**Journal of Information Systems Engineering and Management**
2025, 10(52s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
**Research Article**

# Development of Ensemble Stock Trader Based on the Using of Price Information Converted into Images, Fundamental and Technical Analysis Indicators

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**ARTICLE INFO**

Received: 12 Mar 2025

Revised: 15 May 2025

Accepted: 22 May 2025

**ABSTRACT**

The usage of computer-aided stock trading techniques has been gaining popularity in recent years, mainly because of their ability to efficiently process historical information through machine learning to predict future market behaviour. There are several approaches to this task, with the most effective ones utilizing the fusion of multiple classifier decisions to predict future stock prices. However, usage of price information in individual supervised classifiers has been shown to lead to poor results, mainly because there is not enough historical market data to determine future market behaviour. In this paper we describe project to solve this problem by usage of methods from different fields of sciences: finance, computer vision and neural networks.

**Keywords:** Stock trend forecasting, Convolutional neural network, Deep Learning, Gramian angular field, Technical indicators, Fundamental analyses, Ensemble forecasting.

## INTRODUCTION

The main goal of this work is to develop a convolutional neural network (CNN) ensemble-based stock trading model for identifying stock's buy and sell points using graphical representations of historical price data, fundamental analysis indicators and technical indicators as inputs.

The stock market or share market is one of the most important places for investment [1, 2] where an investor can get high returns by investing his resources in stocks. However, stock trading is a very risky task, the decision-making process in stock trading is a very important process because it must be taken correctly and on time. Three approaches are commonly used to analyze and predict financial market behaviour: (1) fundamental analysis, (2) technical or chart analysis and (3) time series analysis. Fundamental analysis is suitable for long-term forecasting. Technical analysis is most suitable for short-term forecasting. Time series analysis is further divided into linear and non-linear models. Linear models such as ARIMA [3, 4] and ARCH [5-7] have been used to forecast stock price. These models are based on some predetermined assumptions such as postulated normality [8]. However, these models have not been able to capture the patterns present in stock data. Nonlinear models include artificial neural networks (ANN), adaptive neuro-fuzzy inference system (ANFIS) and deep learning neural networks [9-14]. These models have been commonly used for stock market forecasting because they can extract nonlinear relationships between stock data without prior knowledge of the input data [15-17]. Recently, deep learning neural networks (DNNs) have established themselves as a powerful soft computing tool and have a wide range of applications [18-20]. DBM, CNN, LSTM and AE are widely used deep learning architectures for time series forecasting. Meanwhile, CNN-based model performs better for various reasons [20-28].

Search of Kazakhstani publications in Scopus database related to the project topic does not accumulate 10 publications. Among relevant publications, two studies [29-30] were conducted by Kazakhstani scientists from Nazarbayev University and their Turkish colleagues. These studies used LSTM to predict the behaviour of DOW-30 financial market and ETFs. Another study [31] conducted by researchers from KBTU compared the accuracy of machine learning and deep learning algorithms such as SVM, KNN, Decision Tree, Random Forest, XGBoost, CNN

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and LSTM in analyzing sentiment towards financial news. According to their findings, the CNN algorithm consistently outperformed other models in terms of accuracy when analyzing news sentiment in the financial market.

Novelty of the Project's findings.

a) Using "standard" and "transformed" FA, TA, time series data sets as input variables that are correlated with price dynamics. Utilizations of not only time series of stock price dynamics, but also usage of financial reports indicators, experts' expectation indicators, strong technical indicators in the projected predictive model.

b) Conversion of the dataset into images of three types. We will use a new preprocessing step based on meta-recognition generation after converting the dataset into GAF images to generate input data for further processing in our ensemble fusion approach.

c) We propose an improved Ensemble of three types of CNNs to capture stock market characteristics.

d) To demonstrate the performance of the proposed method, the experimental results will be evaluated from two perspectives: computational performance evaluation and financial evaluation. In the computational performance evaluation, we will compare the proposed method with several well-known trend forecasting methods. In the financial evaluation, we will model stock trading based on different forecasts and several common stock trading strategies.

## RESEARCH METHODS

The main hypothesis of the study is that ensemble stock trader using image-transformed price information, fundamental analysis and technical analysis will outperform traditional stock trading strategies based solely on numerical data. This is because usage of visual data representation allows for more efficient and accurate identification of trends and patterns in the stock market, leading to more informed investment decisions. In addition, usage of an ensemble method combining several models will improve the overall performance of the trading system by reducing the impact of errors of individual models and increasing the system's resistance to unexpected market changes. In addition, usage of FA and TA information in combination with price data will provide a more complete view of the stock market, as each type of information provides a different understanding of market behaviour. FA information such as financial statements, industry trends and economic indicators can provide insight into a company's underlying value and growth potential, while TA information such as chart patterns and technical indicators can help identify short-term trends and entry/exit points for trades. Converting this information into images offers several advantages. Firstly, it allows the use of deep learning techniques such as convolutional neural networks (CNNs), which are well suited for image recognition tasks. This allows features to be automatically extracted from the data, reducing the need for manual feature design. Second, it provides a visual representation of the data that is easier for people to interpret and may facilitate the identification of patterns and trends that may be difficult to discern from numerical data alone. Several experiments will be conducted to test this hypothesis. One approach would be to compare the performance of the stock trader ensemble with that of traditional trading strategies by usage of historical stock market data. Measures such as return on investment, volatility and drawdown could be used to evaluate the performance of each strategy. Another approach would be to run a series of simulations to test the performance of the stock trader ensemble under different market conditions such as bull and bear markets, high volatility and low liquidity.

This will help to assess the robustness of the system and identify any limitations or areas for improvement. Ultimately, the success of the ensemble stock trader will depend on several factors such as the quality of the data used to train the models, the effectiveness of the image conversion methods and the ability of the ensemble method to combine multiple models effectively. However, the hypothesis suggests that by combining multiple sources of information and converting it into a visual format, the ensemble stock trader can exceed known prediction models and

To start solving the above hypotheses, data will be collected from financial reports. The main objective is to find a correlation between the price dynamics and the published data from the reports. The financial performance of the company that we will use as a sample for the study: EPS expected by analysts EPS, calculated formula for the

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https://www.jisem-journal.com/
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difference between current EPS and analysts' expectations is given in %, EPS for the last quarterly report, EPS expected by analysts for the last quarterly report, the estimated formula for the difference between EPS and analysts' expectations for the last quarterly report, revenue, analysts' expected revenue figure, the formula for the difference between the current revenue figure and analysts' expectations, revenue for the last quarterly report, analysts' expected revenue for the last quarterly report, estimated formula for the difference between the current revenue figure and analysts' expectations for the last quarterly report, maximum share price over the last 52 weeks, share price before market opening after report publication, the calculation formula for the difference of the stock price with the price of the one-year high, stock price at market open, the calculated formula for the difference of the stock price at market open with the price before the market open after the report was published, the stock price at market open with the price before the market open after the report was published, the maximum price of the stock on the day after the report was published, the first approximation price of the share sale by the trading robot, the calculation formula for the difference of the maximum share price with the share price at market opening on the day after the report was published, share price at market close on the day after the report publication, the second approximation of the selling price of the share by the trading robot, calculation formula for the difference between the share price at the close of trading and the share price at market opening on the day after the report was published, maximum stock price on the day after publication of last quarterly report, calculation formula for the difference of the maximum share price with the share price at market opening on the day after the publication of the last quarterly report, share price at market close on the day after publication of the last quarterly report, calculation formula for the difference between the share price at the close of trading and the share price at market opening on the day after the publication of the last quarterly report, SMA, EMA, MACD, ADX, RSI, Stochastic %K, Stochastic %D, ROC, William's R % [1, 2].

The GAF method [32-34] will be used to transform time series of price, FA indicators, and TA indicators into images. GAF represents time series in polar coordinate system instead of Cartesian coordinates. To construct such images, it is necessary to rescale time series. The indices are normalized using the following equation to scale the data range from 0 to 1 and improve the convergence rate. The polar coordinate values are transformed into an image by considering the trigonometric sum between each point to determine the temporal correlation at different time intervals given in the equations. An example of the transformation is shown in Fig. 1. The Gramian Summation Angular Field (GSAF) [35] and Gramian Difference Angular Field (GDAF) [36] matrices are calculated by the sum/difference between the points in the time series.

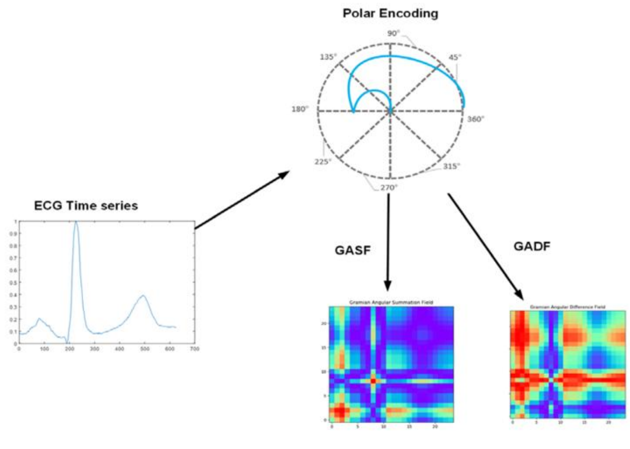


**Figure 1.** Example of ECG time series conversion into an image

Convolutional neural networks. CNNs can recognize patterns with extreme variability and some geometric transformations such as scaling, rotation, displacement and noise. A CNN consists of several convolutional layers, pooling or subsampling layers followed by a fully connected layer. A CNN will consist of 8 layers, namely an input layer (64×64), two convolution layers (64×64×16, 32×32×32), two maximum union layers (2×2), a dropout layer, a fully connected layer and an output layer. Mathematically, the convolution operation can be defined as [37-39]. The ReLU activation function is used to introduce nonlinearity. The feature maps of the first convolution layer will be the input data of the first convolution layer, and they will be down sampled to reduce the dimensionality and the amount

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of computation. The down sampled features used will be input to the second convolution layer. The second convolution layer re-combines the second set of features. This is followed by a dropdown layer, a fully connected layer and an output layer. The SoftMax function [40-42] is used to obtain the output data.

At the last level, we propose to merge multiple trading signals of multiple CNN agents to take more trading decisions into account. Given previous meta-learning results, the final agent operates in an ensemble (or late merge) mode that considers most decision votes to generate the final trading signal. The idea behind this approach is that the same agent trained on different iterations can complement each other as agents have different experiences with the environment, making the approach more robust to uncertainties in stock market behavior.

In fact, by merging the decisions of individual agents using majority voting, we want the final agent to perform a trade action only when the merger has good choice certainty [43-47].

The technical aspect. To implement the project, Python will be used as the main programming language. The project plans to use a paid subscription to access real-time market data via the TWS API provided by Interactive Brokers. The team will automate trading strategies using this API, as well as use fundamental and technical analysis data from sources such as https://finance.yahoo.com/ and yfinance API. To ensure minimal data latency, the project team decided to rent the closest Azure cloud server to Wall Street. The team already has the software code for obtaining favorable trading prices for securities, and the selected server ensures synchronization of the obtained data with real prices on the NASDAQ and NYSE brokerage floors.

Using a paid subscription and a server located in the Wall Street neighborhood, we will have access to high-quality real-time data with a minimum latency of less than a millisecond. We will also evaluate the performance of the proposed model to improve the efficiency of image transformation methods and the ability of the ensemble method to efficiently combine multiple models. The performance will be compared with several well performing variations of prognostic models such as LSTM, CNN-TA, GC-CNN, Dual-CNN, CNN-LSTM, GAF-CNN and others.

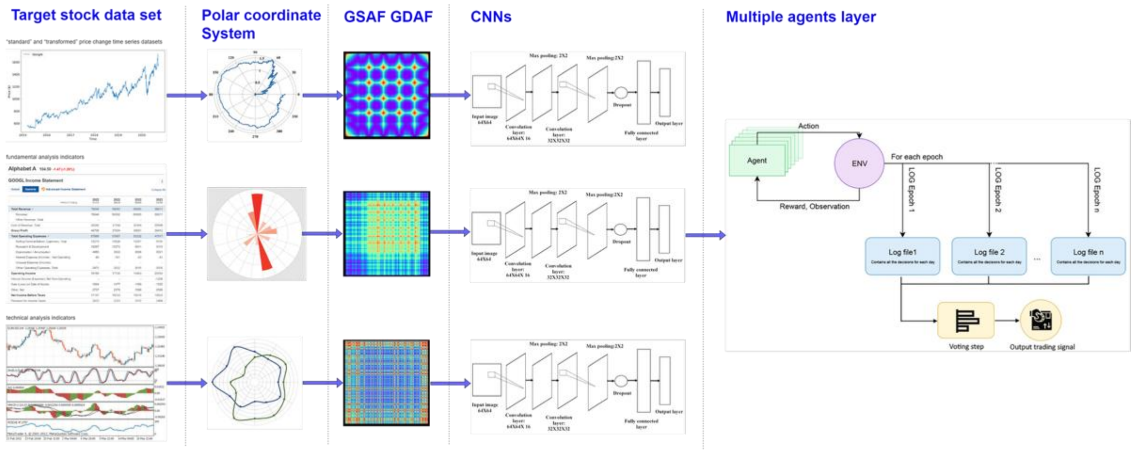


**Figure 2.** Conceptual architecture of the proposed solution

## CONCLUSION

The expected results of the project can have a significant impact on the development of the main scientific direction of machine learning and related fields of science and technology, such as finance and economics. This can lead to the development of new theories, models and applications that can have a significant impact on related fields of science and technology. Here are some possible impacts of the project results:

The results of the project can contribute to the development of new and more effective machine learning methods that can be applied in various fields, including finance and economics. The use of ensemble methods and image transformation techniques may pave the way for future research in machine learning.

The results of the project may lead to the development of new and more effective stock trading strategies that can provide higher profits and reduce risks. This can have a significant impact on the financial sector and the financial industry.

The results of the project can contribute to a better understanding of financial data and underlying patterns. This may have an impact on the development of finance and economics, which will lead to the development of new theories and models.

**Acknowledgements**

This research has been funded by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. AP23489994).

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