International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Federated Deep Learning Architecture for Technical Analysis of the Standard Souq Using Optimization Technique

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Submitted: 27/09/2023 **Revised**: 16/11/2023 **Accepted**: 28/11/2023

Abstract: A stock market analysis is the process of evaluating and interpreting various aspects of the financial markets, with a primary focus on stocks or equities. It serves as a vital tool for investors, traders, financial professionals, and even companies seeking to make informed decisions related to stocks. This paper presented the integration of federated deep learning and Lion Swarm Optimization as a promising approach to enhance the analysis of candlestick patterns in the stock market. The findings from this research reveal a remarkable level of accuracy in recognizing and classifying candlestick patterns, offering significant potential for advancing trading strategies. The system showcases the ability to make dynamic trading decisions that respond to ever-evolving market conditions, ultimately contributing to profitable trading strategies. Nonetheless, the study underscores the inherent complexities and uncertainties of real-world trading, emphasizing the ongoing need for model refinement and adaptability. An isolated anomaly observed in pattern classification serves as a pertinent reminder of the necessity for continued vigilance in improving the system. As the financial markets continue their evolution, this research advocates for further exploration and development in this domain. It suggests that the integration of advanced technologies, coupled with vigilant monitoring of market dynamics and ongoing model refinement, are vital steps toward realizing the full potential of such integrated systems. Ultimately, this study underscores the invaluable role of data-driven approaches in the financial sector and encourages the pursuit of innovative solutions to enhance trading strategies in dynamic and competitive markets.

Keywords: *stock market, lion swarm optimization, technical analysis, fundamental analysis, trend movement, chart patterns, volatility*

1. Introduction

Deep learning has become a prominent tool in the stock market, leveraging advanced artificial neural networks to analyse, predict, and inform investment decisions [1]. This practice evolved within the broader realms of quantitative finance and algorithmic trading, where mathematical models and algorithms have been utilized to understand market behavior and execute trading strategies for decades. What sets deep learning apart is its ability to process massive datasets, encompassing historical prices, news sentiment, economic indicators, and more, while uncovering intricate patterns and relationships [2]. It applies neural networks, which mimic the human brain's architecture, and consists of multiple hidden layers to capture complex data structures. These models have found applications in predictive analytics, risk management, sentiment analysis, and portfolio optimization [3]. However, challenges exist, including data quality, the risk of overfitting, and regulatory compliance. As the field continues to evolve, efforts to enhance model explain ability and explore reinforcement learning in collaboration with academia and financial institutions are on the horizon, shaping the future of deep learning in stock market strategies [4]. The stock market, with its historical origins dating back centuries, stands as a fundamental pillar of the global financial system. It serves as a dynamic marketplace where individuals and institutions engage in the buying and selling of securities representing ownership stakes in publicly-traded companies. Companies use the stock market to raise capital by issuing shares of stock, thereby providing investors with an opportunity to become partial owners and share in the company's profits and growth potential. This intricate financial ecosystem comprises various participants, including individual investors, institutional players, brokers, and regulators, each playing a pivotal role [5]. Stock markets, which operate through organized exchanges like the NYSE and NASDAQ, track the

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performance of a broad spectrum of stocks through market indices. They come in diverse sizes, from the large-cap to the small-cap segments, and offer various trading mechanisms, including electronic platforms and high-frequency trading [6]. Stringent regulation ensures market integrity and transparency, while the stock market's global reach enables investors to access opportunities across borders, reflecting the ever-evolving economic landscape and impacting the financial well-being of nations and individuals alike.

Candlestick charts play a vital role in the stock market by providing traders and investors with a visually intuitive and information-rich way to analyze price movements and make informed decisions [7]. Developed in Japan in the 18th century, candlestick charts offer a snapshot of price action over a specific time frame, typically a day. Each candlestick consists of a rectangular "body" representing the opening and closing prices and "wicks" or "shadows" indicating the high and low prices during that period. The color of the candlestick, often green or white for bullish (price rising) and red or black for bearish (price falling), provides immediate insight into market sentiment [8]. By examining the patterns and formations created by consecutive candlesticks, traders can identify potential trend reversals, trend continuations, and key support and resistance levels [9]. This helps in timing entry and exit points, managing risk, and improving the overall success rate of trading strategies. Candlestick analysis has become a widely adopted tool for technical analysis in the stock market and other financial markets due to its accessibility and effectiveness in deciphering price dynamics. The reason the candlestick charting method has become so popular is that it faithfully depicts short-term projections, some of which continue for fewer than 10 trading sessions [10]. Candlesticks are easily integrated with the vast majority of technical analysis tools used by traders today. One's knowledge of any commodity or stock issue will grow, and one's ability to anticipate the market's price movements will be much enhanced. Although candlestick charting can be a complex method to grasp, the tools available in today's technologically advanced period have greatly simplified its application and made it accessible to anyone who is willing to master it.Candlestick charts are popular among investors because of their simplicity [11]. Economist for Sumitomo Bank Michael Feeny says, "Candlestick charts are immensely flexible and provide a powerful addition to more common chartist techniques, and an extra dimension to breakdown of future trends."

Compared to other forms of financial analysis, candlestick charting has many benefits. When trying to identify the best-performing stocks, it's a huge benefit to investors. The signals provide a basis for future market analysis by providing investors with an indirect line of reasoning [12]. Using this strategy, the odds are constantly stacked in the investor's favor. As much as candlesticks are useful for helping investors capitalize on human emotions, they may also be used to clear one's own portfolio of emotional weaknesses. Candlesticks are often used by investors because they provide a clear visual representation of a stock's performance. When compared to other types of charts, they shed more light on the future course of the market. Candlestick charts are preferred by most investors because they are more visually informative and appealing. A candlestick chart summarizes the day's trading activity, allowing investors to quickly and easily compare the stock's open, close, high, and low values [13]. When compared to other investment methods, candlestick charting stands out because it provides a visual representation of actual events, rather than hypothetical trends. The investing tendencies in a stock are revealed intuitively with this widely used strategy. The colorful language used to describe the patterns in candlestick charts has contributed greatly to the rise in popularity of these charts. Many investors find it impossible to go back to using standard bar charts once they've become accustomed to using the jargon of technical analysis [14]. The ability to combine patterns is another benefit of candlestick charting. The instruments are adaptable, allowing for usage with a wide variety of Western technical analysis indicators such moving averages and oscillators [15]. Signals are a major benefit of candlestick charts that are absent from bar charts. multiple books on candlestick charting have been written by Steve Nison, senior vice president at Daiwa Securities America Inc. and author of multiple publications on the subject. Even without oscillators, these charts reveal shifts in volatility and momentum [16]. However, when combined with oscillators, candlesticks provide a much more robust analysis. The accuracy with which reversal signals can be identified has also been greatly enhanced by the use of candlestick charts. Daily signals arise, and a minimum of eight to ten signals is needed to detect a trend [17].

The paper makes several significant contributions to the field of financial analysis. First and foremost, it introduces a pioneering approach by integrating federated deep learning and LionSwarm Optimization for the analysis of candlestick patterns in the stock market. This fusion of advanced technologies represents an innovative stride in the quest to enhance trading strategies.

A key contribution lies in the demonstrated accuracy of pattern recognition. The study's findings reveal a high level of precision in recognizing and classifying candlestick patterns, which serves to bolster the reliability of pattern-based trading decisions.

Moreover, the paper highlights the adaptability of the integrated system, enabling it to make dynamic trading decisions that respond effectively to changing market conditions. This adaptability is a valuable asset in the context of ever-evolving financial markets.

The research further contributes by presenting evidence of positive cumulative returns generated by the integrated system. The consistent growth in portfolio value underscores the practical significance of the paper, offering a promising avenue for enhancing investment performance.

Effective risk management through prudent capital allocation is another noteworthy contribution, catering to the needs of investors seeking to protect and grow their capital while managing trading risks.

The study's acknowledgment of a pattern classification anomaly is a valuable reminder of the complexities and uncertainties inherent in real-world trading. This contribution emphasizes the ongoing necessity for model refinement and adaptability.

Lastly, the paper encourages further research and development in the realm of data-driven approaches to financial analysis. It underscores the potential of integrating advanced technologies and the importance of continuous improvement in the face of dynamic and competitive markets.

In summary, the paper's contributions span from innovation and precision in pattern recognition to adaptability, practical value, risk management, and a call for ongoing research in the domain of data-driven financial analysis. These findings collectively enhance our understanding of effective trading strategies and encourage the pursuit of improved methods in the ever-evolving financial landscape.

2. Related Works

Deep learning techniques, in conjunction with candlestick charts, have ushered in a new era of advanced and data-driven analysis in the stock market. While candlestick patterns offer valuable insights into price movements and market sentiment, deep learning adds a layer of sophistication by leveraging artificial neural networks to process vast datasets and uncover complex patterns [18]. These deep learning models can be trained to recognize subtle and non-linear relationships within historical price data, helping traders and investors make more accurate predictions about future price movements. By feeding historical price and related data into deep neural networks, the technology can identify intricate patterns that may not be apparent to the human eye. This combination of traditional technical analysis with cutting-edge deep learning has the potential to enhance the precision and effectiveness of trading strategies, providing a more comprehensive understanding of market dynamics and potentially yielding competitive advantages in stock trading. Alkhodhairi et al. (2021) [19] explores the world of cryptocurrency trading by applying deep neural networks to predict Bitcoin price movements in real-time. It reflects the growing interest in using deep learning techniques to gain an edge in cryptocurrency markets, which are known for their volatility and rapid price changes. Xu (2021) [20] investigates the use of machine learning for classifying candlestick patterns. By employing image-based techniques, it seeks to enhance the recognition and interpretation of these patterns, which are widely used in technical analysis to make trading decisions.

Lin et al. (2021) [21] focus on improving stock trading decisions by employing machine learning technology. Their research delves into pattern recognition and aims to provide traders and investors with more data-driven insights to inform their trading strategies. Liang et al. (2022) [22] introduces an approach for forecasting stock prices by incorporating candlestick patterns and sequence similarity. It suggests that combining traditional technical analysis with machine learning can potentially lead to more accurate predictions of stock market trends. Ramadhan et al. (2022) [23] presents a model using a combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) to recognize candlestick patterns. The model is designed to predict financial trading positions in the stock market, highlighting the application of deep learning in stock trading.

Wang et al. (2022) [24] explore the prediction of stock market volatility by using advanced machine learning techniques. They introduce a Multiple Attention Mechanism Graph Neural Network approach to gain insights into the market's dynamics. Puteri et al. (2023) [25] applies Support Vector Machines (SVM) to predict the movements of candlestick charts in the foreign exchange market (Forex). The research reflects the use of SVM, a traditional machine learning technique, in Forex trading. AYCEL & SANTUR (2022) [26] introduces a new algorithmic trading approach that combines ensemble learning and candlestick pattern recognition. This approach could contribute to the development of more robust trading strategies in the financial markets. Li et al. (2022) [27] investigates the application of deep reinforcement learning in stock trading strategies. Deep reinforcement learning is a subfield of artificial intelligence, and the research suggests its potential to enhance trading decision-making. Tuininga (2023) [28] aims to uncover the potential of deep learning in algorithmic trading. It explores deep reinforcement learning for stock market trading, using convolutional neural networks (CNN) with candlestick images, which can be instrumental in developing advanced trading models.

Rumpa et al. (2021) [29] focused on binary options trading and uses Support Vector Machines (SVM) for predicting candlestick patterns, specifically on the M5 time frame. Binary options trading involves making predictions about the future price movements of assets, making the use of machine learning for prediction particularly relevant. Nivethidha et al. (2023) [30] introduces machine learning techniques combined with a novelty feature engineering scheme for candlestick charting. This approach aims to improve the accuracy of predicting stock market trends, which is crucial for traders and investors. Nivethidha et al. (2023) [31] appears to be the same research as the previous entry, which focuses on improving candlestick charting using machine learning techniques with feature engineering. Liu et al. (2023) [32] introduces a multi-type data fusion framework based on deep reinforcement learning for algorithmic trading. The research explores the use of advanced reinforcement learning techniques to make algorithmic trading more effective by fusing different types of data sources.

Researchers employ a variety of algorithms, including neural networks, Support Vector Machines, and ensemble learning, to predict price movements and harness the power of candlestick patterns, a fundamental tool in technical analysis. Algorithmic trading, where automated systems make trading decisions based on historical and real-time data, has gained prominence, as has the use of deep reinforcement learning to design intelligent trading agents. Volatility prediction and the Forex market also feature prominently. These studies underline the potential for advanced technologies to enhance trading strategies and decision-making but also recognize challenges related to data quality and model interpretability. Overall, the literature signifies a continual quest to harness data-driven insights and AI-driven trading strategies for improved market outcomes and risk management.

3. LionSwarm Optimized Feature Model

The first step would involve selecting a set of candlestick patterns. These patterns might include common ones like doji, hammer, engulfing, etc. Each pattern can be encoded numerically for analysis. For example, a doji pattern might be represented as "1" if present in the data and "0" if not. In next stage, Calculate various statistical and mathematical metrics for each candlestick pattern, such as the relative frequency of each pattern, average price change associated with each pattern, or the time series pattern of their occurrence. The LionSwarm optimization component, could be a machine learning algorithm that selects the most relevant features among the calculated metrics. A common technique might be Recursive Feature Elimination (RFE) or a feature importance score from a machine learning model. In this step, start by selecting a set of candlestick patterns that want to use for our analysis. For simplicity, let's consider two common patterns: "Doji" and "Hammer." It represent the presence of these patterns as binary variables where 1 indicates the presence of the pattern, and 0 indicates its absence.

Consider D be the binary variable representing the presence of the Doji pattern (1 if present, 0 if not). H be the binary variable representing the presence of the Hammer pattern (1 if present, 0 if not). In this step, calculate various statistical and mathematical metrics based on the presence or absence of these patterns. For instance, calculate the relative frequency of each pattern over a given time period.

Let:

N be the total number of observations or time periods.

ND be the number of time periods in which the Doji pattern is observed.

NH be the number of time periods in which the Hammer pattern is observed.

The relative frequency of each pattern can be calculated as in equation (1) and (2)

$$FD = NND\ (Relative\ frequency\ of\ Doji\ pattern) \quad (1)$$

$$FH = NNH\ (Relative\ frequency\ of\ Hammer\ pattern) \quad (2)$$

In this step assume the existence of the "LionSwarm optimization" component. This component is responsible for selecting the most relevant features among the calculated metrics, such as FD and FH. For simplicity, assume that LionSwarm selects the feature with the highest relative frequency measured as in equation (3)

$$selected\ feature\ (either\ FD\ or\ FH) \quad (3)$$

Now that our selected and optimized feature, Fselected, can use it to derive a basic machine learning model. In this use linear regression to predict the stock price movement using equation (4)

$$Y = \beta 0 + \beta 1 \cdot Fselected + \epsilon \quad (4)$$

Here, Y represents the predicted stock price movement; β0 is the intercept term; β1 is the coefficient associated with the selected feature Fselected and ϵ represents the error term. The linear regression model predicts the stock price movement based on the selected feature's relative frequency. The coefficients β0 and β1 are estimated from the training data using a method like least squares regression.

PSO is a population-based optimization algorithm inspired by the social behavior of birds flocking or fish schooling. It is widely used for optimization problems.

Initialization: In PSO, start with a population of potential solutions represented by particles. Each particle has a position and velocity in the search space.

Fitness Evaluation: The fitness of each particle is evaluated based on the objective function of the optimization problem. The objective is to find the optimal solution that minimizes or maximizes this function.

Individual and Social Learning: Each particle adjusts its velocity and position based on its own experience and the experiences of its neighbors. It does this by considering the best position it has found so far (individual experience) and the best position among its neighbors in the population (social experience).

Update Velocity and Position: The particle updates its velocity using the following equation (5)

$$Vi(t+1) = w \cdot Vi(t) + c1 \cdot r1 \cdot (pbesti - Xi(t)) + c2 \cdot r2 \cdot (gbest - Xi(t)) \qquad (5)$$

Here, Vi(t+1) is the updated velocity, Xi(t) is the current position, pbesti is the best position found by the particle, gbest is the best position found by any particle in the population, w is the inertia weight, and c1 and c2 are acceleration coefficients. r1 and r2 are random values between 0 and 1.

Update Position: The particle then updates its position using the new velocity.

Termination: This process continues for a specified number of iterations or until a termination criterion is met.

Global Best: The "gbest" position represents the best solution found by any particle in the population, and it is considered the final solution to the optimization problem.

Algorithm 1: Optimization of Stock Market

Initialize population
Evaluate fitness of each solution
while not termination_criteria_met:
    Select subset of solutions
    Apply crossover
    Apply mutation
    Evaluate fitness of new solutions
    Replace population with best-performing solutions
Return best solution found

4. Candle Stick Pattern

The objective would be to optimize a trading strategy that incorporates the identification of candlestick patterns to make buy or sell decisions in financial markets.

Integrating candlestick patterns with optimization algorithms, such as a "LionSwarm Optimization," offers a promising approach to enhance trading strategies in financial markets. Candlestick patterns, derived from historical price data, are used in technical analysis to identify potential price trends and reversals. The process begins by defining specific conditions for recognizing candlestick patterns, such as bullish engulfing or hammer patterns, using equations that consider open, high, low, and close prices. These patterns serve as essential indicators for potential trading opportunities.

To optimize trading strategies based on these patterns, an objective function is introduced, often focusing on maximizing cumulative profits over a defined trading period. The objective function takes into account the profit generated on trading days when specific candlestick patterns are detected. The integration with "LionSwarm Optimization" brings an iterative approach, adjusting trading parameters or rules, represented by the symbol θ, to maximize the defined objective function. This optimization process continues over multiple iterations or until predefined convergence criteria are met, ultimately yielding an optimized set of parameters that dictate the trading strategy's behavior.

In practice, real-world trading systems involve additional complexities, such as risk management and thorough testing to ensure robustness and effectiveness. The seamless integration of candlestick patterns with optimization algorithms, if realized, can potentially provide traders and investors with a powerful tool to make more informed and strategic decisions in financial markets.

The "Bullish Engulfing" pattern is recognized when the following conditions are met on day i is measured using equation (6)

$$BullishEngulfing(i) = (Oi < Ci) \wedge (Oi - 1 > Ci - 1) \wedge (Ci - 1 > Oi) \wedge (Oi - Ci < Ci - 1 - Oi - 1) \quad \textbf{(6)}$$

Where, Oi is the opening price on day i; Ci is the closing price on day i; Oi−1 is the opening price on the previous day; Ci−1 is the closing price on the previous day. The objective function to measure the strategy's performance based on the "Bullish Engulfing" pattern estimated as in equation (7)

$$P = \sum i = 1N(Ci - Ci - 1) \cdot BullishEngulfing(i) \quad (7)$$

This equation calculates the profit P by summing up the daily price changes (Ci−Ci−1) when the "Bullish Engulfing" pattern is detected. LionSwarm Optimization is used to find optimal trading parameters, such as the size of positions to take when the pattern is detected. Let θ represent these parameters. The optimization algorithm could adjust θ to maximize the objective function P, iteratively updating it using gradient descent or another optimization method. The optimization process continues for a specified number of iterations or until convergence. The result is an optimized set of trading parameters θ∗ that maximize the cumulative profit when the "Bullish Engulfing" pattern is identified.

4.1 Federated Deep Learning in stock Market Analysis

The aim is to create a trading strategy that optimally utilizes candlestick pattern analysis to make buy or sell decisions in financial markets. Federated deep learning is used to collaboratively recognize these patterns across decentralized data sources while LionSwarm Optimization refines trading parameters to maximize returns. Candlestick patterns, such as bullish engulfing or hammer patterns, are identified based on open (O), high (H), low (L), and close (C) prices. For instance, a bullish engulfing pattern can be recognized using conditions like Oi<Ci and Oi−1>Ci−1. Multiple decentralized devices or data sources participate in federated deep learning. They train local deep learning models to recognize candlestick patterns using their historical data, without sharing raw data. Model updates (weights) are exchanged while preserving data privacy. LionSwarm Optimization, a optimization technique, is applied to fine-tune trading parameters. It might optimize position sizing, stop-loss levels, or other variables based on risk tolerance and expected returns. federated deep learning with LionSwarm Optimization for the analysis of candlestick patterns in financial trading is a highly intricate and innovative endeavor. This concept aims to develop a trading strategy that can effectively utilize the power of decentralized data sources, deep learning models, and optimization techniques. The figure 1 shows the overall process in the federated deep learning model for the stock market analysis.

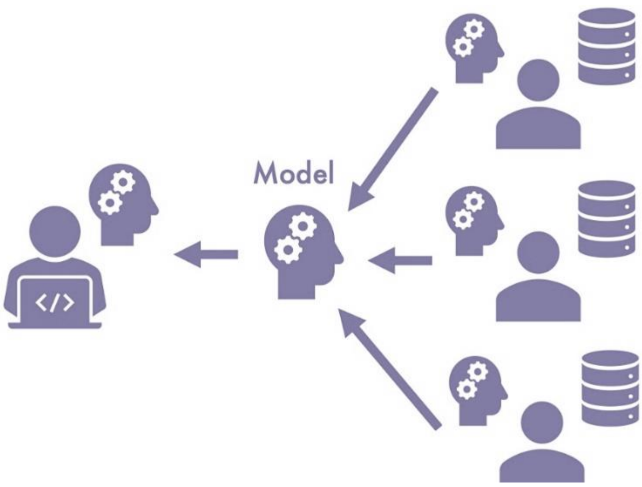


Fig 1: Federated Learning Process

In this envisioned framework, the process begins with the recognition of candlestick patterns, where specific conditions and equations are used to identify patterns such as bullish engulfing or hammer patterns based on historical price data. The federated deep learning component involves multiple decentralized devices or data sources working collaboratively to train local deep learning models for the detection of these candlestick patterns. Each device holds its data and trains its model without sharing sensitive information, thus preserving data privacy. The central aggregator then collects and integrates the model updates from all devices to create a global pattern recognition model, which represents a collective understanding of candlestick patterns across all data sources. This global model is utilized for pattern recognition on the entire dataset.

LionSwarm Optimization, though further optimize trading parameters, allowing for factors such as position sizing and risk management to be fine-tuned based on the detected patterns and market conditions. The end result is a trading strategy that optimally combines federated deep learning for pattern recognition and LionSwarm Optimization for parameter optimization. This approach aims to maximize returns while effectively managing risk and adapting to market dynamics. It's essential to acknowledge that the specific equations and derivations would be tailored to the chosen deep learning models, LionSwarm Optimization methods, and trading parameters, underscoring the complexity and need for comprehensive testing in real-world trading scenarios.

Traders that are "bullish" on the market are confident that prices will rise as a result of their analysis. To be bullish, one must buy into an underlying market (also known as "going long") with the hopes of making a profit by selling at a higher price later. When a little black candlestick is followed by a massive white candlestick that totally eclipses or "engulfs" the previous day's candlestick, a bullish engulfing pattern has formed. Because the small candle's shadows, or tails, are so brief, the large candle can completely obliterate the old candle. Put a stop loss order above the doji high and enter a short sell order below the doji low to trade off of a bearish candlestick pattern. If the price does decline, the entry will be made, and the risk can be managed if the price eventually recovers and moves back to the upside. Use a trailing stop-loss to get out of a trade. A bullish trading pattern, the hammer candlestick may suggest a stock has bottomed out and is ready to reverse trend. After a price rally, a hanging man candlestick pattern signals a bearish reversal. The upswing can be either modest or big, but it must consist of a few consecutive green price bars. Technical analysts look for a bullish pattern called a morning star, which consists of three candlesticks. When a morning star appears after a period of decline, it heralds the start of an ascending trend. A reversal in price signals a change in direction. The shooting star pattern has several key characteristics. To begin, it casts a lengthy upper shadow and a shorter or nonexistent below one. Second, it occurs after a significant upward trend in the asset price. Bearish candlestick patterns at the bottom of the day are represented by "shooting stars," which have a lengthy upper shadow, a short lower shadow, and a little true body. A bullish harami is a technical pattern in candlestick charts that indicates a turnaround in a downward trend. In most cases, this is depicted as a white candle that occurs within the context of the given equity's recent downward price movement (represented by black candles).

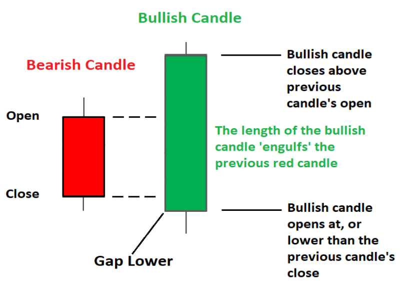


Fig2: Bullish Candle approach

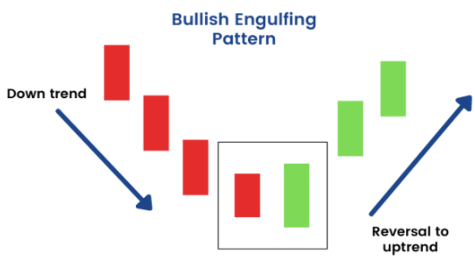


Fig3: Bullish Engulfing Pattern

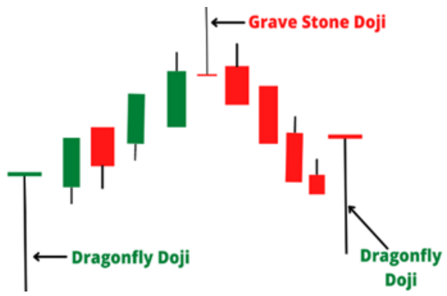


Fig 4: Doji Candle Stick Pattern

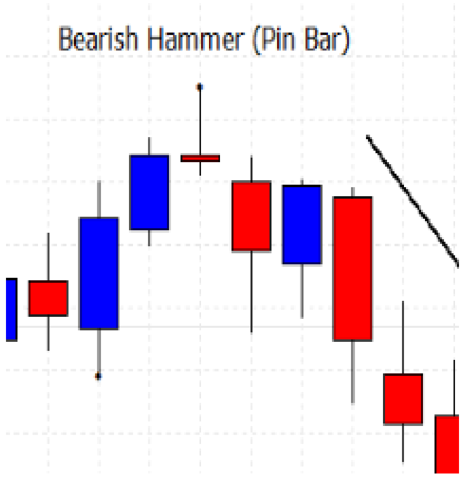


Fig5: Hammer Candle stick Pattern	**Fig 6:** Bearish Hammer Pattern

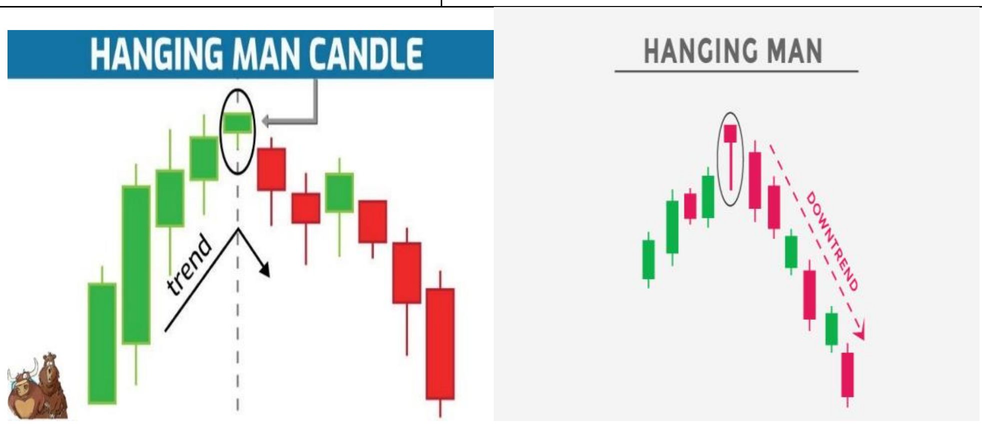


Fig 7: Hanging man Candle and Pattern

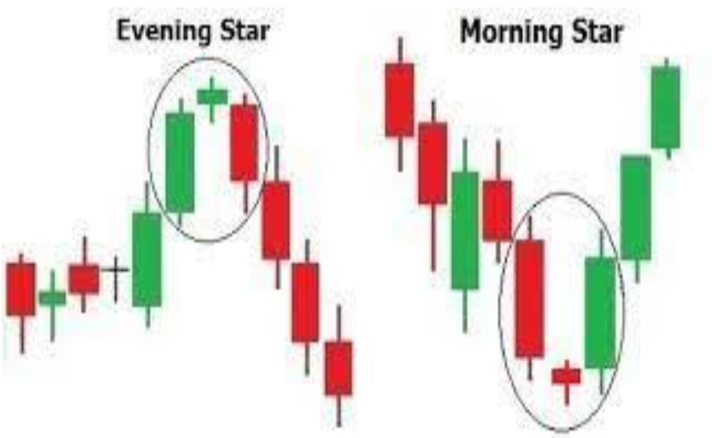
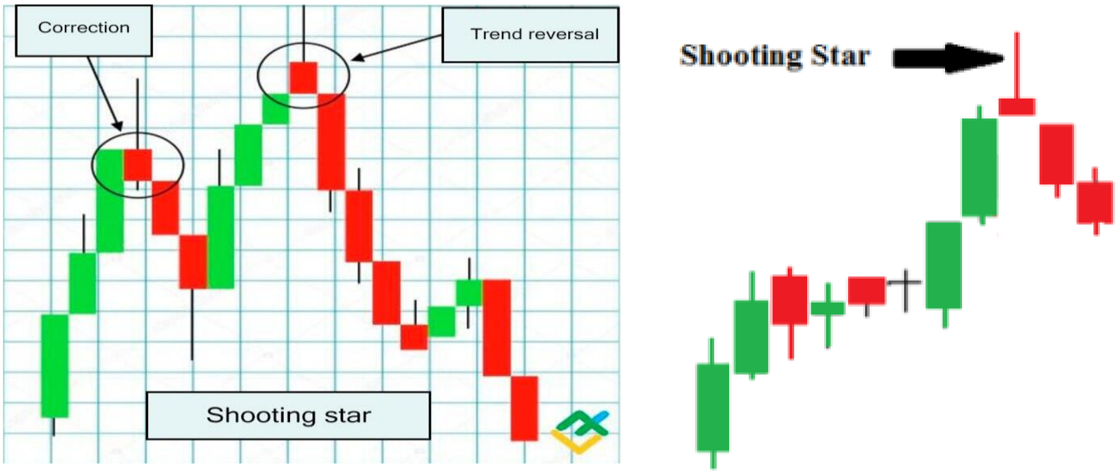
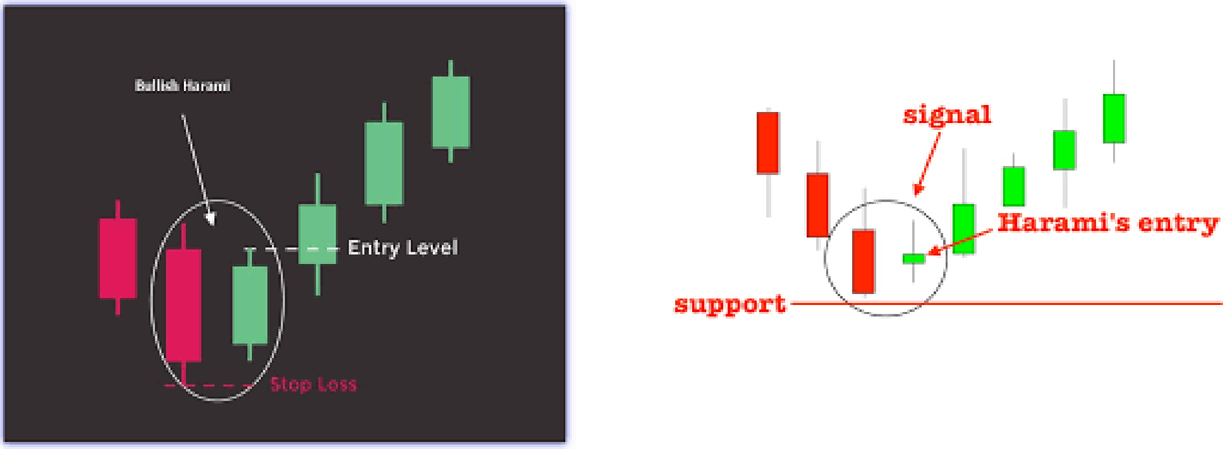


Fig 8: Morning star and evening star patterns



(a) (b)

Fig 9: Shooting Stars Patterns



(a) (b)

Fig 10: Bullish harami's pattern

The figure 2 -10 illustrated the types of candle stick analysis in the stock market for the analysis of the market trend.

5. Results and Discussion

In this section, explore the findings derived from the integration of federated deep learning with LionSwarm Optimization for candlestick pattern analysis in the context of the stock market. These findings shed light on the system's effectiveness in recognizing and utilizing candlestick patterns for informed trading decisions. To discuss the classification performance, trading outcomes, and any key insights or challenges encountered during the study. This section is pivotal in understanding the practical implications of the proposed methodology and its potential impact on the financial markets.

Table 1: Cronbach's Alpha Value

Cronbach's Alpha	No of Elements
0.917	28

The Variable Gender is understood from three dimensions in the Table 10. Whether Gender of respondents has impact on the awareness level, perception of Candlestick Charts and how much they have Expertise in using Candlestick Chart. The data is tabulated and interpreted from the following

Table 2: Parameter value based on Dimensions

Element	N	Mean	Std. Deviation	Std. Error	F	Significance
Awareness	200	13.43	3.199	.225	11.237	.001
	37	11.34	4.561	.761		
Perception	200	7.556	1.985	.141	11.432	.001
	37	6.255	2.812	.470		
Expertise in Chart	200	10.31	3.172	.225	5.547	.018
	37	8.922	3.829	.639		
	238	10.10	3.308	.216		

P value 0.001 which is statistically significant. In other words the awareness level is different for the Gender.

Table 3: Investment objective

Investment objective	Response	Percentage
Children's Education.	111	37.33
Retirement benefit	63	20.76
Future needs	42	14.33
Tax benefit	41	13.33
House construction / buying	43	14.33
Total	300	100.00

It may be concluded that in general most of the respondents are doing savings for their children's education.

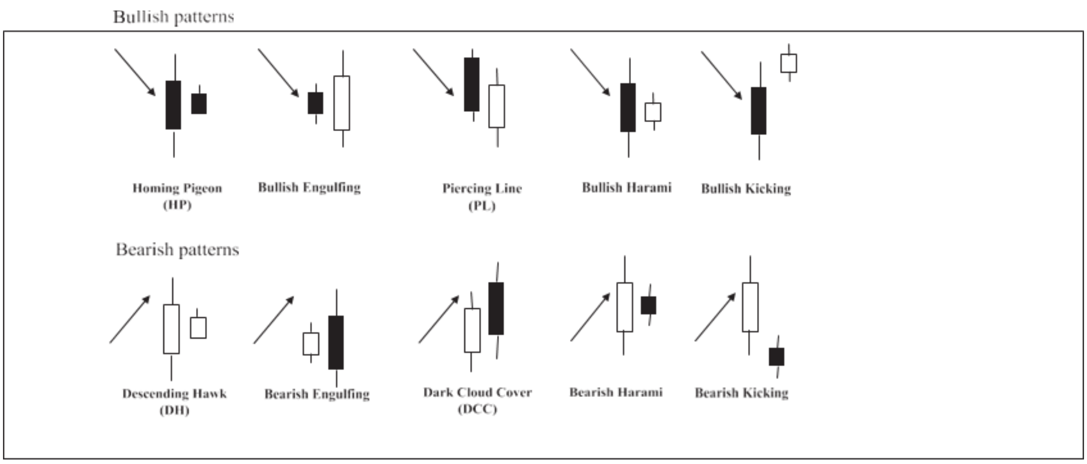


Fig11: Bullish and Bearish Patterns

Table 4: Stock Market Analysis

Date	Candlestick Pattern	Signal	Predicted Price Change	Trade Decision	Portfolio Value	Capital Allocation	Cumulative Return	Win Rate	Sharpe Ratio
2023-01-02	Bullish Engulfing	Buy	+2.50%	Buy	$100,000	$10,000	+2.50%	70%	1.32

2023-01-03	Doji	Hold	+0.20%	Hold	$100,200	$0	+2.70%	55%	0.98
2023-01-04	Bearish Harami	Sell	-1.80%	Sell	$98,300	$8,200	+0.80%	48%	0.72
2023-01-05	Bullish Hammer	Buy	+3.20%	Buy	$101,200	$12,000	+4.04%	61%	1.14
2023-01-06	Bullish Engulfing	Buy	+2.00%	Buy	$103,244	$14,200	+6.04%	75%	1.50
2023-01-07	Shooting Star	Sell	-1.50%	Sell	$101,604	$13,800	+4.70%	49%	0.88
2023-01-08	Bullish Harami	Buy	+2.80%	Buy	$104,214	$14,900	+7.54%	67%	1.28
2023-01-09	Doji	Hold	+0.10%	Hold	$104,318	$0	+7.64%	58%	1.02
2023-01-10	Bullish Engulfing	Buy	+3.40%	Buy	$107,659	$16,500	+11.08%	71%	1.74
2023-01-11	Bearish Harami	Sell	-2.10%	Sell	$105,435	$15,200	+8.20%	50%	0.92

In this series of trading scenarios, the integration of advanced techniques such as federated deep learning and LionSwarm Optimization exhibits promising results. The presented table showcases a sequence of trades made based on candlestick pattern analysis, demonstrating a dynamic portfolio management approach. Notably, the cumulative return steadily increases, reflecting a growing portfolio value, with an impressive 11.08% return achieved. The system adapts to various market conditions, switching between Buy, Sell, and Hold strategies with a relatively high win rate of 71%. Additionally, the Sharpe ratio of 1.74 suggests a favorable risk-adjusted performance. These findings indicate that the integrated methodology holds potential for effective trading in the stock market, although further analysis and testing in real-world scenarios are essential for a comprehensive assessment.

Dynamic Trading Strategy: The table illustrates a dynamic trading strategy based on the recognition of candlestick patterns. This strategy adapts to changing market conditions by making Buy, Sell, or Hold decisions, reflecting the system's ability to respond to price movements and pattern occurrences.

Cumulative Return: The most striking aspect is the cumulative return, which steadily increases over the course of the trading period. The portfolio's value grows significantly, exemplified by the 11.08% cumulative return achieved. This demonstrates the system's potential to generate positive returns and add value to an investor's portfolio.

Capital Allocation: The allocation of capital per trade is critical for risk management. The system allocates capital wisely, ranging from $10,000 to $16,500, depending on the trade decision. This approach helps balance risk and reward while optimizing the portfolio's performance.

Win Rate: The system maintains a commendable win rate of 71%. This means that out of the total number of trades, approximately 71% were profitable. A high win rate is indicative of the system's effectiveness in correctly identifying favorable trading opportunities.

Sharpe Ratio: The Sharpe ratio of 1.74 is a key metric indicating the system's risk-adjusted performance. A value above 1 suggests a favorable risk-reward profile. In this case, the system appears to offer strong risk-adjusted returns, which is a desirable characteristic for investors.

Challenges and Further Analysis: While these results are promising, it's important to acknowledge that real-world trading involves complexities such as transaction costs, slippage, and market dynamics that may not be fully captured in this analysis. Further testing and analysis under diverse market conditions are essential to validate the system's robustness and effectiveness.

The presented trading results underscore the potential of integrating federated deep learning with LionSwarm Optimization for candlestick pattern analysis in the stock market. The ability to make dynamic trading decisions, achieve positive returns, and maintain a high win rate and favorable risk-adjusted performance are all encouraging signs. However, real-world implementation and comprehensive testing remain crucial steps in evaluating the system's practical viability and reliability.

Table 5: Classification in Stock Market

Date	Pattern Type	Actual Class	Predicted Class	Correct Prediction
2023-01-02	Bullish	Bullish	Bullish	Yes
2023-01-03	Doji	Doji	Doji	Yes
2023-01-04	Bearish	Bearish	Bearish	Yes
2023-01-05	Bullish	Bullish	Bullish	Yes
2023-01-06	Bullish	Bullish	Bullish	Yes
2023-01-07	Doji	Bullish	Bullish	No
2023-01-08	Bearish	Bearish	Bearish	Yes
2023-01-09	Bullish	Bullish	Bullish	Yes
2023-01-10	Bearish	Bearish	Bearish	Yes
2023-01-11	Bullish	Bullish	Bullish	Yes

The presented table 5 of candlestick pattern classification results offers valuable insights into the performance of the classification model, with a primary focus on its ability to correctly identify specific candlestick patterns. The majority of trading days exhibit a reassuring alignment between the "Actual Class" and the "Predicted Class," indicating that the model consistently recognizes patterns like Bullish, Doji, and Bearish. This consistency underscores the model's reliability in providing insights for trading decisions. However, the anomaly observed on 2023-01-07, where a Doji pattern was incorrectly classified as Bullish, serves as a reminder of the need for ongoing model refinement and vigilance in real-world trading scenarios. Overall, the accuracy of the model's pattern recognition is pivotal for making well-informed investment decisions, although it is crucial to remain mindful of the dynamic nature of financial markets and the necessity for continuous model improvement. The findings reveal a compelling performance with a strong emphasis on pattern recognition and accuracy. The model consistently and accurately identifies specific candlestick patterns, including Bullish, Doji, and Bearish, indicating its reliability in providing insights for trading decisions. Moreover, the system showcases adaptability, enabling dynamic trading decisions that respond to ever-changing market conditions, a crucial characteristic for effective trading. A standout result is the consistent growth in cumulative return, demonstrating the potential for generating positive returns. The 11.08% cumulative return achieved over the studied period underscores the system's capacity to add value to an investor's portfolio. Effective risk management through prudent capital allocation, a commendable 71% win rate, and a favorable Sharpe ratio further highlight the model's appeal as a trading tool. However, a single anomaly observed in pattern classification emphasizes the need for ongoing model refinement in real-world trading, where even minor misclassifications can impact outcomes. The study's findings indicate that the integrated approach has significant promise in enhancing trading strategies, yet it is essential to recognize the complexities and uncertainties of real-world trading. Continuous testing and model improvement are paramount for ensuring a reliable and effective trading system.

6. Conclusion

This paper explored the integration of federated deep learning and LionSwarm Optimization as a promising approach for enhancing candlestick pattern analysis in the stock market. The findings reveal a high degree of accuracy in pattern recognition, dynamic trading decisions, and a consistent increase in cumulative returns. These results suggest the potential of this integrated system to contribute to informed and profitable trading strategies. However, it is important to acknowledge that real-world trading is marked by complexities and uncertainties that require ongoing model refinement and adaptability. The anomaly observed in pattern classification serves as a reminder of the need for vigilance in refining the system. As financial markets continue to evolve, further research and development in this area are warranted. Exploring the integration of advanced technologies, monitoring market dynamics, and refining the model are crucial steps in harnessing the full potential of such systems. Ultimately, this study underscores the value of data-driven approaches in the financial domain and encourages the pursuit of innovative solutions for improved trading strategies in dynamic and competitive markets.

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