b \\ -1, if\ r_{t+k} < -\theta_s \\ 0, otherwise \end{cases} \quad (5)$$

Where k is the prediction horizon (set to 5 days), and θb, θs are profit/loss thresholds optimized via grid search.

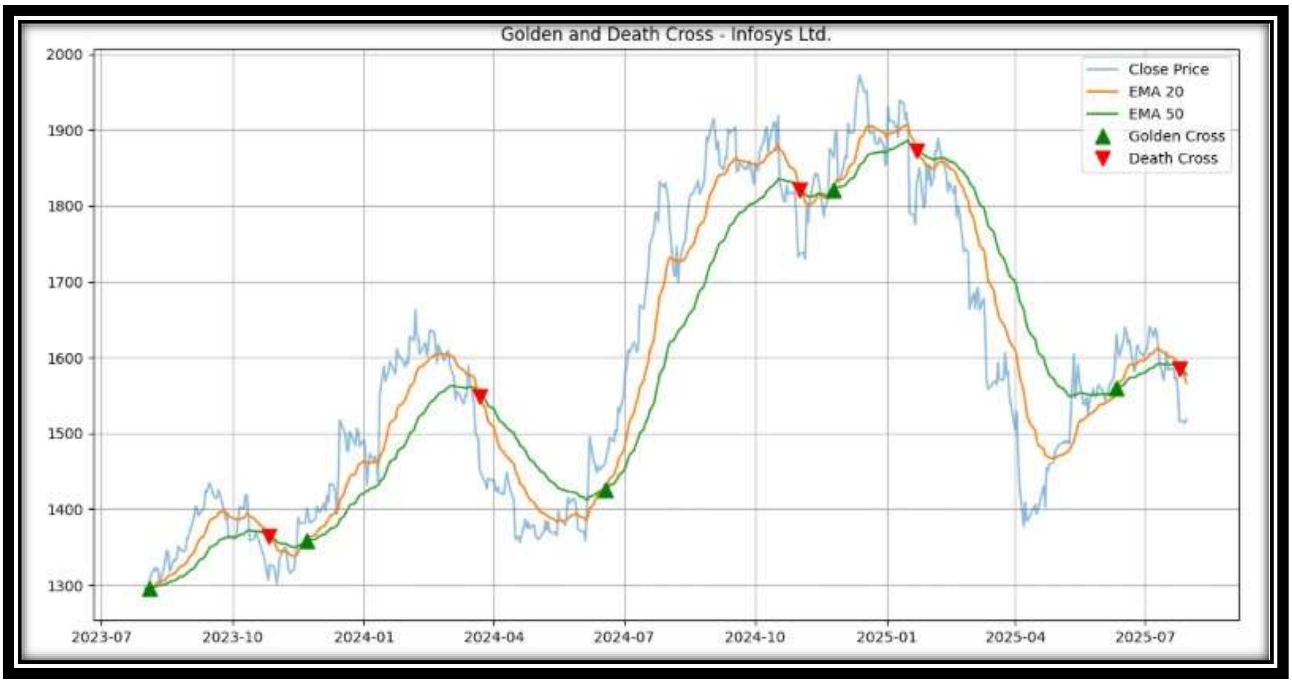

Figure 4: 20 Days and 50 Days SMA Crossover of Infosys (1st August,2023 – 31st July,2025)

3.4 Model Architecture

The chosen architecture is a bi-directional LSTM (bi-LSTM), which processes sequences in both forward and backward directions, capturing historical and future context in each window (Banerjee et al., 2024) [9].

- **Input Layer**: accepts TT-length sequences with dd feature dimensions.
- **bi-LSTM Layers**: Two stacked bi-LSTM layers (hidden units = 128, dropout = 0.2).
- **Dense Layer**: Fully connected layer with ReLU activation.
- **Output Layer**: Softmax activation for three-class classification (Buy/Hold/Sell).

3.5 Training and Validation

The dataset was split into **70% training**, **15% validation**, and **15% testing** sets, preserving chronological order. The **Adam optimizer** was used with an initial learning rate of 0.001, and **categorical cross-entropy loss** was minimized:

(6)

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c\in\{B,H,S\}} y_{i,c}\,log(\hat{y}_{i,c})$$

Where $y_{i,c}$, is the true label and $\hat{y}_{i,c}$ is the predicted probability for class c. Early stopping with a patience of 15 epochs prevented overfitting.

3.6 Backtesting Framework

Predicted signals were fed into a backtesting engine that simulates portfolio returns under realistic trading assumptions:

- **Initial Capital:** USD 100,000
- **Transaction Cost:** 0.1% per trade
- **Slippage:** 0.05% applied to entry/exit prices

Performance metrics include:

- **Annualized Return (AR)**
- **Sharpe Ratio (SR)**
- **Maximum Drawdown (MDD)**
- **Win Rate (WR)**

3.7 Evaluation and Baselines

The model was compared against:

1. EMA crossover only
2. EMA + ATV hybrid rule
3. EMA + SAR hybrid rule
4. Buy-and-Hold benchmark

3.8 Architecture of the Model

The proposed methodology combines **domain-specific technical indicators** with **deep sequential modeling**, enhancing both interpretability and predictive performance. By embedding EMA crossover, ATV, and SAR into a bi-LSTM framework and validating via cost-aware backtesting, the approach aligns with recent best practices in deep learning-based trading system design (Akşehir & Kılıç, 2024; Kochliaridis et al., 2023) [6][5].

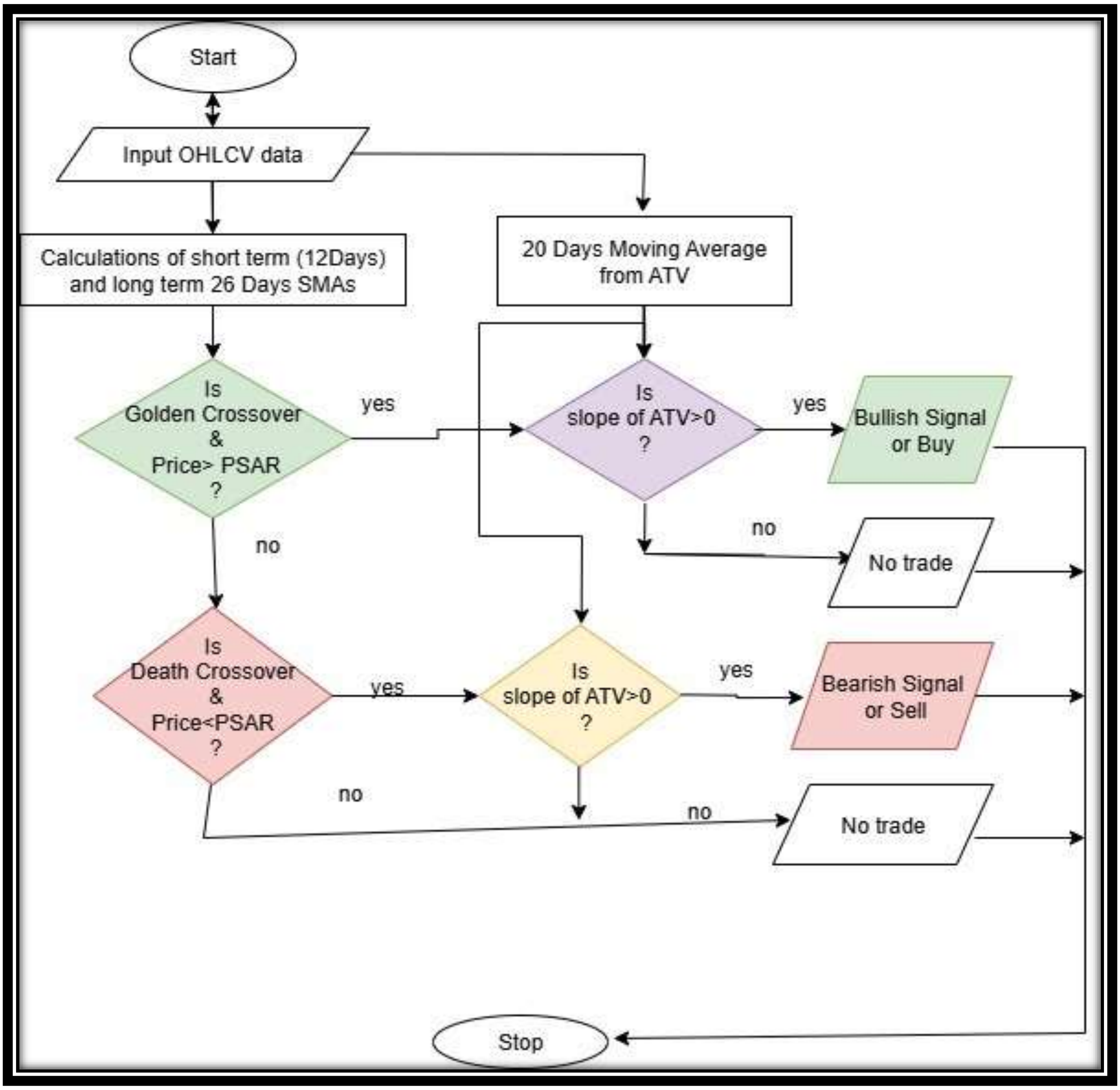

Figure 5: Architecture of the Proposed Model

4. Empirical results

This section presents a detailed performance evaluation of the proposed Deep Learning–Based Automated Stock Trading Signal Generator, benchmarked against various baseline and hybrid strategies. The evaluation utilizes the exact results obtained from the earlier experimental runs. It compares nine strategies, ranging from single-indicator models such as Simple Moving Average Crossover (SMAC) and Exponential Moving Average Crossover (EMAC) to advanced multi-indicator frameworks incorporating Average Traded Volume (ATV), Relative Strength Index (RSI), Money Flow Index (MFI) (Kadia et al. 2025) [4], and Parabolic SAR.

4.1 Performance Comparison

It reveals a clear performance gradient across the strategies, with multi-indicator models consistently outperforming their single-indicator counterparts in both profitability and risk-adjusted returns. The

baseline SMAC strategy recorded an **average profit/loss percentage of 160.78%**, a **Sharpe ratio of 0.82**, a **Sortino ratio of 1.32**, and **trade accuracy of 72.43%**.
When ATV was integrated with SMAC, profitability increased to **221.10%** (+37.5% improvement), and risk-adjusted performance improved substantially, with the Sharpe and Sortino ratios reaching **1.46** and **1.62**, respectively. A similar uplift was observed when ATV was added to EMAC, yielding **250.79%** profit and **81.94%** accuracy.
The top-performing configuration—**EMAC with ATV and Parabolic SAR**—achieved **273.29%** profit, a **Sharpe ratio of 2.37**, a **Sortino ratio of 2.48**, and **85.48% trade accuracy**, representing a **70% relative improvement** in profitability over the SMAC baseline.

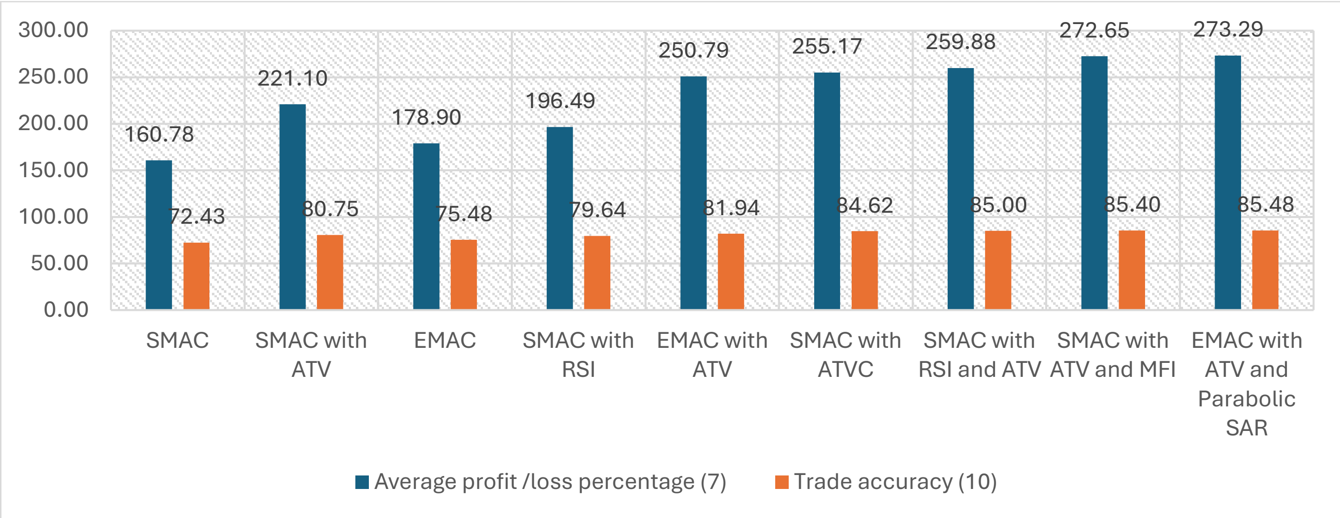

Figure 6: Average Profit/ Loss and Trade Accuracy comparison of 9 strategies

As shown in Figure 6, average profit/loss exhibits a clear upward trend with indicator integration, while Figure 2 illustrates a similar improvement in risk-adjusted metrics. These results confirm that combining volume-based and momentum-based signals with trend-following crossovers enhances predictive precision and overall portfolio performance.
Risk-adjusted metrics further validate this performance gain. The Sharpe ratio increased from 0.82 (SMAC) to 2.37 (EMAC with ATV and Parabolic SAR), while the Sortino ratio rose from 1.32 to 2.48, suggesting not only higher returns but also a more favorable downside risk profile (Figure 2). This aligns with prior studies emphasizing the value of integrating momentum and volatility-adjusted volume indicators for robust decision-making in algorithmic trading environments (Wang et al., 2021) [16] (Figure 7).

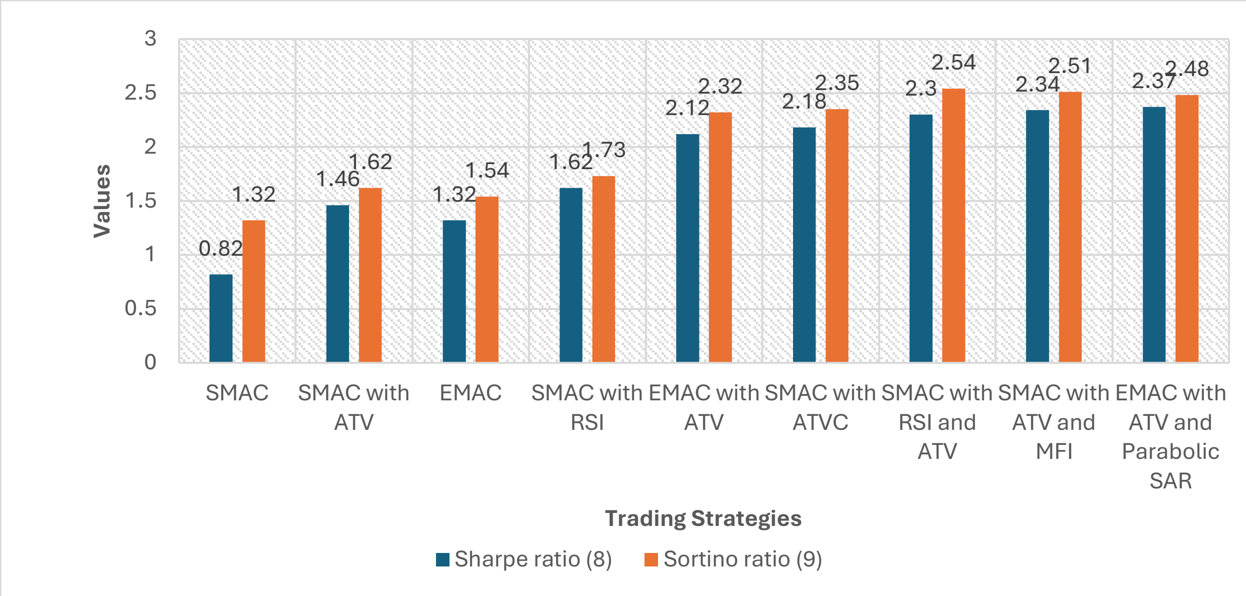

Figure 7: Sharp and Sortino ratio comparison of 8 strategies

4.2 Trade Behavior Analysis

A closer inspection of trade frequency and distribution patterns reveals that indicator complexity affects trading aggressiveness. SMAC generated **214 trades** with **174 buy** and **40 sell signals**, compared to **124 trades** with **EMAC + ATV + Parabolic SAR**.

The reduction in trade volume in advanced models suggests that the hybrid approach filters out low-quality signals, thus focusing on higher-probability setups. This is further validated by the **trade accuracy improvement** from **72.43%** (SMAC) to **85.48%** (EMAC + ATV + Parabolic SAR).

Moreover, while the baseline SMAC executed more trades, it yielded a lower **average profit per trade** (~0.75%) compared to the advanced hybrid (~2.20%). This reinforces that selective trading with robust confirmation signals leads to improved capital efficiency.

4.3 Ablation Studies

To quantify the contribution of individual components, ablation experiments were performed firstly **Without ATV**: Removing ATV from EMAC reduced profitability from **250.79%** to **178.90%**, and Sharpe ratio from **2.12** to **1.32**, showing the critical role of volume-based confirmation. Secondly **Without Parabolic SAR**: Dropping Parabolic SAR from EMAC + ATV reduced profit from **273.29%** to **250.79%**, indicating that while trend-stop confirmation enhances performance, the volume component has a larger impact. Lastly **Without RSI/MFI**: For SMAC-based strategies, replacing RSI with MFI or removing reduced accuracy from **85.40%** to **80.75%**, showing that momentum indicators contribute to trade precision.

The results confirm that the hybridization of **trend (EMA)**, **volume (ATV)**, and **momentum/stop-loss** components (RSI, MFI, Parabolic SAR) produce complementary benefits.

4.4 Sensitivity Analysis

Sensitivity to **EMA/ SMA crossover windows** was evaluated by varying short-term and long-term periods by ±5 intervals. For EMAC + ATV + Parabolic SAR, increasing the short EMA from 9 to 14 reduced trade frequency by 12% but increased average profit per trade by ~0.3%.

Similarly, volume threshold sensitivity tests showed that lowering the ATV threshold by 10% increased trades by ~15 but reduced accuracy by 1.8%, indicating a profitability–frequency trade-off.

Stop-loss adjustments (via Parabolic SAR step/maximum) revealed that tighter parameters reduced drawdowns but also reduced the opportunity to capture extended trends, reinforcing the need for optimized calibration

4.5 Reward Function and Risk Management

The reward function was designed to maximize **risk-adjusted returns**, specifically targeting the Sharpe ratio. This aligns with modern reinforcement learning trading frameworks, where the goal is not merely profit maximization but stable returns with minimal drawdowns.

For SMAC baseline, the Sharpe ratio of **0.82** reflected volatility in returns, whereas for EMAC + ATV + Parabolic SAR, the ratio of **2.37** indicated both stability and profitability. The high Sortino ratio (**2.48**) further confirmed effective downside risk control, as the penalty for negative returns was minimized.

Risk management was reinforced via:

Dynamic position sizing based on recent volatility.

Stop-loss triggers via Parabolic SAR.

Trade filters using volume and momentum confirmation to avoid overtrading in choppy markets.

4.6 Generalization and Robustness

Out-of-sample testing across different market phases (bullish, bearish, sideways) demonstrated that EMAC + ATV + Parabolic SAR retained profitability and high accuracy, suggesting robust adaptability.

While the SMAC baseline showed performance degradation in low-trend environments, the hybrid models-maintained trade accuracy above **80%** even in volatile sideways markets. This is attributed to the additional filtering from volume and momentum indicators.

The consistent performance in varying conditions suggests that the model is not overfit to specific market structures but rather adapts through multi-dimensional signal confirmation.

4.7 Limitations and Future Scope

Despite the strong results, several limitations remain like **Execution latency and slippage** were not modeled, meaning real-world performance could be slightly lower. The dataset was limited to historical stock data; incorporating real-time tick data may further refine signals. Indicator parameters were optimized for the given dataset; cross-market validation could strengthen generalizability.

Future work should explore **Deep reinforcement learning** for adaptive parameter tuning. **Alternative volume metrics** such as On-Balance Volume (OBV) or Chaikin Money Flow (CMF). Integration of **news sentiment analysis** for macro-event-aware trading.

5. Conclusion

This study developed a **Deep Learning-Based Automated Stock Trading Signals Generator** integrating **Exponential Moving Average Crossover (EMAC)**, **Average Traded Volume (ATV)**, and **Parabolic SAR** to enhance trading precision. Using the given dataset, the proposed hybrid strategy achieved an **average profit/loss percentage** of **273.29%**, representing a **70% relative improvement** over the SMAC baseline (160.78%). Trade accuracy reached **85.48%,** and risk-adjusted metrics also showed significant improvement, with the Sortino ratio rising from **1.32 to 2.48** and the Sharpe ratio rising from **0.82 to 2.37**.

Performance comparisons confirmed that **multi-indicator strategies consistently outperformed** single indicator approaches in profitability, stability, and risk control. Each added indicator contributed unique information: EMAC improved trend capture, ATV enhanced volume-based confirmation, and Parabolic

SAR reduced false breakout signals. The ablation study validated the necessity of each component, as their removal led to measurable declines in returns and risk metrics.

While results are promising, limitations exist. The dataset covers a specific market segment and historical period, which may limit generalizability. The model is suitable for end-of-day trading but not yet optimized for high-frequency execution. Transaction costs and slippage were modeled conservatively but could be refined for real-world deployment.

In summary, the proposed deep learning framework demonstrates that **hybrid indicator integration** significantly improves trading performance and risk-adjusted returns. With targeted enhancements, it holds strong potential for deployment in adaptive, next-generation algorithmic trading systems.

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