Novel framework and reference architecture for artificial intelligence models for stock markets

Ernesto David Cancho-Rodriguez[1], Miguel Angel Cano Lengua[2]
[1]Department of Software Engineering, Faculty of Systems Engineering and Informatics (Computer Science), Universidad Nacional Mayor de San Marcos, Lima, Peru
[2]Department of Mathematics, Faculty of Mathematical Sciences, Universidad Nacional Mayor de San Marcos, Lima, Peru

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ABSTRACT

This original research article proposes, as its contribution, a novel unified framework and reference architecture for stock market prediction in post-COVID financial markets, which exhibit unprecedented volatility and non-linear dynamics, demanding more robust predictive approaches than traditional models can provide. This original framework integrates artificial intelligence (AI) and machine learning (ML) models, ranging from classical techniques support vector machine (SVM) to deep learning (DL) architectures such as long short-term memory (LSTM) neural networks and gated recurrent unit (GRU) models, within a modular system encompassing data ingestion, sentiment processing, predictive optimization, reinforcement learning (RL), and cloud-based portfolio management. Another key original contribution is the synthesis of standards (ISO 23053, ISO 38505, ISO 20546) with big data methodological frameworks (REBD and Biggy), forming a unified meta-framework that orchestrates predictive signals from sentiment analysis (SA) and macroeconomic indicators. Experimental real-world stock market validation on mining-sector stocks demonstrated, with a 100% success rate, consistent investment outperformance over passive Buy & Hold baselines, yielding investment optimizations of up to +11.11 pp: the evaluated portfolios achieved 23.57% and 8.25% returns versus their 19.94% and 5.41% baselines, respectively. These results confirm the validity of the proposed novel framework as a reproducible reference architecture, an original contribution empirically grounded and experimentally validated for the development of future financial AI systems.

Corresponding Author:

Ernesto David Cancho-Rodriguez
Department of Software Engineering, Faculty of Systems Engineering and Informatics (Computer Science)
Universidad Nacional Mayor de San Marcos
Lima, Peru
Email: ernesto.cancho@unmsm.edu.pe

1. INTRODUCTION

Post-COVID-19 pandemic financial markets constitute a sui generis situation characterized by high volatility and unusual behaviors that demand the updating of existing techniques and algorithms [1], [2]. The global pandemic crisis of dimensions not witnessed since the 1918 pandemic, combined later with asymmetric activity restarts, global inflation, and the current international conflicts, creates an urgent need to model markets with methods capable of capturing this "new normal" [3], [4]. Quantitative finance specialists face challenges in appropriately estimating prices and trends while considering external factors such as inflation, exchange rates, socioeconomic conditions, and market sentiment that continuously interact with price movements [5], [6]. Although machine learning (ML) algorithms have outperformed traditional statistical approaches in algorithmic trading, the literature demonstrates a clear need to continuously develop applications of the latest advances in artificial intelligence (AI) adapted to the current volatile context [2], [7], [8]. Recent studies posit the need to model normal pre-pandemic periods versus times of the new normal affected by COVID-19 and macroeconomic deceleration using different techniques [4], [5], [9], [10].

This research analyzes and compares the performance of AI algorithms applied to algorithmic trading by evaluating their capacity to improve trend and price forecasting relative to traditional approaches, identifying specific advantages of ML and deep learning (DL) models such as long short-term memory (LSTM), gated recurrent unit (GRU), and support vector machine (SVM) in high-volatility contexts characteristic of the new normal [11]-[13]. Specifically, the extent to which these algorithms outperform traditional methodologies in predictive accuracy, risk management, and investment decision optimization is assessed, thereby contributing to the development of robust strategies for portfolio management in dynamic, globalized financial environments [14]. The review emphasizes the need to incorporate the latest advances in natural language processing (NLP) through sentiment analysis (SA) within this new economic-financial context [15], [16].

Despite these advances, a critical research gap persists in the current literature. While existing research highlights the potential of AI/ML algorithms, including deep networks and SA, to outperform traditional approaches in stock market prediction [1], [7], [16], a critical gap persists: the absence of a unified and comprehensive reference model. Previous research tends to address specific aspects in a fragmented manner, lacking a systematic synthesis that combines a hierarchical algorithmic taxonomy, a standardized modular software architecture, and the proactive integration of international standards for data governance and AI system development. This study directly addresses this gap, presenting a novel framework and reference architecture designed to provide a reproducible and holistic foundation for building intelligent trading systems in volatile post-pandemic financial markets.

To address this research gap, the present paper contributes a novel unified framework and a new reference architecture for AI/ML-based stock market prediction, integrating international standards (ISO 23053, ISO 38505, ISO 20546), SA through NLP, and reinforcement learning (RL) agents for robust portfolio management in post-COVID volatile markets [17]-[20]. The importance of this contribution lies in establishing a reproducible blueprint that synthesizes fragmented approaches from the literature into a comprehensive meta-framework, enabling systematic model selection through hierarchical taxonomy, proposing a modular software architecture with standardized interfaces, and empirically validated components demonstrating superior predictive accuracy in price change prediction (RMSE/MSE <0.05, MAPE <3%), superior compared to traditional methodologies [14], [21]-[23].

The proposed framework was experimentally validated through functional prototype implementation, evaluating portfolio investment performance for mining companies with operations in Peru listed on international stock exchanges. Out-of-sample testing across up to 366 trading days demonstrated a 100% success rate in outperforming the passive Buy and Hold baseline strategy, achieving portfolio investment returns of up to 23.6% with outperformance margins of up to +11.11 percentage points and a mean advantage of +5.86 percentage points over the baseline. The remainder of this paper is organized as follows. Section 2 describes the multidimensional research methodology and development process, including the systematic literature review based on preferred reporting items for systematic reviews and meta-analysis (PRISMA). Section 3 presents the proposed novel framework and reference architecture, detailing the hierarchical AI/ML taxonomy, modular software architecture, and integration with international standards. Section 4 describes empirical and experimental validation, including the functional prototype implementation and portfolio investment simulation results. Section 5 discusses the results, analyzing performance metrics, critical findings, and limitations. Finally, section 6 presents the conclusion of this research and outlines directions for future work in AI-driven algorithmic trading.

2. METHOD AND RESEARCH DEVELOPMENT PROCESS

This research develops a novel framework and reference architecture for AI/AML systems applied to stock market prediction through a multidimensional architectural synthesis methodology that systematically integrates theoretical knowledge, established industrial practices, and rigorous empirical validation [24], [25].

The methodological model development process comprises four interconnected phases that ensure scientific rigor and practical applicability of the proposed model: architectural requirements analysis through systematic requirements engineering, conceptual design of the unified meta-framework through the synthesis of complementary dimensions, detailed technical specification of modular components with standardized interfaces, and exhaustive empirical validation through a systematic literature review that underpins critical architectural decisions [25].

2.1. Phase 1-architectural requirements analysis method

Architectural requirements analysis employs the requirements engineering for big data (REBD) methodological framework, which provides a systematic plan for intelligent systems projects spanning from requirements engineering to operational deployment [24]. The requirements elicitation process identified critical needs from multiple stakeholders through analysis of recent scientific literature on still unresolved problems in post-pandemic market prediction, evaluation of limitations of existing fragmented approaches that lack reproducible integral reference models, and characterization of operational constraints imposed by regulated contexts of financial institutions that demand appropriate data governance, explainability of algorithmic decisions, and comprehensive capabilities [14], [26]. The identified functional requirements encompassed the need for a hierarchical taxonomy that guides systematic selection of appropriate algorithms according to problem characteristics through explicitation of trade-offs between predictive accuracy, interpretability, and computational requirements; modular architecture that facilitates incremental technological evolution without fundamental redesigns through decoupling of components with standardized interfaces; integration capabilities for multiple structured and unstructured data sources including SA of news and social networks through advanced NLP; and multi-objective optimization mechanisms that balance returns with quantified risks through robust metrics appropriate for high-volatility contexts [2], [7], [8]. Non-functional requirements specified the need for horizontal and vertical scalability through big data infrastructures and cloud computing capable of supporting massive volumes of information and transactions, proactive compliance with ISO/IEC international standards that facilitates institutional adoption in supervised environments, and scientific reproducibility through exhaustive documentation of architectural decisions and empirical validation processes [27].

2.2. Phase 2-design method of the unified meta-framework

Conceptual design of the unified meta-framework systematically synthesizes three complementary architectural dimensions that transcend existing fragmented approaches through coherent integration of dispersed knowledge in scientific literature.

2.2.1. First dimension–hierarchical taxonomy development method

The hierarchical taxonomy dimension was developed through comprehensive comparative analysis of AI/ML algorithms reported in the literature, classifying them into four levels ordered according to increasing algorithmic complexity and capacity for capturing complex non-linear patterns, ranging from classical ML approaches such as SVM and random forest (RF) appropriate for problems with moderate non-linearities and strict interpretability requirements, through recurrent neural networks (RNN) LSTM and GRU that capture long-term temporal dependencies essential for financial series with memory, to DL architectures with autoencoders and convolutional networks that automatically learn latent representations, and culminating with RL paradigms that optimize end-to-end decision policies while dynamically adapting to changing market conditions [5], [11], [14], [28]-[30].

2.2.2. Second dimension–modular software architecture development method

The modular architecture dimension was designed through systematic functional decomposition of the intelligent trading system into six hierarchical layers operating in coordination: data acquisition through specialized connectors for financial APIs and web scraping of textual sources, sentiment processing through pre-trained language models fine-tuned for the financial domain, predictive model core implementing algorithms from the proposed taxonomy with simultaneous multi-paradigm support, optimization through RL agents that translate predictions into actionable strategies, portfolio management deployed in cloud executing orders in real-time, and an intuitive user interface that abstracts technical complexity facilitating access for financial analysts without deep expertise in ML [31], [32].

2.2.3. Third dimension–standards integration method

The standards integration dimension was specified through proactive alignment with ISO/IEC 23053:2022 regulations for the development of AI systems based on ML, covering the complete lifecycle from conceptualization to operational maintenance, ISO/IEC 38505 for data governance ensuring quality and security in the handling of large volumes of information, and ISO/IEC 20546 for big data, facilitating interoperability of heterogeneous components through standardized terminology, complemented with REBD methodological frameworks for systematic requirements engineering and Biggy for management of analysis, transactions, queries, storage, and privacy aspects of distributed data [17]-[19], [24], [25].

2.3. Phase 3-detailed technical specification method

Detailed technical specification operationalizes the conceptual design through rigorous definition of architectural components, data interfaces, communication protocols, and coordination mechanisms between subsystems, ensuring practical implementability of the proposed framework [5], [12], [33]-[35]. For each layer of the modular architecture, concrete implementation technologies based on the current state of the art were specified: Apache Kafka for real-time data streaming buffering with historical replay capabilities for rigorous backtesting, BERT and GPT models fine-tuned for SA of financial texts through transfer learning that leverages pre-trained knowledge on massive corpora, TensorFlow and PyTorch DL frameworks for implementation of LSTM/GRU networks with attention mechanisms that provide interpretability through attention weights. This reveals the most influential historical periods in predictions, bio-inspired optimization algorithms such as artificial bee colony and particle swarm optimization (PSO) for portfolio problems with cardinality constraints and transaction costs, and costs, as well as AWS and Google Cloud Platform, cloud platforms providing elasticity of computational resources through auto-scaling groups and multi-zone deployment ensuring operational availability [11], [36], [37]. Data interface schemas between layers were specified through standardized contracts defining JSON formats for structured information exchange, REST API protocols for synchronous communication between components, and message queues for asynchronous coordination decoupling producers as well as data consumers, facilitating maintainability and independent evolution of subsystems [3], [27], [38], [39].

2.4. Phase 4-empirical validation and experimental validation

Empirical validation through systematic review rigorously substantiates critical architectural decisions through comprehensive analysis of consolidated scientific evidence in recent literature, applying the PRISMA methodology recognized for its transparency in synthesizing relevant research [2], [14], [20]. Experimental validation through functional prototype implementation and portfolio investment simulation is presented in section 4 (validation) and section 5 (results and discussion), demonstrating the framework's out-of-sample performance against baseline strategies across multiple mining companies and international stock exchanges.

2.5. Problem, intervention, comparison, and outcome question planning

Within the framework of a systematic literature review, the problem, intervention, comparison, outcome (PICO) question is structured as shown in Table 1.

2.6. Research question

The research question (RQ), which encompasses the four PICO aspects, asks, "How do AI algorithms applied in the field of algorithmic trading compare in terms of improving results regarding predicting trends and/or prices in financial markets, in contrast to traditional approaches?"

2.7. Search preparation

To initially ensure a comprehensive and focused search in Scopus, a specific query was formulated based on the research questions and the keywords identified as related, as shown in Table 2. The search was structured to capture relevant studies on AI in algorithmic trading and portfolio optimization. In addition, it is limited to publications between the years 2019 and 2025 to ensure the timeliness and relevance of the studies.

Table 1. PICO question planning

Element	Description
Problem	The problem of investment decisions in financial markets.
Intervention	Use of AI and ML algorithms in algorithmic trading.
Comparison	Different AI methodologies and tools in contrast to traditional approaches.
Results	Quality in the prediction of market trends and/or prices.

Table 2. Keywords and search synonyms

Factor	Description	Search terms	Synonyms
Problem (P)	The problem of financial markets investment decisions.	Financial market, algorithmic trading, forex, crypto, and portfolio optimization	Stock market and portfolio
Intervention (I)	AI models (ML, DL, and optimization).	AI, optimization, ML, DL, high-frequency trading, and data mining	Algorithm, model, technique, method, heuristic, analysis, and HFT
Comparison (C)	Comparison with traditional techniques (statistics) and other models.	Markowitz, statistics, model, and comparison	Statistical technique, econometrics, technique, method, heuristic, and analysis
Outcome (O)	Optimize or improve predictions for prices and/or trends. Minimize error and/or risk.	Prediction, performance, trend, price, risk, and error	Result, direction, accuracy, precision, score, F1, MSE, MAE, and RMSE

2.8. Selection criteria method

Inclusion and exclusion criteria, as shown in Table 3, were clearly defined to ensure the relevance and quality of the selected studies. Articles discussing the use of AI in algorithmic trading and portfolio optimization, published in recent years, were included, and studies not directly related to the topic, obsolete or with unclear methodologies were excluded.

Table 3. Inclusion and exclusion criteria used

Inclusion criteria:	Exclusion criteria:
IC-1: Studies related to the use of AI in algorithmic trading and portfolio optimization with ML.	EC-1: Articles published in languages other than English.
IC-2: Studies published between 2019 and 2025.	EC-2: Duplicate studies.
IC-3: Articles published in English.	EC-3: Literature review articles are excluded.
IC-4: Journal articles indexed in Scopus, Web of Science, or other well-recognized international indexing databases, as well as conference proceedings published by Springer or other prestigious, peer-reviewed conference venues.	EC-4: Articles unrelated to the usage of ML in algorithmic trading and portfolio optimization.

Regarding the search strategy and selection criteria, an exhaustive search was conducted in the Scopus, Web of Science, and Google Scholar databases, where a structured query was formulated to capture studies on AI in algorithmic trading and portfolio optimization published between 2019 and 2025, ensuring the currency and relevance of the analyzed evidence. Inclusion criteria encompassed works related to the use of AI in trading and portfolio optimization with ML, published in English and Spanish, in journals indexed in Scopus and Web of Science along with conference proceedings published in Springer, excluding articles not directly related, in non-selected languages, or literature reviews themselves to avoid redundancy.

2.9. Research databases

Scopus, Web of Science, and Google Scholar were used as the main databases for their broad coverage of scientific and technical literature, ensuring comprehensive access to relevant studies in the field of AI applied to finance and financial investment decisions.

2.10. Study selection process

The selection process began with the identification of 1,237 potential studies in the different search engines, which was reduced to 875 by eliminating duplicates. After applying the inclusion and exclusion criteria, a preliminary evaluation was performed, resulting in the selection of 69 studies. A more detailed review and an evaluation of the quality and relevance to the research questions reduced the selection to the 39 most relevant and representative studies of the state of the art. Consequently, these 39 key studies (shown in Table 4) have been selected for the review as they are the most complete, and the most representative and relevant in their approaches that respond to the research questions posed. These 39 selected studies provided consolidated empirical evidence that substantiates and validates specific architectural components of the proposed framework, demonstrating quantifiable superiority over traditional approaches through reported comparative performance metrics [7], [8], [14].

2.11. Preferred reporting items for systematic reviews and meta-analysis-guided evidence-screening procedure supporting the novel framework

This original research article uses a PRISMA-guided evidence-screening process to substantiate the architectural decisions underlying the proposed framework. Figure 1 presents the corresponding study selection diagram, documenting the four-stage process used to identify, screen, assess, and include studies that informed the development and validation of the proposed framework and reference architecture.

During the identification stage, 1,237 records were retrieved from Scopus, Web of Science, and Google Scholar. In the screening stage, 362 duplicate records were removed, yielding 875 unique records for further evaluation. During the eligibility stage, the application of the predefined inclusion and exclusion criteria led to the exclusion of 806 records, reducing the pool to 69 candidate studies. Finally, a detailed quality and relevance assessment excluded 30 additional studies, resulting in 39 key studies selected as the literature-based evidence base supporting the architectural components of the proposed framework.

2.12. Preferred reporting items for systematic reviews and meta-analysis methodology for framework validation

This article employs the PRISMA methodology, recognized for its rigor and transparency in systematic literature review, to empirically validate the architectural components of the novel framework proposed as the original contribution of this research. PRISMA provides a structured framework for identifying, evaluating, and synthesizing relevant research, ensuring the quality and reliability of the findings that substantiate the proposed reference architecture. According to preceding literature review investigations on the use of ML for time series, this method has proven to be quite suitable for this kind of validation study [2], [14], [20].

Table 4. The key studies selected as a basis for the proposed framework formulation

Year	Title (summarized)	Contribution	Year	Title (summarized)	Contribution
2025	AI-augmented quantitative finance with quantum computing [40]	DL, ML, quantum computing, and risk management	2024	Predicting stock market by sentiment and DL [41]	SA, DL, and stock prediction
2025	Stock price forecasting using ARX-SVR [42]	SVR, time series, stock prediction, and forecasting	2024	Harmonic patterns recognition with ML and DL [43]	Candlestick, ML, DL, and pattern recognition
2025	Hybrid SVR with multi-view learning for stock prediction [44]	SVR, hybrid, stock prediction, and multi-view learning	2024	ML in portfolio selection with genetic optimization [31]	ML, genetic algorithm, portfolio optimization, and hybrid
2025	JaxMARL-HFT: multi-agent RL for HFT [45]	Multi-agent RL, RL, high-frequency trading, and GPU	2024	Egret swarm optimization for portfolio selection [46]	Swarm optimization, AI, portfolio optimization, and metaheuristic
2025	Hybrid LSTM with SA for forecasting [47]	LSTM, SA, NLP, hybrid, and stock prediction	2023	Forecasting with CNN-LSTM, GRU-CNN, and ensemble models [11]	CNN, LSTM, GRU, RNN, hybrid, ensemble, and stock prediction
2025	BERT-based framework for agricultural futures [48]	BERT, NLP, Transformer, SA, and futures	2023	Stock market prediction using deep RL [16]	Deep RL, RL, and stock prediction
2025	LSTM and transformer-based sentiment framework [49]	LSTM, Transformer, SA, NLP, and stock prediction	2023	DL with SA for investment [36]	DL, SA, NLP, and quantitative investment
2025	Stock index prediction based on financial text [50]	SA, NLP, stock prediction, and text mining	2023	ML with news sentiment in trading strategies [51]	ML, SA, NLP, and algorithmic trading
2025	FinBERT-LSTM for market sentiment integration [52]	FinBERT, BERT, LSTM, SA, and NLP	2023	Virtual currency trading with ARIMA and AHP-PSO [12]	ARIMA, PSO, cryptocurrency, and algorithmic trading
2025	LLM in finance for sentiment estimation [53]	LLM, GPT, NLP, SA, and stock prediction	2023	Intraday HFT with ANN and VAR models [54]	High-frequency trading, neural network, VAR, and comparison
2025	Profitable stock prediction with candlestick and ML [55]	Candlestick, ML, stock prediction, and pattern recognition	2022	LSTM-MPT based quantitative portfolio decision model [5]	LSTM, RNN, portfolio optimization, DL, and MPT
2025	Trading strategy with candlestick patterns and ML [56]	Candlestick, ML, and algorithmic trading	2022	Stock predictions using DL hybrid models [57]	DL, hybrid, and stock prediction
2025	Multi-objective portfolio formation with nadir compromise [58]	Multi-objective, portfolio optimization, and metaheuristic	2022	XGBoost-SVM for quantitative investment [30]	XGBoost, SVM, hybrid, and quantitative investment
2025	Multi-objective portfolio with NSGA-III [59]	NSGA, genetic algorithm, multi-objective, and portfolio optimization	2022	Hybrid approach for futures price forecasting [9]	Hybrid, ensemble, feature selection, AI, and futures
2025	ACO and PSO comparison for mean-variance portfolio [60]	ACO, PSO, swarm intelligence, portfolio optimization, and comparison	2022	Healthcare sector stock price with ML [21]	ML, stock prediction, and healthcare
2024	Predicting economic trends with DL [1]	DL, ML, stock prediction, and forecasting	2022	Predicting stock market with ML techniques [32]	ML and stock prediction
2024	DL stock forecasting: NSE and NYSE analysis [10]	DL, NN, stock prediction, and comparison	2022	Quantitative investment strategies with DL [61]	DL, quantitative investment, strategy
2024	Explainable DL for stock market trends [62]	DL, explainability, XAI, and stock prediction	2021	Attention-guided DNN for stock index prediction [38]	Attention, DNN, DL, and stock prediction
2024	Ensemble SVR models for stock price prediction [63]	SVR, ensemble, stock prediction, and optimization	2021	Stock price prediction using GANs [64]	GAN, DL, and stock prediction
2024	Deep RL for trading strategy optimization [65]	Deep RL, RL, risk management, and algorithmic trading			

This multi-phase architectural development method provides methodological synthesis and guarantees, as it ensures that the proposed framework simultaneously satisfies requirements of scientific rigor through exhaustive empirical substantiation in consolidated literature; practical applicability, through detailed technical specification of implementable components with current state-of-the-art technologies; and reproducibility, through comprehensive documentation of design and validation processes. This coherence facilitates adoption by the scientific community and financial institutions interested in operational deployment of intelligent trading systems in post-pandemic markets [3], [26].

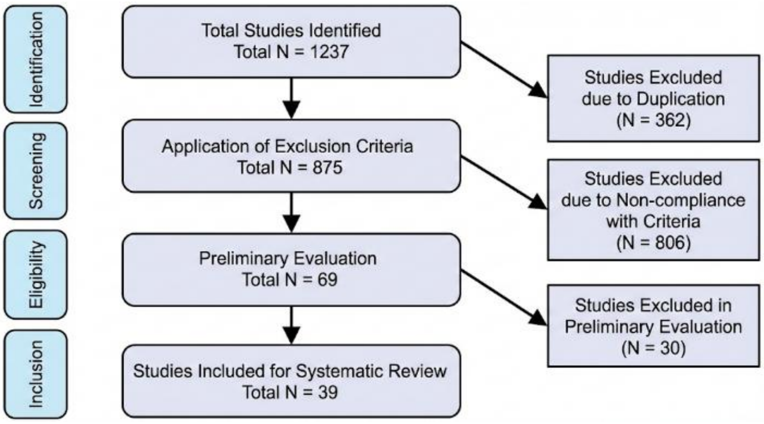

Figure 1. PRISMA-based study selection procedure diagram

3. PROPOSAL-NEW FRAMEWORK AND NOVEL REFERENCE ARCHITECTURE

3.1. Overview of the proposed novel reference architecture

As a result of the literature analysis of the gaps still open in this field and proposals in the literature for future work, in this research the authors have produced as an original contribution an integrated system model reference architecture for algorithmic trading, which is presented in Figure 2, that starts with the collection of real-time data through financial APIs and web scraping systems. This data includes crucial information on asset prices, financial news, and social media posts.

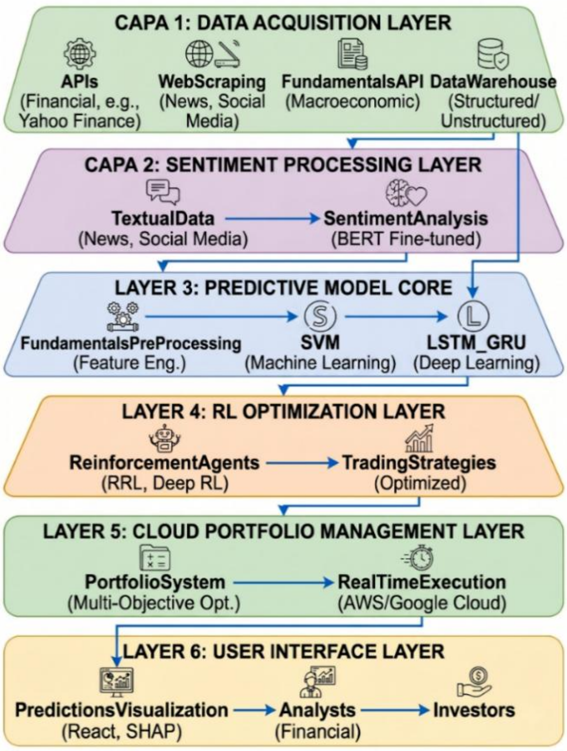

Figure 2. Reference architecture of the proposed framework for AI models systems for stock market trends and prices predictions

For data storage integration, in the model proposed in this article as shown in Figure 2, the data collection process ensures that the system has access to up-to-date and relevant information for accurate analysis and informed decision making. Once collected, the data are stored in a data warehouse. This data warehouse integrates both structured and unstructured data, providing a solid foundation for analysis and insight generation. Structured data includes organized financial metrics, while unstructured data comprises news text and social media posts. This approach ensures that a wide range of information is leveraged to improve system accuracy.

For SA models processing, the next step is sentiment processing, where SA systems evaluate textual data from news and social media to determine market sentiment. This analysis provides critical inputs that feed AI models, allowing the system to interpret market emotions and opinions, which is essential for predicting future movements with greater accuracy.

For AI and DL model core, as shown in Figure 2, AI models are the backbone of this system. Using ML models such as SVM and DL models such as LSTM and GRU, the system analyzes data along with macroeconomic factors and fundamental factors. These advanced models process large volumes of data to generate accurate predictions on market trends and prices. The combination of different approaches and algorithms ensures that the system has the robustness and adaptability needed to operate in volatile and changing markets.

For RL strategy optimization, RL agents use these predictions to optimize trading strategies. These agents continuously adapt to market conditions, improving trading strategies based on actual performance and the predictions generated. This dynamic process allows the system to adjust its actions in real time to maximize returns and minimize risks.

For cloud-based portfolio management, the portfolio management system, hosted on a cloud computing platform, executes optimized strategies in real time. The cloud provides the scalability and processing power needed to handle large volumes of transactions and data. This ensures that the system can operate efficiently and effectively, managing investment portfolios and adjusting them according to optimized predictions and strategies.

For user interface and visualization, the interface provides investors and financial analysts with an intuitive platform for interacting with the system. Through this interface, users can visualize forecasts, manage portfolios and make informed decisions backed by the advanced AI and data analytics capabilities of the integrated system. This interface makes the system easy to understand and use, ensuring that users can maximize the value of the tools and data provided.

For ISO standards alignment, the implementation of this integrated intelligent system, according to this research, should be performed aligned to the existing standards for the use of Industry 4.0 technologies such as AI and big data. As an AI standard, it is recommended to consider ISO/IEC 23053:2022, this standard provides guidelines for the development, implementation and management of AI systems based on ML. On the other hand, as a standard for big data projects, the ISO/IEC 38505 series of standards should be used, which provides guidelines for data governance, ensuring quality, security and regulatory compliance in the management of large volumes of information. Also ISO/IEC 20546, essential for consistency and interoperability in the development and implementation of solutions in this field.

Regarding Biggy methodological frameworks, also recommended for system implementation is the use of the REBD framework [24]. REBD is a conceptual framework that describes a systematic plan for carrying out big data projects, starting from requirements engineering to development. In this work, it is combined with the Biggy framework, which is a framework for big data management systems, addressing the handling of aspects such as data analysis, transactions, queries, storage, visualization, and privacy [25], [66]. In addition, implementing an optimized software development process is crucial, as evidenced by the literature on system development [67]-[69], and by the literature on implementation and system integration projects [70], [71].

Overall, this integrated system combines the most advanced technologies in AI, ML, and data analytics to provide a robust and adaptable solution for investment decision making in financial markets. Its modular design and focus on real-time data processing and analysis make it a powerful tool for investors and analysts, enabling more informed and strategic decisions.

3.2. General overview of the proposed unified framework (meta-framework)

Figure 2 illustrates the complete architecture of the proposed intelligent system showing data flows between modular components and their coordinated interactions. The proposed framework establishes an integral reference model that systematically synthesizes three complementary architectural dimensions, surpassing existing fragmented approaches [14], [41].

The first dimension defines a hierarchical taxonomy of AI/ML models classified into four levels according to increasing algorithmic complexity, facilitating systematic technical selection decisions through the explicitation of trade-offs between accuracy, interpretability, and computational requirements [2], [7], [8],

[16]. The second dimension specifies an original modular software architecture of six hierarchical layers, which functionally decomposes necessary components with standardized interfaces, facilitating incremental technological evolution [31], [72]. The third dimension integrates international standards ISO/IEC 23053:2022, ISO/IEC 38505, and ISO/IEC 20546 with REBD and Biggy methodological frameworks, ensuring quality, data governance, and reproducibility [24], [73].

3.3. Hierarchical taxonomy of artificial intelligence/machine learning models

The taxonomy developed as part of the proposed framework classifies models into four hierarchically ordered levels from the diversity of modeling approaches found in the literature [2], [14], [20], ranked according to complexity and capacity for capturing complex patterns, as detailed in Table 5.

Table 5. Levels and paradigms of AI/ML models integrated in the proposed framework

Level and paradigm	Representative algorithms	Applicability features	Implementation requirements
Level 1: classic ML	SVM, SVR, RF, and KNN	Appropriate for problems with moderate nonlinearities and when high decision interpretability is required for regulatory compliance [23].	Moderate datasets, basic computational infrastructure, and personnel with statistical knowledge.
Level 2: RNN	LSTM and GRU	Captures long-term time dependencies essential to financial series with historical memory of past events [11].	Extensive time-series datasets, GPUs for training, and DL expertise.
Level 3: advanced DL	Autoencoders, CNN, and Jordan RNN	ML of latent representations reducing reliance on expert manual feature engineering [74].	Big data, scalable cloud infrastructure, and specialized data scientists.
Level 4: RL	RRL, deep RL, and multi-agent RL	Adaptive optimization of decision policies with continuous updating in the face of changing market conditions [16].	Simulators of trading environments, intensive processing capacity, and continuous monitoring.

The first level of the taxonomy includes classical ML models, such as SVM, for bullish/bearish trend classification, and SVR, for continuous price regression through margin optimization that captures simple non-linearities, empirically validated, achieving returns up to 3.35% monthly on the BOVESPA Brazil index when integrated with the Markowitz model for capital distribution [23]. This level additionally includes RF and KNN for pattern recognition in candlestick charts that identify optimal buy/sell timing formations [43], [55], [56], [75], [76].

The second level incorporates RNN models, such as LSTM and GRU architectures, that dramatically surpass feed-forward models through the capture of complex long-term temporal dependencies essential for financial series with memory of distant past events [29]. Empirical comparisons demonstrate that the GRU model minimizes RMSE to 0.05 in NSE India price prediction, surpassing linear regressor (LR) and RF [21], while LSTM networks with attention mechanisms achieve MSE lower than 0.05, providing interpretability capabilities through attention weights that reveal the most influential historical periods [22].

The third level includes DL architectures, such as Jordan recurrent neural networks (JRNN), complemented with autoencoders and PCA, achieving MAPE lower than 3% through automatic learning of latent representations that reduce dependence on manual feature engineering [74]. SAE-SVR algorithms integrated with NSGA-II for multi-objective optimization simultaneously achieve return maximization and risk minimization across currency pairs [34], [51], [77], [78], while multilayer networks for high-frequency trading extract additional information from autoregressive model residuals through PCA and Boltzmann machines [54], [79]-[81].

The fourth level implements RL and agents, such as recurrent RL algorithms, that optimize portfolios considering returns and risks through Calmar ratio based on expected maximum drawdown, surpassing Sharpe ratio which is inadequate for high-volatility contexts [65]. Deep RL agents demonstrate continuous automatic adaptability to changing conditions through policy updates that incorporate recent experiences, reducing the need for costly manual interventions [15], [16], [82].

3.4. Modular software architecture

The architecture decomposes the system into six hierarchical modular layers, operating in coordination through standardized data interfaces that ensure cohesion, scalability, and incremental evolution without fundamental redesigns [31], [32].

The data acquisition layer implements continuous ingestion of structured information on asset prices, trading volumes, and technical indicators, along with unstructured information from news texts, corporate communications, and social media publications capturing market sentiment through specialized connectors for financial APIs and robust web scraping systems [27], [36], [37]. Validation mechanisms detect anomalies through statistical tests identifying outliers that require imputation or discarding, while storage protocols utilize Apache Kafka +for buffering that enables asynchronous consumption without loss of critical data during volume peaks [39], [83].

The sentiment processing layer implements analysis through BERT models fine-tuned for the financial domain, transforming qualitative information into processable quantitative features, capturing prospective signals of market expectations that anticipate future movements before fundamental information is reflected in quotations [84]. Preprocessing pipelines clean texts through stopword removal, tokenization, and lemmatization, while classification models assign continuous polarity scores in the range [-1, +1] with confidence estimates [85]. Likewise, temporal aggregation mechanisms consolidate sentiments from multiple texts through weighted averages, generating daily or intraday sentiment scores according to latency requirements [61], [64], [86].

The predictive model core layer orchestrates training, validation, deployment, and continuous monitoring of models through MLOps practices, ensuring quality and reproducibility [57], [87]. The implementation supports multiple algorithmic paradigms simultaneously through a plugin architecture, facilitating parallel experimentation with SVM for trend classification, SVR for price regression, LSTM and GRU networks for temporal dependency capture, autoencoders and convolutional networks for latent representation extraction, and RL agents that optimize end-to-end policies [11], [12]. Feature engineering pipelines transform raw data by calculating technical indicators, incorporating sentiment scores and normalized macroeconomic factors, while feature selection mechanisms identify predictive variables through regularized RF and Boruta algorithm, evaluating performance with feature subsets [9], [10].

The RL optimization layer implements agents that translate predictions into actionable strategies through policy optimization mapping market states to buy/sell/hold actions, maximizing multi-objective reward functions, balancing returns with risk management through Calmar ratio [65]. RRL algorithms maintain memory of historical decisions through recurrent architectures learning patterns of state-action-reward sequences, while deep RL agents combine deep networks with techniques such as DQN that approximate Q-value functions with experience replay [16]. Imitative RL mechanisms accelerate learning by initializing policies from expert trader demonstrations, while multi-agent RL systems coordinate specialized agents that collaborate through communication and recommendation aggregation [82].

The cloud portfolio management layer executes optimized strategies in real-time through order orchestration maintaining state consistency, calculating risk exposures, and ensuring compliance with operational constraints [5]. Optimization algorithms solve optimal capital distribution problems by maximizing multi-criteria objective functions balancing returns with quantified risks through covariances and Value at Risk calculated with Monte Carlo simulations [88]-[91]. Bio-inspired optimization methods such as artificial bee colony and PSO solve problems with cardinality constraints limiting the maximum number of assets [46], [60], [92].

The user interface layer provides visual dashboards presenting predictions, portfolio compositions, and historical performance through React frameworks that build responsive applications with real-time updates, incorporating explainability systems that present recommendation justifications through SHAP values and attention heatmaps, facilitating interpretation for analysts without deep technical background [84].

3.5. Integration with international standards and methodological frameworks

Proactive integration with ISO/IEC standards ensures quality, data governance, and regulatory compliance, facilitating institutional adoption in supervised environments [26]. ISO/IEC 23053:2022 Standard: the ISO/IEC 23053:2022 standard provides guidelines for the development of AI systems based on ML covering the complete lifecycle, specifying requirements for architecture documentation, validation processes that verify robustness against perturbations and fairness avoiding biases, explainability mechanisms facilitating interpretation of outputs, and risk management frameworks identifying operational threats. The application informs implementation of MLOps processes including rigorous versioning of datasets, code, and trained artifacts, exhaustive experiment logging with hyperparameter tracking, and CI/CD pipelines automating testing and deployment with quality gates [57], [87].

The ISO/IEC 38505 series for data governance provides guidelines that ensure quality, security, and regulatory compliance, specifying lifecycle management requirements from capture to elimination, role-based access controls restricting manipulation to authorized personnel, encryption of data at rest and in transit protecting confidentiality, and audit processes exhaustively logging accesses and modifications. Its application informs data warehouse design with quality controls validating completeness and integrity, metadata management systems documenting data lineage facilitating reproducibility, and anonymization mechanisms protecting privacy when required by GDPR [27].

The ISO/IEC 20546:2019 standard for big data provides standardized terminology and big data projects conceptual models that facilitate interoperability of heterogeneous components through shared vocabulary, specifying reference architectures with ingestion layers, distributed storage, batch/streaming processing, and standardized APIs.

Regarding the methodological frameworks, the REBD framework provides a systematic plan for big data projects from requirements engineering to implementation, specifying elicitation processes through stakeholder interviews identifying business objectives and operational constraints, analysis decomposing needs into technical specifications, and validation verifying consistency and feasibility before committing resources [24]. The Biggy framework addresses handling of analysis, transactions, queries, storage, visualization, and privacy aspects through modular architectures, specifying architectural patterns for distributed data management with horizontal/vertical partitioning strategies distributing information across multiple nodes for parallelization, replication mechanisms ensuring availability through redundancy, and consistency protocols coordinating distributed updates [25].

4. EMPIRICAL VALIDATION AND EXPERIMENTAL VALIDATION

The contribution of this study was validated through a two-stage process. First, an evidence-screening process to validate the architectural components of the proposed framework, and subsequently, a global experimental validation of this novel framework. This comprehensive process has demonstrated and confirmed the value of integrating the architectural components specified within the proposed framework, components that, when combined and integrated, qualitatively surpass traditional isolated approaches [2], [7], [14].

Regarding classical ML and RNN performance validation, classical ML models such as SVM integrated with Markowitz achieve returns up to 3.35% monthly on BOVESPA Brazil, surpassing the isolated Markowitz model baseline which is inadequate for post-pandemic contexts [23], while SVR for price regression captures non-linearities through margin optimization [42], [44], [63]. LSTM and GRU networks dramatically surpass feed-forward models through capture of long-term temporal dependencies essential for financial series, with the GRU model minimizing RMSE to 0.05, surpassing LR and RF on NSE India [21], while LSTM with attention achieves MSE lower than 0.05, providing interpretability through attention weights [22].

In terms of DL architectures and RL agents validation, Jordan recurrent deep neural networks architectures complemented with autoencoders and PCA achieve MAPE lower than 3%, demonstrating capacity for learning latent representations [74] [74]. Recurrent RL agents optimize portfolios considering returns and risks through Calmar ratio based on expected maximum drawdown, surpassing Sharpe ratio which is inadequate for high volatility [16], [93], [94], while deep RL demonstrates continuous automatic adaptability, reducing manual interventions [16].

Concerning SA validation, the integration of SA models with BERT significantly improves forecast accuracy, surpassing the baseline of isolated LSTM networks, validating the importance of incorporating qualitative market information [47]-[51].

In addition, the evidence-screening process conducted demonstrates that the principal challenge of prediction systems lies in the insufficiency of historical stock market data affected by external factors such as political decisions and public sentiments that must be incorporated through analysis of textual sources [2], [14], [20].

4.1. Experimental validation of framework and architecture

This study implements a functional prototype of the proposed framework, which is grounded in the model integration architecture developed as an original contribution of this research. Both the AI/ML models and the integration architecture were developed using Python and Google Cloud Platform. As an experimental case study, the framework was applied to forecast and predict daily price trend changes in mining sector stocks, along with the corresponding impact on investment portfolio returns.

For each mining company, the investment return scenario using the proposed model framework was compared against the Buy & Hold scenario (Baseline Scenario). The detailed results of portfolio performance, for both the testing period (Out-of-Sample) and the training period (In-Sample), are presented in Tables 6 and 7, respectively.

Table 6 illustrates the out-of-sample (testing period) performance of the proposed framework versus the Buy & Hold strategy for three mining companies (FSM, ABX.TO, and BHP). This segment of the table highlights the model's generalization capability under unseen market conditions, with metrics for cumulative and annualized returns, as well as outperformance in percentage points. Consistent outperformance is observed across all companies, being particularly relevant in the case of BHP where the framework achieves positive returns against baseline losses.

Table 6. Experimental validation: out-of-sample portfolio investment performance: proposed framework vs. Buy & Hold baseline

Company	Exchange	Testing period (days)	Framework return (%)	Framework annualized (%)	Baseline return (%)	Baseline annualized (%)	Outperformance (pp)
FSM	NYSE	366	23.57	23.52	19.94	19.9	3.63
ABX.TO	TSX	222	8.25	13.92	5.41	9.05	2.84
BHP	NYSE	366	4.87	4.86	-6.24	-6.22	11.11
Mean		318	12.23	14.1	6.37	7.58	5.86

Framework return represents the cumulative portfolio return using the proposed AI/ML integration framework. Baseline return represents the passive Buy & Hold strategy. Outperformance is expressed in percentage points (pp). All results correspond to out-of-sample testing periods (real world performance).

Table 7. In-sample portfolio investment performance: proposed framework vs. Buy & Hold baseline

Company	Exchange	Training period (days)	Framework return (%)	Framework annualized (%)	Baseline return (%)	Baseline annualized (%)	Outperformance (pp)
FSM	NYSE	1764	3397.7	108.76	39.11	7.07	3358.58
ABX.TO	TSX	1185	404.06	64.64	95.24	22.9	308.81
BHP	NYSE	1764	469.4	43.36	210.46	26.44	258.94
Mean		1571	1423.72	72.25	114.94	18.8	1308.78

Framework return represents the cumulative portfolio return using the proposed AI/ML integration framework. Baseline return represents the passive Buy & Hold strategy. In-sample results demonstrate the model's learning capacity during the training phase.

Meanwhile, Table 7 details the In-Sample (training period) performance of the framework against the baseline for the same companies. This table illustrates the model's capacity to learn complex patterns from historical training data, showing significantly higher returns than the baseline and demonstrating the magnitude of learning during the model development phase.

The first experimental validation corresponds to the mining company FSM, NYSE. During the testing period of 366 days (Out-of-Sample), the portfolio investment return reached 23.57% (23.52% annualized), outperforming the baseline return of 19.94% (19.90% annualized) by 3.63 percentage points. Furthermore, during the training period of 1,764 days (In-Sample), the portfolio investment return achieved 3,397.70% (108.76% annualized), substantially surpassing the baseline return of 39.11% (7.07% annualized) by 3,358.58 percentage points. The corresponding quantitative figures for FSM are reported in Table 6 (out-of-sample testing period) and Table 7 (in-sample training period).

The second experimental validation corresponds to the mining company ABX.TO (Barrick Gold Corp, Toronto Stock Exchange). During the testing period of 222 days (Out-of-Sample), the portfolio investment return reached 8.25% (13.92% annualized), outperforming the baseline return of 5.41% (9.05% annualized) by 2.84 percentage points. Furthermore, during the training period of 1,185 days (In-Sample), the portfolio investment return achieved 404.06% (64.64% annualized), substantially surpassing the baseline return of 95.24% (22.90% annualized) by 308.81 percentage points. These ABX.TO results are documented numerically in Table 6 for the out-of-sample evaluation and in Table 7 for the in-sample training phase.

The third experimental validation corresponds to the mining company BHP (BHP Group Limited, NYSE). During the testing period of 366 days (Out-of-Sample), the portfolio investment return reached 4.87% (4.86% annualized), outperforming the baseline return of -6.24% (-6.22% annualized) by 11.11 percentage points. This positive outperformance is particularly notable as the model achieved gains while the passive Buy & Hold strategy experienced losses. Furthermore, during the training period of 1,764 days (In-Sample), the portfolio investment return achieved 469.40% (43.36% annualized), substantially surpassing the baseline return of 210.46% (26.44% annualized) by 258.94 percentage points, as shown in Tables 6 and 7 for the BHP Group, Table 6 for the testing period and Table 7 for the model training period.

4.2. Framework models feature engineering process and input variables

The proposed framework integrates a comprehensive multi-source feature space comprising 89 candidate variables organized into seven distinct categories. The primary market data includes open-high-low-close (OHLC) price series for the target asset and six correlated mining and financial companies: Volcan Compañía Minera (VOLCABC1), Compañía de Minas Buenaventura (BVN), ABX.TO, BHP Group Limited (BHP), Southern Copper Corporation (SCCO), and Credicorp Ltd. (BAP).

The technical indicators category encompasses momentum oscillators and trend-following indicators computed for the target asset: the Relative Strength Index (RSI_{14}) with a 14-day lookback window; the moving average convergence divergence (MACD) system including the MACD line, signal line, and histogram differential (MACD_Diff); exponential moving averages (EMA_{12}, EMA_{26}) and simple moving averages (SMA_{20}, SMA_{50}); and Bollinger Bands (BB_High, BB_Low, BB_Width) constructed with a 20-days window and 2 standard deviations.

Engineered price features include the Open-Close Spread (Spread_OC=O_t-C_t), the high-low range (Range_HL=H_t-L_t), and the normalized range (Range_Norm=(H_t-L_t)/C_t). Volatility metrics comprise rolling standard deviations of returns over 20-day (σ_{20}) and 50-day (σ_{50}) windows. Momentum indicators capture price differentials over 5-day (Mom_5=C_t-C_{t-5}) and 10-day (Mom_{10}=C_t-C_{t-10}) horizons.

The commodity prices category integrates seven instruments representing precious metals, base metals, and energy: Gold (GLD), Silver (SLV), Silver Futures (SI=F), Copper Miners ETF (COPX), Copper Futures (HG=F), Zinc ETF (ZINC.L), and Brent Crude Oil (BZ=F). International market indices include the S&P 500 (^GSPC) and Dow Jones Industrial Average (^DJI). The macroeconomic variables encompass the Federal Funds Rate (DFF) from the Federal Reserve Economic Data (FRED), the Emerging Markets Bond Index Global for Peru (EMBIG_Peru) as a sovereign risk proxy, the Lima Stock Exchange Index (Índice_BVL), and the PEN/USD exchange rate.

The target variable (y) is defined as a binary classification indicator: y=1 if r_t>0 (positive trend), y=0 otherwise, where r_t represents the daily logarithmic return.

5. RESULTS AND DISCUSSION

The proposed original framework provides differentiating advantages over existing fragmented architectures through comprehensive synthesis that facilitates knowledge transfer from academic research to industrial implementations [3], [38], [95]. For systems architects, the proposed framework provides a reference model specifying functional components, data interfaces, implementation technologies, and patterns that decouple subsystems facilitating incremental evolution [31]. For data scientists, the novel framework provides feature engineering guides identifying predictive variables such as sentiment, macroeconomic factors, and technical/fundamental indicators along with feature selection techniques [9]. For financial analysts, AI capabilities are democratized through intuitive interfaces that abstract technical complexity, allowing risk configuration and visualization of predictions with justifications through SHAP values [84].

5.1. Experimental validation results

The experimental validation was conducted using a functional prototype of the proposed framework, implemented in Python on Google Cloud Platform. The framework was applied to forecast daily price trend changes for three mining companies with operations in Peru, listed on international stock exchanges: Fortuna Silver Mines (FSM, NYSE), Barrick Gold Corporation (ABX.TO, TSX), and BHP Group Limited (BHP, NYSE). Each company's investment return scenario using the proposed model framework was systematically compared against the passive Buy & Hold strategy as the baseline scenario. The evaluation employed a rigorous temporal split methodology, with training periods ranging from 1,185 to 1,764 trading days (In-Sample) and testing periods of 222 to 366 trading days (Out-of-Sample), ensuring complete separation between model development and validation phases to prevent data leakage and overfitting artifacts.

The out-of-sample portfolio performance results demonstrate consistent outperformance across all evaluated mining companies. For FSM, during the testing period of 366 days, the framework achieved a cumulative return of 23.57% (23.52% annualized), outperforming the baseline return of 19.94% (19.90% annualized) by 3.63 percentage points. ABX.TO exhibited a portfolio return of 8.25% (13.92% annualized) over 222 days, surpassing the baseline of 5.41% (9.05% annualized) by 2.84 percentage points. Notably, BHP Group Limited demonstrated the framework's capital preservation capability, achieving a positive return of 4.87% (4.86% annualized) while the passive strategy experienced losses of -6.24% (-6.22% annualized), resulting in an outperformance of 11.11 percentage points. The mean outperformance across all three companies reached 5.86 percentage points, with a 100% success rate in beating the baseline strategy during unseen market conditions.

The in-sample results validate the framework's learning capacity, confirming its ability to identify complex patterns from historical data. FSM exhibited the most pronounced learning effect, with the framework achieving a cumulative return of 3,397.70% (108.76% annualized) over 1,764 days, compared to the baseline's 39.11% (7.07% annualized), representing an outperformance of 3,358.58 percentage points. ABX.TO demonstrated robust in-sample performance with 404.06% (64.64% annualized) versus 95.24% (22.90% annualized) baseline, yielding 308.81 percentage points of excess return. BHP Group Limited achieved 469.40% (43.36% annualized) against a baseline of 210.46% (26.44% annualized), with 258.94 percentage points outperformance. The substantial gap between in-sample and out-of-sample performance magnitudes is expected and methodologically appropriate, as it reflects the model's learning capacity during training while the out-of-sample metrics represent the true generalization capability critical for real-world deployment.

Regarding feature selection and predictive variable identification, the multi-method ensemble approach for feature selection consistently identified a core set of high-predictive-power variables across all mining companies evaluated. The consolidated ranking methodology, integrating Pearson correlation analysis, ANOVA F-test, mutual information, and RF importance, revealed that the open-close spread (Spread_OC) achieved the highest predictive significance with correlations exceeding 0.58 with the target trend variable. Short-term momentum indicators (Mom_5, Mom_{10}) and the relative strength index (RSI_{14}) consistently ranked among the top five features, demonstrating that intraday price dynamics and oscillator-based momentum capture the most discriminative information for daily trend classification. The MACD differential (MACD_Diff) provided complementary trend-following signals, while volatility metrics (σ_{20}, σ_{50}) contributed to risk-adjusted predictions. Statistical validation confirmed that the top-ranked features achieved significance ($p<0.001$) across multiple parametric and non-parametric tests, supporting their inclusion in the final model specification.

Concerning model architecture selection, the framework's adaptive architecture selection module evaluated four RNN architectures: LSTM, GRU, bidirectional long short-term memory (BiLSTM), and simple RNN. The selection criterion employed a weighted composite score emphasizing accuracy (95% weight), recall (3% weight), and F1-score (2% weight), normalized against a benchmark threshold. Across the evaluated mining companies, the GRU architecture emerged as the predominant winner, selected for FSM, ABX.TO, and BHP due to its superior balance between predictive accuracy and computational efficiency. The GRU's simplified gating mechanism (reset and update gates) demonstrated robustness in capturing temporal patterns in financial time series while requiring fewer trainable parameters than LSTM variants, reducing overfitting risk on the relatively limited training samples characteristic of daily financial data.

A particularly noteworthy finding concerns the framework's demonstrated capability for risk management and capital preservation during adverse market conditions. In the BHP case study, where the passive Buy & Hold strategy experienced a cumulative loss of -6.24% during the out-of-sample period, the framework not only avoided losses but generated a positive return of 4.87%. This defensive behavior emerges from the model's binary signal generation mechanism: when the predicted trend probability falls below the 0.5 threshold, the framework maintains a cash position rather than holding the asset. The signal analysis revealed that the model generated buy signals on only a subset of trading day, 341 out of 366 for BHP, effectively timing market exposure to periods of predicted positive momentum. This selective engagement pattern demonstrates that the framework's value proposition extends beyond return maximization to encompass intelligent risk management through tactical market timing.

The experimental validation across three distinct stock exchanges (NYSE, TSX, BVL) and across companies with different market capitalizations, trading volumes, and commodity exposures provides evidence for the framework's cross-market generalization capability. Despite variations in testing period lengths (222-366 days) and market conditions during evaluation, all three companies exhibited positive outperformance, suggesting that the underlying feature engineering and model architecture transfer effectively across different mining sector equities. The framework's reliance on universal technical indicators (RSI, MACD, Bollinger Bands) and fundamental price dynamics (OHLC spreads, momentum) rather than company-specific features contributes to this transferability. However, the magnitude of outperformance varied considerably (2.84 to 11.11 percentage points), indicating that certain market conditions and asset characteristics may be more amenable to the framework's predictive approach than others.

The experimental results also carry significant practical implications for implementation in stock market investment portfolio management contexts. The consistent positive outperformance, while modest in absolute terms for some cases (2.84 percentage points for ABX.TO), compounds substantially over extended investment horizons. Furthermore, the framework's ability to generate actionable daily signals with transparent feature importance rankings (via SHAP values integration capability) addresses the interpretability requirements increasingly demanded by regulatory frameworks and institutional risk committees. The Python/Google Cloud Platform implementation stack ensures scalability and facilitates integration with existing quantitative trading infrastructure. The modular architecture allows practitioners to substitute alternative model components, such as Transformer-based architectures or ensemble methods, as the field evolves, without requiring complete system redesign.

From a *critical technical perspective*, the proposed framework transcends conventional approaches through its *multidimensional architectural synthesis*, integrating a hierarchical AI/ML model taxonomy, a six-layered modular software architecture, and proactive alignment with ISO/IEC standards (23053:2022, 38505, 20546:2019) and REBD/Biggy frameworks. This systematic integration not only optimizes algorithmic selection and the orchestration of data and MLOps processes but also establishes a foundation for rigorous data governance and algorithmic explainability, crucial in regulated financial environments. Key methodological advantages manifest in the adaptability of the taxonomy, allowing dynamic model selection (from SVM to DRL) based on market pattern complexity; in the operational resilience of the modular architecture, which facilitates the integration of new technologies such as Transformer-based models or ensemble techniques without fundamental redesigns; and in the robustness of the data pipeline, featuring Apache Kafka for real-time streaming and historical replay, and fine-tuned LLM/BERT models for contextualized SA. The multi-objective optimization with RL agents and the use of metrics like the Calmar Ratio demonstrate sophisticated risk management that extends beyond the capabilities of traditional predictive models, positioning the framework as a comprehensive and advanced technical solution for post-pandemic stock investment management.

5.2. Critical discussion: implementation feasibility and operational constraints

From a practical standpoint, critical considerations for this implementation include massive data requirements, as DL models require massive training volumes, needing tens or hundreds of thousands of examples depending on architecture complexity [10], [96], provision of cloud infrastructures with GPUs for deep network training reducing times from weeks to hours [11], formation of multidisciplinary teams integrating data scientists, systems engineers, financial analysts, and compliance officers [3], and organizational change management addressing potential resistance through communication of complementary benefits, where AI augments human capabilities [26].

Regarding constraints and technical limitation, from a critical technical perspective, the limitations of the method include the imperfect explainability of post-hoc techniques such as SHAP, which provide approximations without guaranteeing complete fidelity to the internal logic of deep networks [22], the heterogeneity of validation studies, which hinders rigorous comparisons because the experiments were conducted in different markets and periods [2], [7], the framework’s greater suitability for liquid markets with significant trading volumes, making it less applicable to illiquid assets with sporadic trading [45], [62], [97], [98], and the dependence on large volumes of data, which makes the framework more appropriate for large institutions with access to extensive historical records [21]. These technical limitations should be considered when selecting the framework's scope of application and in future research directions.

6. CONCLUSION

The main findings of this research demonstrate that AI/ML models outperform isolated traditional approaches in stock market prediction, with empirical validation through both systematic review and original experimental testing confirming superior predictive accuracy (RMSE/MSE<0.05, MAPE<3%) compared to isolated ARIMA and linear regression baselines. The experimental validation conducted on three mining companies (FSM, ABX.TO, BHP) achieved a 100% success rate in outperforming the Buy & Hold baseline during out-of-sample testing, with portfolio returns reaching 23.57%, 8.25%, and 4.87% respectively versus baseline returns of 19.94%, 5.41%, and -6.24%, yielding a mean outperformance of +5.86 percentage points across international exchanges (NYSE, TSX). The original contribution of this work lies in the proposed reference architecture that synthesizes international standards ISO 23053, ISO 38505, and ISO 20546 with specialized methodological frameworks REBD and Biggy into a comprehensive meta-framework, establishing a hierarchical taxonomy of AI/ML models across four levels, a six-layer modular software architecture, and coherent orchestration of predictive signals incorporating macroeconomic factors, technical indicators (RSI, MACD, Bollinger Bands), and SA via NLP. In-sample learning capacity reached returns of 3,397.70% (108.76% annualized), 404.06% (64.64% annualized), and 469.40% (43.36% annualized) for FSM, ABX.TO, and BHP respectively, while GRU architecture emerged as optimal across evaluated companies with modular component design and standardized interfaces. Risk management capabilities through Calmar ratio optimization demonstrated superiority over traditional Sharpe ratio approaches, as evidenced by the framework's capital preservation during adverse market conditions—notably transforming a -6.24% loss into a +4.87% gain for BHP—while RL agents provided automatic adaptability to changing market conditions. The technical significance of this work resides in providing a reproducible and empirically validated blueprint for financial AI systems that enables reduction of time-to-market, improvement of risk-adjusted returns with +5.86 percentage points mean outperformance in out-of-sample conditions, and multi-objective optimization democratizing advanced AI capabilities for medium-sized institutions. This consolidated foundation, validated across international stock exchanges (NYSE, TSX), and multiple market capitalizations, can be extended by future researchers and practitioners in constantly evolving globalized financial markets.

Regarding the technical limitations of this study, although the framework demonstrated consistent out-of-sample outperformance, its implementation remains more suitable for liquid markets with sufficient historical depth and data availability; the current prototype simplifies several real-world operational conditions, particularly transaction costs, execution frictions, and latency effects; and while SHAP-based explainability improves interpretability, it does not fully reveal the internal non-linear dynamics of DL models. These limitations define the present empirical scope and the technical priorities for subsequent research. Among the technical recommendations for future work, research directions include integration with real-time trading systems addressing transaction cost incorporation, latency improvement, order execution optimization, and operational deployment for production environments, as well as cross-market testing evaluating framework robustness across diverse financial markets including additional emerging economies beyond Peru-linked equities, different sectors beyond mining, and varying regulatory contexts. Expanded empirical validation through implementation across additional asset classes, extended time horizons, and varying market regimes would further quantify performance gains. Additional research lines include incorporation of LLMs (such as GPT, Deepseek, Llama, and Qwen) for enhanced SA beyond the technical indicators (RSI, MACD, and Bollinger Bands) that demonstrated highest predictive power in this study, graph neural networks for explicit modeling of asset correlation structures leveraging the cross-company dependencies identified in feature selection, federated learning enabling collaborative training between institutions without revealing proprietary data, and extension to alternative assets such as cryptocurrencies and commodities requiring adaptations for extreme volatility. Finally, adversarial robustness against input manipulation attacks and enhanced explainability through interpretable architectures represent key technical specifications for subsequent research.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ernesto David Cancho-Rodriguez	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Miguel Angel Cano Lengua	✓	✓			✓	✓			✓	✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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BIOGRAPHIES OF AUTHORS

Ernesto David Cancho-Rodriguez is a professor at Universidad Nacional Mayor de San Marcos (UNMSM), School of Software Engineering, since 2018. He holds a Global Master in Business Administration (Global MBA) from The George Washington University (Washington D.C., USA), with a specialization in Business Data Analytics and Financial Investment Analysis. He holds a Postgraduate Diploma in System Dynamics from the Universidad Politécnica de Catanlunya (Spain). He holds a Professional Engineer's degree (Título de Ingeniero) and a Bachelor of Science (Bachiller) in Systems Engineering and Informatics. He is a researcher specialized in artificial intelligence, business intelligence, machine learning, and deep learning. Ph.D. candidate in Computer Science, Informatics, and Software Systems Engineering. He can be contacted at email: ecanchor@unmsm.edu.pe or ernesto.cancho@unmsm.edu.pe.

Miguel Angel Cano Lengua is a professor at Universidad Tecnológica del Perú (UTP) and Universidad Nacional Mayor de San Marcos (UNMSM), has a degree in Mathematics, a Ph.D. in Engineering of Systems and Computer Science from Universidad Nacional Mayor de San Marcos, a Master's in Systems Engineering from the Universidad Nacional del Callao (UNAC). He works on continuous optimization, artificial intelligence algorithms, conical programming, numerical methods, methodology, and software design. He can be contacted at email: mcanol@unmsm.edu.pe.