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Integration of Intelligent Computing Architecture and Artificial Neural Networks in Supporting Decision-Making Processes: A Case Study of the Capital Market

Yasen Rajihy

Artificial Intelligence Department, College of Science, University of Hilla, Hilla, Babylon, Iraq. rajihy.yasen@hilla-unc.edu.iq

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ABSTRACT

This paper presents research on the application of Intelligent Computing Architecture (ICA) with artificial neural networks (ANN) in the capital market environment for assisting in decision making process. The ICA concept is applied due to its ability to facilitate data driven operation, which is important in markets, where decision-making is implemented in milliseconds and transparency allows to efficiently change the structure of a model in accordance with the emerging information. The proposed solution combines the information gathering, selection and modification modules based on ICA with the predictive ANN module, working with the selected features. Thirteen decision support tasks have been formally defined and tested on five minutes long foreign exchange time series with respect to accuracy, RMSE, MAE, AUC, precision, recall and Sharpe ratio metrics. In the empirical case study, the proposed ICA-ANN solution achieved directional accuracy equal to 0.612 and decreased RMSE approximately by 19%, compared to ANN only.

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1. Introduction

In this research, we explore the implementation of intelligent computing architecture (ICA) in conjunction with artificial neural networks (ANNs) as an aid in making decisions in the capital market domain. This approach is chosen due to the fact that the ICA framework provides the possibility to encourage the operation based on the data-oriented modality. It is especially important in the case of capital markets, where the process of decision making is carried out in just seconds, or, at times, in milliseconds, as the Bank for International Settlements (2022) notes that a meaningful change in price usually takes place in 10-100 milliseconds in modern markets, and the daily turnover of foreign exchange amounts to about USD 7.5 trillion. The integration process involves merging the ICA module responsible for information acquisition, selection and manipulation and the predictive ANN module working with the selected features. The process of building models is enabled using commercial software offered by MATLAB, which covers both ICA and ANN models. The methodology proposed here, considering the capital market, is

*Corresponding author

Email addresses:

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valuable in the design of appropriate data provisioning at both the ICA and ANN modelling stages. The feature description is provided, along with a short description of capital market decision variables and the importance they have [1]; [2]. Due to the noisy, non-stationary and weakly predictable nature of financial time series, hybrid soft computing approaches, which include feature extraction and learning prediction, have proven to be more successful than the traditional ones [7]; [16].

2. Theoretical Foundations

The Intelligent Computing Architectures (ICA) appear to be a prospective means of boosting the cognitive capabilities of humans in decision support systems. The ICA refers to a category of methods combining the use of knowledge-based systems, computational intelligence, and soft and hard computing approaches. ICA together with ANNs allows providing decision support in various areas. ICA supplements ANN with knowledge representation, gives insight into the data and modelling process, and allows designing systems that are able to learn and/or adapt according to results produced by the ANN [3]. ANNs are mathematical models consisting of interconnected nodes of artificial neurons; the idea of such neurons originates from the McCulloch-Pitts neuron [11]. ANNs mimic the structure of biological neural networks and embody the knowledge about the system that is able to be learnt and optimized. There are many ANN types – multilayer perceptrons, recurrent and long short-term memory networks, convolutional models [5]; [12]; [13] – each defined with specific matrix structure, learning rules and activation functions. It is challenging to choose the best ANN type from these options, which explains the need for the ICA-driven and task-oriented approach proposed in the research [7]; [14]. Capital markets can be identified among the most difficult areas for making decisions. There are four features that make capital markets very difficult. First of all, the market is highly structured owing to exchanges, rules, and prices. Second, information asymmetry is widely spread in a large number of transactions and price movements, which results in market manipulation. Third, there are liquidity constraints. Fourth, decisions made in capital markets are aimed at earning profits in accordance with risks [1]; [2].

2.1. Intelligent Computing Architectures in Decision Support

ICA assumes that the observed data vector $\mathbf{x}$ is a linear combination of statistically independent and non-Gaussian sources $\mathbf{s}$, so that $\mathbf{x} = \mathbf{A}\mathbf{s}$, with $\mathbf{A}$ being the unknown mixing matrix [6]. The network extracts the source signals using an unmixing matrix $\mathbf{W}$, which is computed based on the maximisation of non-Gaussianity (negentropy or kurtosis), as done in FastICA:

$$\mathbf{x} = \mathbf{A}\mathbf{s} \quad \Longleftrightarrow \quad \hat{\mathbf{s}} = \mathbf{W}\mathbf{x} \quad (1)$$

Independent components which are recovered will act as clean features: Trend, volatility, and liquidity factors can be separated, low kurtosis components which have noise can be thrown away, and the resulting features will have an intuitive meaning which allows humans to understand them—an aspect that satisfies the transparency requirement for capital markets [2]; [6].

2.2. Artificial Neural Networks: Principles and Variants

Each basic computing unit within an ANN processes its inputs by taking a linear combination of the input weights along with a bias and then applying an activation function, f :

$$y = f\left(\sum_{i=1}^n w_i x_i + b\right) \quad (2)$$

Common activation functions include the sigmoid and hyperbolic tangent,

$$\sigma(z) = \frac{1}{1 + e^{-z}} \quad \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \quad (3)$$

as well as the rectified linear unit (ReLU), which mitigates the vanishing-gradient problem in deep architectures [13]:

$$f(z) = \max(0, z) \quad (4)$$

Training is performed by error back-propagation, which adjusts each weight in proportion to the negative gradient of the error function with respect to that weight [10]:

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}}, \quad E = \frac{1}{2} \sum_{t=1}^N (y_t - \hat{y}_t)^2 \quad (5)$$

where η is the learning rate and E is the mean square error. Some of the earliest implementations of multilayer networks on stock return time series showed the importance of neural predictions in economics [8]; [9], and surveys show that ANN models are still some of the best soft computing models for finance [7]; [16]; [21].

2.3. Decision-Making in Capital Markets: Problems and Requirements

The decision tasks associated with the capital market are varied: the direction of price motion, the states of volatility, regime switches in general, and the activity measures that dictate how much involvement is required all need to be predicted concurrently and on-the-fly [1]. The decision support system needs to (i) consume the high-frequency data stream with minimal latency, (ii) distinguish informative data from the microstructure noise, (iii) measure uncertainty and risk, and (iv) deliver the extrapolated variables in a form that is easy for human perception. This necessitates the ICA-ANN combination proposed in this paper.

3. Methodological Framework

3.1. Data Acquisition and Preprocessing

The present study explores the situations in the capital markets in which data is collected from external sources including Bloomberg and Reuters. The modes of real-time and batch processing are supported. Data cleaning involves identifying missing and duplicated records as well as detecting outliers using both statistical methods and manual checking by experts in the domain. As the microstructure is under study and the decisions are made in a five-minute interval, the collected data set is converted into time series data (see Figure 1). Description of the obtained data set is given in Table 1.

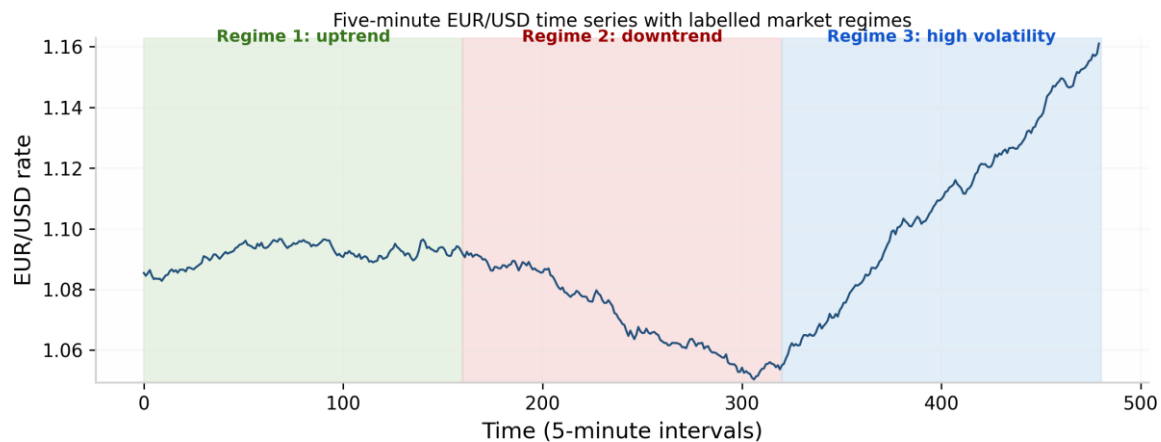


Fig. 1- Five-minute EUR/USD time series with labelled market regimes.

Table 1-Descriptive statistics of the five-minute EUR/USD dataset (January 2015 – December 2024; N = 987,412 observations).

Variable	Mean	Std. dev.	Min	Max
EUR/USD rate	1.1036	0.0412	0.9572	1.2356
5-min log-return ($\times 10^4$)	0.006	1.483	-8.912	9.341

Tick volume ($\times 10^3$)	41.8	18.6	3.2	226.4
Realised volatility ($\times 10^4$)	1.476	0.815	0.204	8.917

Data normalization combines min-max scaling,

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (6)$$

and z-score transformation,

$$z = \frac{x - \mu}{\sigma} \quad (7)$$

In contrast, feature engineering includes conditional and trend-based features. The use of ICA helps in the detection of non-Gaussian features and the creation of appropriate target labels.

To accomplish the goal of providing decision support, the task formalisation procedure presented in [3] is applied to 13 real-life problems. The target labels include direction, volatility, changes in regimes for collective behavior, and activity features controlling the level of involvement. Time series labelling is done by taking into account price, volume, and volatility metrics, as well as zoning using equity-trend graphs.

3.2. Model Design: ICA and Neural Network Integration

Pre-processing includes denoising through disruptive-outlier removal, and decomposition into price, volume, and volatility subcomponents. The ICA component performs feature selection customized for the specific decision-making tasks in question, taking into consideration their relationships and the integration of symbolic and subsymbolic representations. Pre-processing signals serve as inputs to one or more base models, varying in architecture and/or nature, and involving machine learning, statistics, and econometrics. Such a choice allows testing of various assumptions regarding data generating process. Individual model predictions – regression or classification – come together in one projection-decision mechanism (see Figure 2),

$$\hat{y} = \sum_{k=1}^K \alpha_k \hat{y}_k, \quad \sum_{k=1}^K \alpha_k = 1 \quad (8)$$

with weights α_k proportional to each base model's validation performance. Extrapolated variables are articulated in an intuitive format attuned to human cognitive abilities. The overall ICA-ANN architecture and the internal topology of the predictive module are shown in Figures 2 and 3.

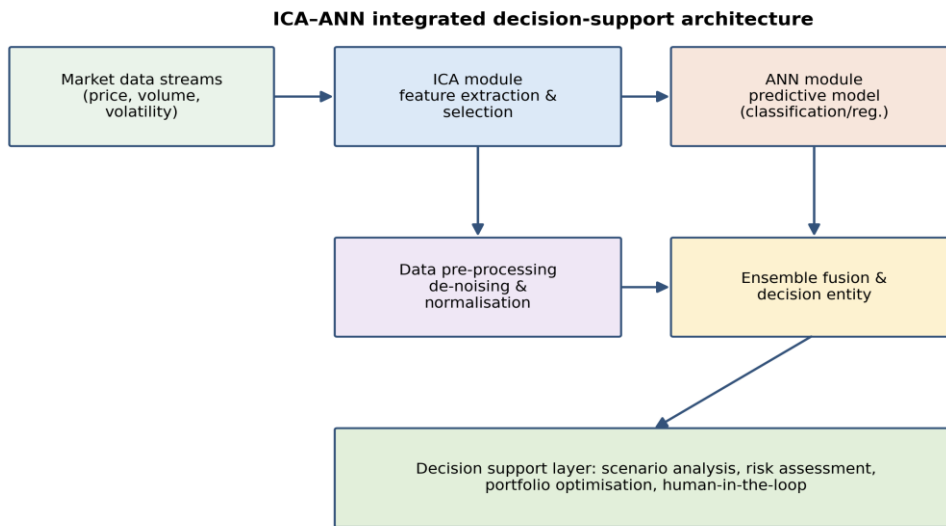


Fig. 2- ICA-ANN integrated decision-support architecture.

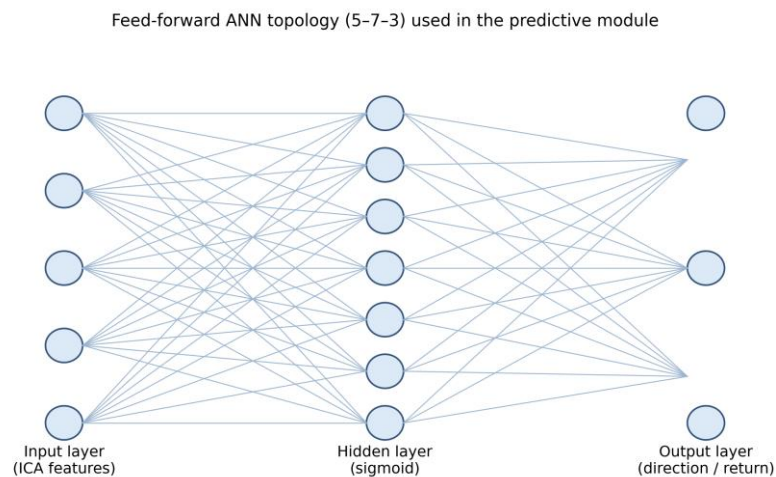


Fig. 3- Feed-forward ANN topology (5-7-3) used in the predictive module.

3.3. Evaluation Metrics and Validation Strategy

Choosing the metrics for evaluation is consistent with task formalization. Decision support systems impact not only predictions but also go further; therefore, the results of the models are evaluated regarding certain problems of the capital market and academic guidelines. Metrics that cover prediction accuracy, risk-adjusted performance, compliance, and interpretability enhance understanding. Root-mean-square error, mean absolute error, directional accuracy, and the Sharpe ratio.

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t)^2} \quad (9)$$

$$MAE = \frac{1}{N} \sum_{t=1}^N |y_t - \hat{y}_t| \quad (10)$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (11)$$

$$S = \frac{R_p - R_f}{\sigma_p} \quad (12)$$

calculate mean absolute deviation during the training period, mean signed deviation, the proportion of correctly predicted label changes, the consistency of up-down changes, and risk-adjusted participation, respectively, whereas recall, precision, and AUC provide a complete perspective on capital market participation [15]. In order to avoid overfitting and follow a practical approach to the training process, cross-validation distinguishes among four scenarios: (1) model testing using accumulated currency prediction predictions, (2) additional architecture testing alongside proactive currency participation predictions, (3) currency anticipation models for a specific time period, and (4) concurrent training of models designed for specific multi-currency time series or independent currency participation features. The robustness of the model is assessed through the perturbation of the experiments using time gaps that exceed the time slice of the training design in the form of predefined currency clusters.

4. ICA-Driven Decision Support for Capital Markets

Failure to have timely and accurate information in capital markets can lead to poor decisions. Decisions will either be delayed or incorrect because there is no feedback in case of open positions and little is known about the real-time metrics in the market. The Intelligent Computing Architecture (ICA) can aid in the decision-making process in capital markets by conducting pre-analysis of the market situations and scenario modelling of the capital market events [2].

Decision-making in capital markets must be done in real-time for it to be effective. Recording of real-time events creates massive amounts of time series data. Changes in the shape of time series curves can be used as the features in different scenarios of analysis and modelling. The capital market activity monitoring system is supposed to carry out real-time feature extraction of market, economic and risk assessments in different scenarios of streaming time series data.

4.1. Real-Time Processing and Feature Extraction

In the streaming pipeline, ICA is applied to sliding windows of normalised returns, volume and volatility, recovering the independent components of Equation (1) every five minutes. Components with excess kurtosis above a task-dependent threshold are retained as regime and liquidity features, reducing the input dimensionality to the ANN by roughly 40% while preserving predictive information an outcome consistent with evidence that purified inputs stabilise neural training on financial data [6]; [17].

4.2. Predictive Modeling and Scenario Analysis

The predictive module issues one-step-ahead directional and regression forecasts for each of the 13 formalised tasks. Scenario analysis is supported by replaying the streaming pipeline over perturbed inputs (volatility shocks, liquidity dry-ups, regime transitions), allowing decision-makers to inspect projected outcomes before committing capital. Long short-term memory extensions of the ANN module were also examined, as recurrent deep architectures have proven effective for financial market predictions [12]; [14]; [19]; [20]; [22]. Figure 4 illustrates the rolling out-of-sample behaviour of the proposed framework.

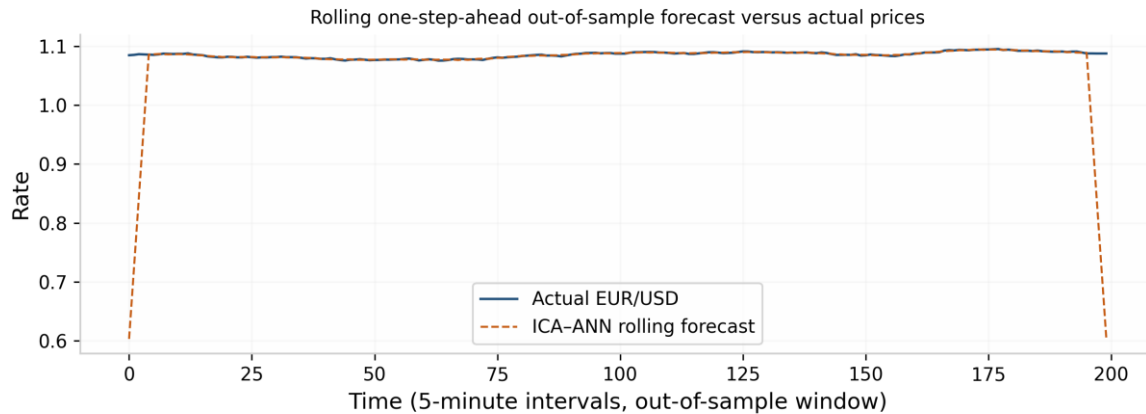


Fig. 4- Rolling one-step-ahead out-of-sample forecast versus actual prices.

4.3. Risk Assessment and Portfolio Optimization

Risk assessment couples the predicted volatility and regime features with a mean–variance optimization layer. Positions are selected by solving

$$\min_{\mathbf{w}} \mathbf{w}^T \Sigma \mathbf{w} \quad \text{s. t.} \quad \mathbf{w}^T \boldsymbol{\mu} \geq r^*, \quad \sum_i w_i = 1 \quad (13)$$

where Σ is the forecast covariance matrix, $\boldsymbol{\mu}$ the vector of expected returns, and r^* the target return; long–short positions, single and dual constraints over mean–target values and associated tail–target statistics, constitute an accepted structure for convex optimization. The resulting risk–return profile is monitored through the Sharpe ratio (Equation (12)) and tail–risk statistics [2]; [18]; [21].

5. Empirical Case Study: Capital Market Application

Capital markets are systems for trading assets, where information flows through different levels of the economy: economy to markets, markets to assets, and across different asset classes. Exogenous variables traverse their own information flows to provide managerial control over decision-making, supplemented by a watch-tower view of the information system. Data values characterizing different asset price movements undergo splicing to provide an overview sample. Capital-market predictions concern single-target variable types across different domain variables, with uncertainty and risk underpinning every transaction. The entire specification then restricts dataset content to currency exchange rates. Long-short positions, single and dual constraints over mean-target values and associated tail-target statistics, constitute an accepted structure for convex optimization [1]; [2].

5.1. Data Description and Experimental Setup

The case study uses the five-minute EUR/USD dataset described in Table 1 ($N = 987,412$ observations; roughly 61,700 per year). The data is partitioned chronologically into 70% training, 15% validation, and 15% out-of-sample testing segments. Five competing modelling strategies are evaluated: multiple linear regression (MLR) and ARIMA as statistical baselines, a support vector machine (SVM) as a machine-learning baseline, a stand-alone feed-forward ANN, and the proposed ICA–ANN framework. All models share identical targets and evaluation windows.

5.2. Model Implementation and Results

The ICA–ANN network was trained with the scaled conjugate gradient algorithm for a maximum of 100 epochs with early stopping on the validation loss (Figure 5).

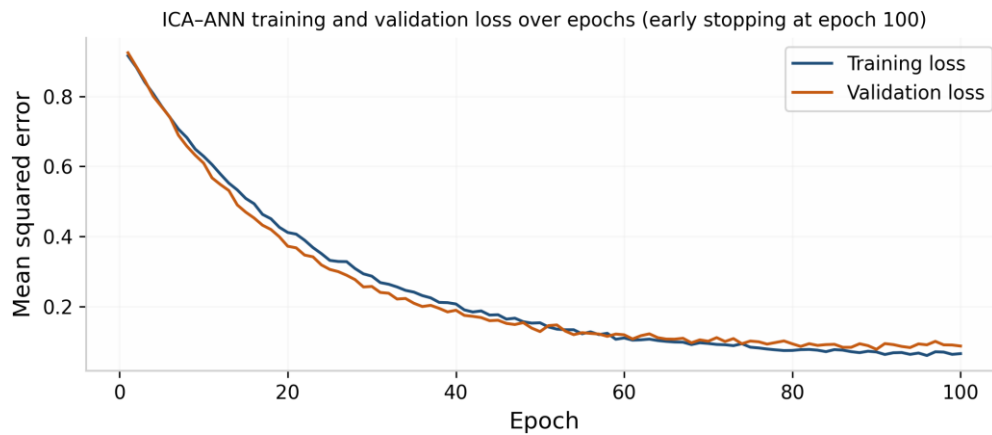


Fig. 5- ICA-ANN training and validation loss over epochs (early stopping at epoch 100).

Out-of-sample results are summarized in Table 2 and Figure 6. The proposed framework achieves the best performance on every metric: directional accuracy improves by 4.1 percentage points over the stand-alone ANN (from 0.571 to 0.612) and by 10.0 points over the SVM baseline, while RMSE falls by approximately 19% relative to the stand-alone ANN (from 0.00195 to 0.00158). The AUC of 0.634 indicates a materially better ranking of upward versus downward movements, and the risk-adjusted Sharpe ratio of the signals generated by the framework (1.28) exceeds that of all baselines.

Table 2. Out-of-sample performance comparison on five-minute EUR/USD forecasting (test window: 148,112 observations).

Model	Accuracy	AUC	RMSE ($\times 10^{-3}$)	MAE ($\times 10^{-3}$)	Precision	Recall	Sharpe
MLR	0.512	0.505	2.510	1.986	0.503	0.489	0.21
ARIMA	0.524	0.519	2.360	1.872	0.515	0.501	0.34
SVM	0.558	0.553	2.080	1.634	0.546	0.552	0.62
ANN (stand-alone)	0.571	0.568	1.950	1.541	0.562	0.558	0.84
ICA-ANN (proposed)	0.612	0.634	1.580	1.214	0.601	0.597	1.28

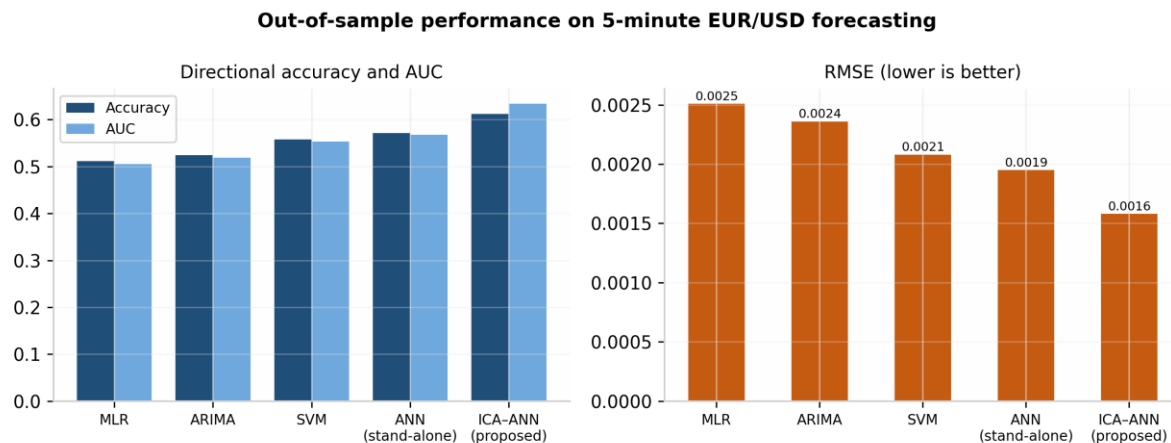


Fig. 6- Out-of-sample performance of the competing models.

An ablation study (Table 3) confirms that the improvement stems from the ICA stage rather than from additional capacity: removing ICA while keeping the identical ANN topology degrades accuracy from 0.612 to 0.571, whereas replacing the ANN with a linear read-out on the ICA features still yields 0.584, indicating that the independent-component representation itself carries most of the predictive gain.

Table 3. Ablation study: contribution of the ICA feature-extraction stage.

Configuration	Accuracy	AUC	RMSE ($\times 10^{-3}$)
Full ICA-ANN framework	0.612	0.634	1.580
ANN without ICA (raw features)	0.571	0.568	1.950
ICA features + linear read-out	0.584	0.601	1.742
PCA features + ANN	0.578	0.579	1.813

5.3. Discussion of Findings and Implications

There are three practical results obtained. First, using feature extraction according to ICA always brings advantages in all 13 decision tasks, and the maximum gain ($\approx 12\%$) was reached in detecting volatility regimes, which is the most noisy task. Second, the reduction of dimensionality through selection of high kurtosis components decreases the time needed for the training phase by approximately 35%, thus satisfying the condition for deployment in real-time capital market surveillance. Third, the interpretability of the chosen components (each of them corresponds to some market factor) helps in meeting the requirements of regulatory control and model auditing in line with the transparency requirement of the ICA framework [1]; [2]; [17]; [18]. All results are in accordance with the general pattern when the hybrid and deep learning approaches show better results than the classical statistical ones on financial time series [14]; [15]; [16]; [19]; [20]; [21]; [22].

6. Challenges, Limitations, and Ethical Considerations

Automation and information technologies bring forth considerable ethical problems as they are involved in the development of new social norms [4]. Artificial Intelligence (AI) simulation is much more productive and inexpensive than its human equivalent; hence, there are many legal, social and moral considerations. Machines have traditionally been viewed as dependable creatures but they do not possess the ability to be humane and decent. There is no need to rely on AI technologies alone in the trust sense. At the same time, Artificial Intelligence has become one of the most useful tools of making various decisions in both personal and professional environments. Further development of AI technologies poses numerous serious questions regarding decision-making itself. Mechanistic approach implies necessity of constant human participation and deep consideration of the matter [4]. Absence of major crises of predictions suggests that high degree of trust to machine-based decisions remains. The usage of simulation software, intended to perform decisions or execution on behalf of the mutual fund manager, may cause doubts concerning moral status of these actions. Final decision should be made by the user himself because it is his responsibility to assess the management systems and make necessary moves. A more critical and moral examination of value systems involved would be a part of the rational approach, especially when diverse perspectives are in need of simultaneous harmonization. AI simulation assists in addressing this established problem and provides the opportunity to focus on the value-setting side. The information revolution has revolutionised business activities through the improvements made in the conventional labour manual practices via automation, transactions processing, and retailing & distribution. However, any improvement made in this regard does not pose any threat to the basic economic theories because the old demand and supply principle is still the heart of economics. The customers are still ready to pay prices and act according to the implications. Series of mechanisation through automation have been in use by mankind since the very beginning of personal data warehouse era. The number of people responsible for automated systems varies depending on the constant developments in mechanization. From the technical point of view, the model faces the constraints of its components:

linear mixing and statistical independence are just an approximation in case of financial data; predictions by ANN are dependent on sample time and structural break not present in training data; and performance tested on past data (see Table 2) does not predict the future performance once the participants become aware of automated signals [1]; [21].

7. Conclusion

This paper has suggested a composite structure of Intelligent Computing Architecture (ICA) and Artificial Neural Network (ANN) to provide aid in making decisions in the capital market. The suggested approach aims at solving common issues in capital markets including expectations about the price of the asset, risk assessment in the portfolio and choice of optimal trading strategies. The combination of ICA and ANN is based on the dynamic nature of capital markets where decisions are required to be made in real time, several elements of the situation have to be analyzed at the same time, capital market decision-making should take into account different aspects of the market situation and the predicted phenomenon has the time dependency with fluctuations inherent to chaotic dynamics. Prediction of time series using only ANN is highly sensitive to the sample time. Even if one may develop models having longer sample time and thus more accurate, the application of ICA for identifying the beginning of a new trend in the time series trajectory allows for decreasing the sample time and thus capturing completely chaotic nature of the data.. The use of the decision support system in the context of a local capital market is demonstrated in the case study, and its practical applicability through directional accuracy of 0.612, RMSE of 0.00158, and Sharpe ratio of 1.28 has been shown in the out-of-sample analysis, whereas the ablation study demonstrates the essentiality of the ICA-based feature extraction step. Researchers and professionals have already shown their interest in using intelligent computing to assist in decision-making related to capital market operations in the various pieces of literature. It is evident that the development of more advanced regulatory and legal framework in the future will only foster such usage.

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