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SURVEY

A Systematic Survey of AI Models in Financial Market Forecasting for Profitability Analysis

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ABSTRACT Artificial intelligence (AI)-based models have emerged as powerful tools in financial markets, capable of reducing investment risks and aiding in selecting highly profitable stocks by achieving precise predictions. This holds immense value for investors, as it empowers them to make data-driven decisions. Identifying current and future trends in multi-class forecasting techniques employed within financial markets, particularly profitability analysis as an evaluation metric is important. The review focuses on examining studies conducted between 2018 and 2023, sourced from three prominent academic databases. A meticulous three-stage approach was employed, encompassing the systematic planning, conduct, and analysis of the selected studies. Specifically, the analysis emphasizes technical assessment, profitability analysis, hybrid modeling, and the type of results generated by models. Articles were shortlisted based on inclusion and exclusion criteria, while a rigorous quality assessment through ten quality criteria questions, utilizing a Likert-type scale was employed to ensure methodological robustness. We observed that ensemble and hybrid models with long short-term memory (LSTM) and support vector machines (SVM) are being more adopted for financial trends and price prediction. Moreover, hybrid models employing AI algorithms for feature engineering have great potential at par with ensemble techniques. Most studies only employ performance metrics and lack utilization of profitability metrics or investment or trading strategy (simulated or real-time). Similarly, research on multi-class or output is severely lacking in financial forecasting and can be a good avenue for future research.

INDEX TERMS Artificial intelligence, financial forecasting, deep learning, stock market analysis, convolution neural network, cryptocurrency.

I. INTRODUCTION

Forecasting asset prices in financial markets pose significant challenges due to the intricate interplay of various micro and macroeconomic attributes that influence price formation including political events, news, and company financial

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statements. These multifaceted factors contribute to the non-linearity and non-stationarity observed in the market, thereby intensifying the complexity of the proposed task. Consequently, market analysis is conducted to study these influences, aiming to predict future market trends and support decision-making based on market behavior.

There are various types of financial markets such as the stock market, foreign exchange, commodities, and

cryptocurrency. *Stock markets* offer a diverse range of instruments, such as stocks, bonds, and derivatives, that can be used for both long-term and short-term capital generation [1]. *Foreign exchange* (Forex) operates continuously 24 hours a day, except for weekends, and is the largest financial market in the world for currency trading [2]. *Commodity markets* trade physical goods, such as agricultural products (grain, tea, wheat salt, etc.), resources (oil, gas coal, etc.), and metals [3]. *Cryptocurrency exchanges* allow for the trade of cryptocurrencies, which are digital currencies using cryptographic functions to conduct financial transactions, and blockchain technology to gain decentralization, transparency, and immutability [4].

The existing literature outlines two primary approaches to this task: fundamental analysis (FA) and technical analysis (TA). While both approaches share the overarching objective, they differ in the information set employed for forecasting and decision-making. FA focuses on considering company data and investor sentiment to ascertain an asset's medium-term to long-term growth potential. In contrast, TA does not consider company-specific data under the assumption that market-moving information is already assimilated and manifested in the market data. In essence, the financial statements, accounting scandals, financial crises, and other pertinent information capable of inducing volatility in an asset are reflected in its price. As a result, this type of analysis allows for the exclusion of subjective FA data and enables the identification of objective patterns inherent in the asset's behavior. Technical analysts extensively employ technical indicators (TI) and candlestick pattern analysis to facilitate price movement forecasts. Numerous scientific articles have utilized price information (open, high, low, and close prices (OHLC)), trading volume, and indicator sets based on these techniques as inputs for modeling purposes [5].

Fundamental analysis is less prevalent in the literature due to the inherent challenges of constructing models that can comprehend the causes of financial asset fluctuation. The predominant information sources in this approach pertain to macroeconomic time series data, such as gross domestic product (GDP), interest rates, currency exchange rates, and consumer price index, among others. Other sources of information, such as general financial news, present challenges of another level owing to their unstructured nature and non-continuous behavior. To tackle this intricacy, text mining techniques have been employed, and more recently, social network analysis has proven instrumental in stock forecasting by leveraging sentiment indexes and other derived series as inputs [6].

The integration of computational methods in finance, since the 1990s, has spurred significant research on the application of artificial intelligence (AI) in stock market investments. The utilization of computational approaches to automating the financial investment process affords several advantages including the mitigation of "momentary irrationality" or emotional decision-making, the capacity to identify and explore patterns overlooked by human observers,

and the real-time assimilation of information [7]. This interdisciplinary field has come to be known as computational finance, and within this realm, there is increasing use of and research on AI techniques applied in financial investments. In the realm of finance, AI finds general application in three distinct areas

- i) the optimization of financial portfolios,
- ii) the prediction of future prices or trends in financial assets, and
- iii) sentiment analysis of news or social media comments about assets or companies.

While each area exhibits distinct nuances, some studies have proposed amalgamations of techniques from different domains [8]. Consequently, the ever-increasing application of AI in this domain retains substantial potential for further development.

Despite extensive research efforts devoted to exploring traditional methodologies in the context of predictive models for the financial market, there remains a lack of comprehensive information concerning hybrid and ensemble techniques as well as multi-class forecasting. To bridge this knowledge gap, we conduct a systematic literature review (SLR) on the employment of AI techniques for financial market forecasting. The objectives of our SLR are twofold:

- i) to gain a comprehensive understanding of current hybrid and ensemble algorithms and models and provide a concise summary thereof, and
- ii) to analyze the evaluation metrics and highlight prevailing challenges, thus guiding future research endeavors.

This SLR aims to examine popular financial markets and assets as previously investigated and explore the training processes utilized for training and assessing machine learning algorithms. Hence, the research questions addressed in our SLR are outlined.

- **RQ1:** Which Financial Markets and Assets are commonly used and what are the peculiarities of datasets employed in the state-of-the-art?
- **RQ2:** Which AI technique is mostly used to forecast the financial market?
- **RQ3:** What Evaluation metrics are mostly used to evaluate a model based on performance and profitability?
- **RQ4:** What investment/ trading strategies are employed to evaluate the performance and profitability of the predictor models?
- **RQ5:** What types of predictive outputs (multi-output or multi-class) are prevalent in the literature?
- **RQ6:** What are the gaps identified and proposed future works in the explored studies?

The rest of this survey is divided into five sections. Important relevant studies are discussed in Section II. Section III presents the research methodology adopted for this SLR while results are discussed in Section IV. Applications and implications of AI are given in Section V. Discussions on results, research gaps, and future directions are provided in Section VI while Section VII concludes this SLR.

II. LITERATURE REVIEW

AI has been comprehensively applied in classification and prediction tasks, computer vision, image processing, and audio-visual recognition [9], [10]. Although deep learning (DL) was developed in the field of computer science, its applications have penetrated diversified fields such as medicine, neuroscience, physics, astronomy, and operations management [11], [12]. The overwhelming success of DL as a data processing technique has sparked the interest of the research community. Given the proliferation of Fintech in recent years, the use of DL in financial and investment markets has become prevalent [13]. The application domains of financial market investment can be divided into three major areas:

- i) prediction,
- ii) portfolio management, and
- iii) trading.

The first contains four major domains: stock prediction, forex prediction, commodity prediction, and the latest addition of cryptocurrency prediction. The trading domain contains trading algorithms, strategies, and optimization techniques for the selection, management, and evaluation of trading of financial assets.

At the same time, there are many review works focused on a specific financial market or comparing multiple markets. For example, [14] provided a synthesis of the literature published from 2009 to 2015, focusing on DL models. The analysis encompassed models such as multi-layer perceptron (MLP), functional link artificial neural network (FLANN), and adaptive weighting neural network. However, it omitted notable DL models such as long short-term memory (LSTM) and reinforcement learning (RL), and techniques like hybrid and ensemble approaches.

Li and Bastos [5] conducted an SLR specifically focusing on DL models applied to financial market forecasting using technical analysis. The study examined four main aspects: predictor techniques, trading strategies, profitability metrics, and risk management. The major contribution of this research was to highlight limitations identified in the literature, including the observation that only 35.3% of the analyzed studies incorporated profitability analysis, with only two articles addressing risk management.

In another SLR conducted on foreign exchange (Forex) prediction [15], DL methodologies are explored and novel approaches are proposed which are distinct from previous studies conducted between 2000 and 2019. It includes analysis of models such as artificial neural networks (ANN), FLANN, hidden Markov model (HMM), support vector regression (SVR), and auto-regressive (AR) models for exchange rate projection. Some of these novel neural network models take into account theoretical support and a systematic approach to model creation.

While the study [16] focused on recent advances in Forex prediction using machine learning algorithms. Keyword-based search approach and selection algorithm are employed to identify and analyze 39 research studies published between

2017 and 2019. The selected articles are sourced from three reputable platforms such as Elsevier Springer, and the Institute of Electrical and Electronics Engineers (IEEE) Xplore, primarily examining the forecasting of future Forex prices. The findings indicate a growing interest in NN models, pattern-based approaches, and optimization methodologies among academics in recent years. Notably, DL algorithms such as the gated recurrent unit (GRU) and LSTM exhibited promising results in time series prediction.

In the context of financial time series forecasting, a comprehensive evaluation of DL is carried out to explore convolutional neural networks (CNNs), deep belief networks (DBNs), and LSTM as categorization frameworks for the reviewed papers [17]. The analysis reveals an increasing interest in the DL community regarding financial forecasting, driven by the utilization of novel DL models.

To highlight the significance of providing up-to-date research on DL techniques applied to the financial market to aid investors in making informed decisions, Berradi et al. [18] gathered articles about DL techniques used for forecasting in various financial markets including the stock market, stock index, commodity forecasting, and Forex. The main objective is to identify the most commonly employed models, elucidate their characteristics and novelty, and explore the different aspects of financial prediction systems. The findings indicate that hybrid models outperform traditional machine learning techniques, underscoring the substantial relationship between the combination of approaches and improved prediction performance.

To emphasize the need for profitability in the context of model evaluation, it is worth mentioning the work of Nazário et al. [19], which analyzed 85 articles and found that only 31 of them employed any trading strategy. Additionally, Wang et al. [20] identified that the metrics used for machine learning models and financial markets have a lower correlation, highlighting the importance of financial validation through a fully autonomous system. The following are the contributions of this SLR

- We took a critical look at 51 studies that present AI/ DL forecasting models in the major financial markets. Prospective researchers can use the findings as a comprehensive beginning to enhance their knowledge in this research field.
- We give a comprehensive summary of the primary studies found. This section focuses on the current trends in (i) financial markets, assets, and data, (ii) AI techniques, (iii) evaluation metrics, and (iv) investment/trading strategies employed.
- Based on our findings, gaps, and limitations in current research and avenues for future research are also discussed.

III. RESEARCH METHODOLOGY

A systematic review aims to identify, evaluate, and discuss relevant works to answer the research questions. Also, they stated that a review of the literature needs to be

complete and fair, otherwise, it has little scientific value. SLR has some advantages, such as research with less biased results through a well-defined methodology. In the case of quantitative studies, the data can be combined using meta-analytic techniques, thus increasing the probability of detecting new insights. Therefore, given the information collected, the criteria adopted in this work are justified and the methodology used for this systematic review will be detailed below.

To select the main publications to be used in this work, some strict criteria must be respected and follow a well-defined research protocol. Three phases are proposed by [21] for the development of an SLR: 1) planning, 2) conducting, and 3) analysis. In the last phase, Quantitative and Bibliographic analysis is carried out based on data synthesized from data extraction.

A. PLANNING THE REVIEW

Therefore, the first stage must formulate some inclusion, exclusion, and quality criteria to select pertinent and quality studies for critical study and analysis to draw relevant conclusions based on defined research questions. Therefore, inclusion (IC), exclusion (EC), and quality (QC) criteria are presented in Table 1, Table 2, and Table 3, respectively

TABLE 1. Inclusion criteria.

Criteria	Description
IC1	Studies that are freely accessible/downloadable from any online source
IC2	Studies focused on ML or DL (including their variants/hybrids)
IC3	Studies Based on Financial Markets

To cover the largest number of articles related to the themes, various keywords for the search descriptors like “Stock Market”, “Deep Learning”, “Forecasting” and “Technical Analysis” along with probable variations defined with the help of PICOC were also used for this selection as presented in Table 4. Thus, the default search string formed was (specific search strings used in digital libraries are given in Annexure A):

(“Financial Market” OR “Commodities” OR “Commodities Exchange” OR “Commodities Market” OR “Crypto” OR “Crypto Currency” OR “Crypto Exchange” OR “Crypto Market” OR “Forex” OR “Stock Exchange” OR “Stock Market” OR “Stocks”) AND (“Hybrid Models” OR “Hybrid CNN” OR “Hybrid RNN” OR “Multi-Class” OR “Multi Class” OR “Technical Analysis” OR “Candle sticks” OR “K line” OR “K-line”) AND (“CNN” OR “MLP” OR “RNN” OR “GRU” OR “LSTM” OR “Technical Indicators” OR “Fibonacci” OR “Fibonacci Retracement” OR “Momentum Indicators” OR “Volume Indicators”) AND (“Prediction” OR “Trade Signal” OR “Trade Signal Prediction” OR “Trend” OR “Trend Prediction” OR “Trend Signal” OR “Trend Signal Prediction” OR “Profitable” OR “Profitability” OR “Profitable Prediction”)

TABLE 2. Exclusion criteria.

Criteria	Description
EC1	Articles not in English
EC2	Studies not published in Journals
EC3	Studies published before 2018
EC4	Review Papers (Survey, systematic or Literature, etc)
EC5	Studies focused only on Fundamental OR Sentimental Analysis

TABLE 3. Quality criteria.

Criteria	Description
QC1	Are research aims clearly defined?
QC2	Is the research methodology clearly explained/ adequately applied?
QC3	Is the study algorithm clearly explained?
QC4	Is the data set clearly explained?
QC5	Is the experimental procedure thoroughly explained and reproducible?
QC6	Are the evaluation metrics used in the study clearly explained?
QC7	Is the predictor algorithm compared with other related algorithms?
QC8	Are the results thoroughly discussed to draw relevant conclusions?
QC9	Does the study discuss and explain its limitations/ gaps/ challenges?
QC10	Does the study provide future work?

B. CONDUCTING THE REVIEW

The second stage consists of extracting the relevant publications for the systematic review and selecting the works based on the criteria previously defined. Thus, three digital repositories were searched: 1) the IEEE Xplore database, 2) the Association for Computing Machinery (ACM) digital library, and 3) Springer Link. Concerning IEEE Xplore and ACM digital library, each search was set to select these terms only on keywords, abstract, and title documents. For Springer, such limitation was not imposed and the search string was directly used in the search field. The publications on each platform based on the keywords were made on May 14, 2023, totaling 585 studies. It is possible to observe a few documents present in the ACM digital library concerning the other platforms which were subsequently identified as duplicates.

With the aid of the ‘parsif.al’ web application, a tool developed especially for systematic reviews, it is possible to remove duplicate publications, resulting in 583 studies. After reading the abstract (and other sections, when necessary), the inclusion and exclusion criteria were applied, resulting in 95 studies.

The shortlisted 94 studies are then selected based on quality assessment (QA) criteria, using a three-point Likert scale (Yes=1, Partially=0.5, and No=0.0), with a max possible score of 10 and a cut-off selection score to be greater than 7.5 points. In this way, 43 studies are excluded and the remaining 51 are selected for analysis in the next phase. Figure 1 shows the trend of articles during quality assessment scores whereas Figure 2 illustrates the flow of the study selection process as described.

TABLE 4. PICOC and synonyms.

	Keyword	Synonym
Population	- Financial Market	- Crypto Market / Exchange - Crypto Currency - Stock Market / Exchange - Commodities Market/ Exchange - Crypto - Commodities - Stocks - Forex
Intervention	- Multi-Class - Hybrid Models - Technical Analysis	- Multi Class - Hybrid CNN - Hybrid RNN - K-line/ Candle sticks
Comparison	- CNN - RNN - MLP - Technical Indicators	- LSTM - GRU - Volume Indicators - Momentum Indicators - Fibonacci - Fibonacci Retracement
Outcome	- Prediction - Profitable	- Trend - Trend Prediction - Trend Signal - Trade Signal - Trend Signal Prediction - Trade Signal Prediction - Profitability
Context	- Evaluation Metrics - Performance Metrics - Profitability Metrics	- Accuracy - ROI - MDD

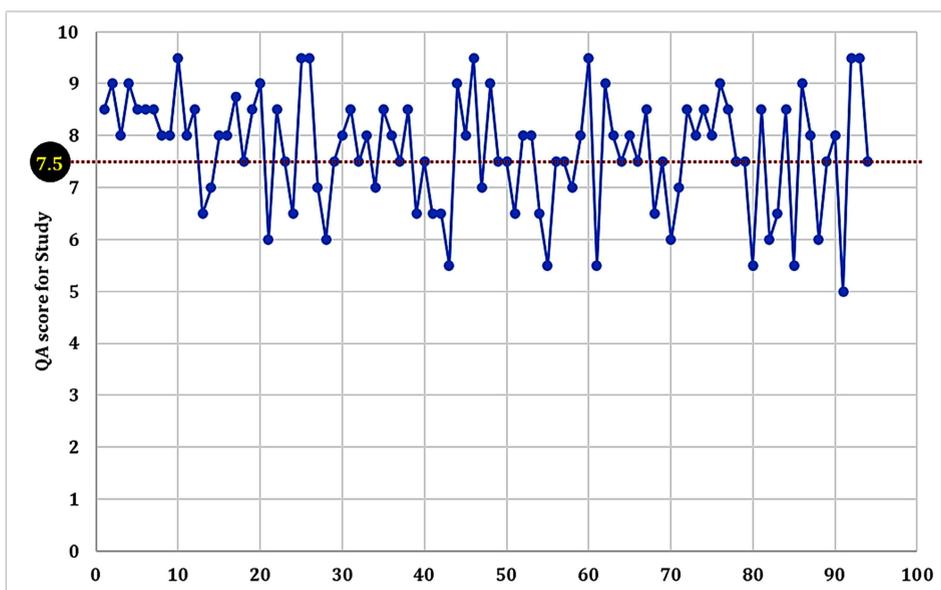


FIGURE 1. Quality assessment score of shortlisted articles.

Table 5 with relevant information for each work such as the market, exchange/ crypto coin, and dataset granularity/time frame. It also shows whether the authors used profitability metrics and trading/ investment strategies.

C. ANALYZING THE SELECTED STUDIES

The third and final step consists of analyzing the selected studies based on financial markets and assets, dataset source, granularity and duration, pre-processing and feature engineering, predictor techniques, evaluation metrics, and

trading/ investment strategies. This phase also analyzed the bibliographic data of studies to take out pertinent information that can be helpful to other researchers in carrying out meaningful research based on state-of-the-art trends.

IV. RESULTS

A. RQ1: WHICH FINANCIAL MARKETS AND ASSETS ARE COMMONLY USED AND WHAT ARE THE PECULIARITIES OF DATASETS EMPLOYED IN THE STATE-OF-THE-ART?

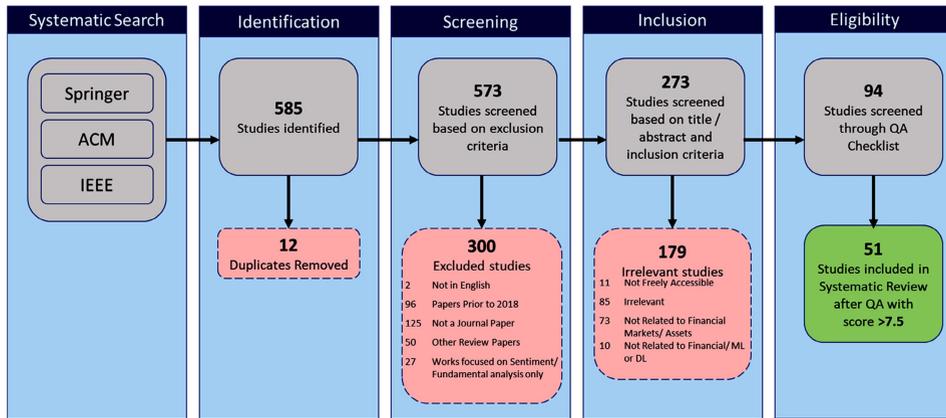


FIGURE 2. Articles selected during conducting phase.

1) FINANCIAL MARKETS AND ASSETS

There are four major financial markets namely stock exchanges, Forex, commodity markets, and crypto exchanges. Out of these crypto exchanges are a recent addition. Analysis of the selected studies shows that 67% of the paper use stock exchange data against 16%, 12%, and 6% for crypto, Forex, and commodity markets respectively Figure 4. In addition, a significant majority of research endeavors rely on data obtained from multiple exchanges or sources to facilitate a more comprehensive analysis and comparison of inter-market and intra-market assets. Among these assets, US stocks and their corresponding indices have garnered the most attention, followed by cryptocurrencies, with particular emphasis on BTC as depicted in Figure 3. This preference for US stocks and crypto assets could be attributed to the author’s familiarity with their respective local markets or the popularity of the financial asset due to stability and data availability. Moreover, when considering the practical implementation of trading assets from a different country, a crucial aspect that arises is the necessity to open an account in that particular jurisdiction, which often entails a cumbersome and costly bureaucratic process.

2) DATASETS

Data represents the utmost critical resource within any financial prediction system and serves as its backbone. The accuracy and desirability of predictions generated by AI-based predictors are largely contingent on the quality of the data utilized. Noisy data resulting from market volatility significantly hampers the ability of AI predictors to yield accurate forecasts. Additionally, the data must be readily accessible from the source itself, facilitating the reproducibility of prior research and enabling the identification of research gaps for future investigation. A quantitative examination of studies based on the datasets employed reveals a prevailing focus on datasets spanning durations of 1 to 5 years and 6 to 10 years. In select cases, datasets with durations exceeding 21 years have been considered, as shown in Figure 5.

Notably, Yahoo Finance, along with its regional websites, emerges as the most frequently utilized data source, primarily due to its free availability and ease. However, it should be noted that Yahoo Finance exclusively provides historical ‘daily’ market data, imposing limitations on the availability of data with different granularities, as shown in Figure 6. This aligns with the observed dataset granularities in our selected studies, wherein 92% of the studies adopt the ‘daily’ data granularity, as shown in Table 6.

The predominance of ‘daily’ granularity can be attributed to multiple factors, including the ease of access, free availability, and the relative reduction in noise and market volatility, which ultimately contributes to better classification accuracy and reduced prediction errors. The scarcity of research exploring smaller timeframes may be justified by two plausible reasons: either it represents an unexplored avenue for investigation that holds promise, or it indicates unremarkable outcomes that have deterred researchers. However, the potential advantage of employing smaller timeframes can be substantial, in principle, as the highest number of ‘daily’ asset data instances is 4,818, spanning the period from 1986 to 2005, averaging 267 instances per year (crypto market not included) [73]. Concerning training DL models, a substantial volume of data is necessary, and the number of daily candles available in these instances remains relatively limited. Nonetheless, when training models with intraday data, the annual instances increase to 28,836, accounting for 9 hours of trading and a 5-minute timeframe.

B. RQ2: WHICH AI TECHNIQUE IS MOSTLY USED TO FORECAST THE FINANCIAL MARKET?

The type of predictor algorithm affects the predictive accuracy of the financial prediction system. Various ML and AI techniques have been implemented by researchers with varying results. Most of the techniques and algorithms produce mixed results due to multiple factors, which increase the difficulty of comparing and reaching a conclusion as to which technique is the best. This can be attributed to (1) data set sourcing, (2) data granularity, (3) financial

TABLE 5. Summary of the selected studies.

Ref.	Market	Exchange/Coin	Data granularity/ Time frame	Profitability metrics	Trading/ Inv. strategy
[22]	Stock	Chinese	daily		
[23]	Stock	US	daily		
[24]	Forex	Multiple Countries	daily		
[25]	Stock	Multiple Countries	daily		
[26]	Index	Korean	daily		
[27]	Stock	Turkish	daily		
[28]	Crypto	Multi coin	daily		
[29]	Stock	Multiple Countries	daily		
[30]	Forex	EUR/USD	daily	Y	Y
[31]	Commodity	US	daily		
[32]	Stock	US	daily		
[33]	Stock	German	daily	Y	Y
[34]	Stock	US	daily	Y	
[35]	Stock	US/Taiwan	daily		
[36]	Stock	Ghana	daily		
[37]	Stock	US	daily		
[38]	Stock	Multiple Countries	15-min		
[39]	Index	Multiple Countries	daily		
[40]	Index	Multiple Countries	daily		
[41]	Stock	Taiwan	daily		
[42]	Forex	Multiple Currencies	daily		
[43]	Stock	Multiple Countries	daily	Y	
[44]	Stock	Multiple Countries	daily		
[45]	Crypto	BTC	daily	Y	
[46]	Stock	Taiwan	daily	Y	
[47]	Stock	Indonesia	daily		
[48]	Stock	Taiwan	daily	Y	Y
[49]	Forex	US	daily		
[50]	Stock	US	daily		
[51]	Stock	US	daily		
[52]	Crypto	BTC	daily	Y	Y
[53]	Stock	US	daily		
[54]	Crypto	Multi coin	daily	Y	
[55]	Stock	US	daily		
[56]	Crypto	Multi coin	5-min		
[57]	Stock	Chinese	daily		
[58]	Stock	Chinese	daily		
[59]	Commodity, Stock	Chinese	daily		
[60]	Forex	Multiple Currency	daily		
[61]	Stock	Chinese	daily		
[62]	Index	Multiple Countries	daily		
[63]	Crypto	BTC	1-min		
[64]	Stock	Multiple Countries	daily		
[65]	Forex	-	1-min		
[66]	Crypto	BTC	daily	Y	Y
[67]	Crypto	BTC	daily		
[68]	Commodity	-	daily		
[69]	Index	Indian	daily		
[70]	Stock	Chinese	daily	Y	Y
[71]	Stock	Saudi Arabia	daily	Y	Y
[72]	Crypto	BTC	daily		

US=United States, EUR/USD=Euro/US Dollar pair, BTC=Bitcoin

market, and assets, (4) data duration, (5) features (raw stock data, technical indicators, macroeconomic data, social forums, news data, etc.). Another difficulty is due to the type of predictor model employed such as a stand-alone/ conventional approach, hybrid, or ensemble. It is pertinent to mention that hybrid and ensemble approaches provide better predictive performance as compared to stand-alone/ conventional approaches. In both cases, the disadvantages of predictors are diminished and advantages are preserved through pre-processing, feature extraction, feature selection, and hyper tuning. This can be seen in Figure 7, where Hybrid

and ensemble approaches have been mostly implemented and compared with the Stand-alone/ conventional approach. The hybrid approach here implies the use of ML/ AI techniques to facilitate the financial prediction systems in all stages/ phases of its implementation to maximize performance, which includes feature selection and extraction. Moreover, in terms of predictors, few have been implemented in most of the studies as shown in Figure 8.

LSTM has been used in almost half the studies (49%) followed by SVM and MLP (35%), and CNN, random forest (RF), and bi-LSTM (18% each). Apart from this

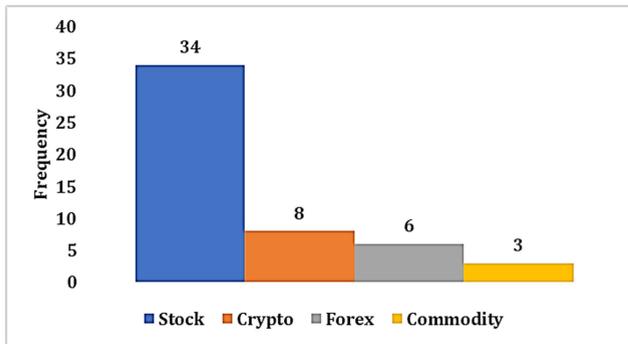


FIGURE 3. Most common exchanges and crypto assets.

other predictor algorithms used include autoregressive integrated moving average (ARIMA), linear regression (LR), GRU, generative adversarial network (GAN), radial bias function network (RBFN), decision trees (DT), k-nearest neighbor (k-NN), stacked LSTM (s-LSTM), extreme learning machine (ELM), and generalized autoregressive conditional heteroskedasticity (GARCH).

Figure 9 shows the distribution of hybrid predictors used for financial market prediction. In the case of hybrid ANN predictors, which are implemented either sequentially or in parallel to provide a prediction of the target feature/ attribute. In this scenario, CNN-LSTM (CLSTM), an implementation of CNN and LSTM has been implemented the most (55%) followed by neuro-fuzzy logic (18%), and LSTM-GRU, LSTM-RNN, and MLP-CNN (9% each).

C. RQ3: WHICH EVALUATION METRICS ARE MOSTLY USED TO EVALUATE A MODEL BASED ON PERFORMANCE AND PROFITABILITY?

To assess the predictive performance of a financial prediction system, we require metrics to measure the performance and facilitate the researcher to evaluate the system quantitatively. In a financial prediction system, apart from performance metrics, profitability metrics are also important as any financial system needs to be efficient to provide cues or possible directions to the decision maker to increase returns/ profit on the invested amount. Despite this importance, profitability metrics are not given much attention and only performance metrics are considered a sufficient indicator of the predictive performance. This might be because researchers are only interested in evaluating the performance predictors and not in the actual application of financial predictive systems. Another reason may be due to the implementation of hybrid and ensemble approaches; thus, researchers focus on performance comparison with conventional predictor algorithms.

Figure 10 shows the most common performance metrics used to evaluate models. In terms of performance metrics, mean absolute percentage error (MAPE) - 33%, root mean square error (RMSE) - 33%, accuracy (31%), mean absolute error (MAE) - 29%, mean squared error (MSE) - 29%, F measure (F1) - 20% and precision (20%) are the most common performance metrics (Figure 10). Apart from this other metrics also used in order of frequent implementation

are: recall, Diebold Mariano (DM) Test, the area under the curve (AUC), directional accuracy (DA), the coefficient of determination (R²), mean, standard deviation, average relative variance (ARV), root mean squared logarithmic error (RMSLE), and skewness. The choice of performance metric is affected by the type of predictive problem being solved by the predictor like classification or regression and continuous or discrete.

In terms of profitability metrics, only 11 papers used profitability metrics, which further confirms the inference of research focuses on performance and not on profitability. In this category of metrics, the Sharpe ratio is the most prominent with implementation in 81% of papers (out of 11); followed by return on investment (ROI), maximum drawdown (MDD), and Sortino ratio. Other metrics include cumulative return on investment, financial beta, rate of daily return, annual return, final profit/ loss, Jensen's alpha, no of trades/ bets, omega ratio, profit accuracy, and risk-return ratio, as shown in Figure 11. Another way to look at it is that researchers' focus is more on risk-related metrics (Sharpe ratio, Sortino ratio, etc.) - 55%, followed by return-based (27%) and trade/bets-based (18%) as shown in Figure 12.

D. RQ4: WHAT INVESTMENT/TRADING STRATEGIES ARE EMPLOYED TO EVALUATE THE PERFORMANCE AND PROFITABILITY OF THE PREDICTOR MODELS?

To evaluate the actual working and efficacy of a financial prediction system, an investment and trading strategy is essentially required to simulate an actual trading environment. This process is also known as backtesting if carried out on historical financial data. During this review, nine studies have been found that have implemented a trading strategy. The use of terms may differ but the purpose as mentioned in this section remains the same. A summary is given in Table 7. Most of the studies use Long (profit on price increasing then buy price) and Long-Short strategy. These strategies are easy to implement and evaluate, due to which are frequently implemented. Other strategies included are specialized techniques and thus require a financial, economic, and statistical understanding of the financial market to implement.

E. RQ5: WHAT TYPES OF PREDICTIVE OUTPUTS (MULTI-OUTPUT OR MULTI-CLASS) ARE PREVALENT IN THE LITERATURE?

The choice of output plays a crucial role in determining the trading strategy and facilitating decision-making for traders in the realm of financial trading. AI models generate various types of outputs, with the most prevalent ones being the expected price values of assets or the corresponding trend or direction of change (i.e., up, down, or no action). In addition to these common predictive outputs, alternative outputs include multi-output configurations (e.g., trend-price, trend-price change, trend-volatility), expected returns, expected volatility, and expected risk. Among the analyzed papers, 42 studies focused on either price (49%) or trend (33%) as

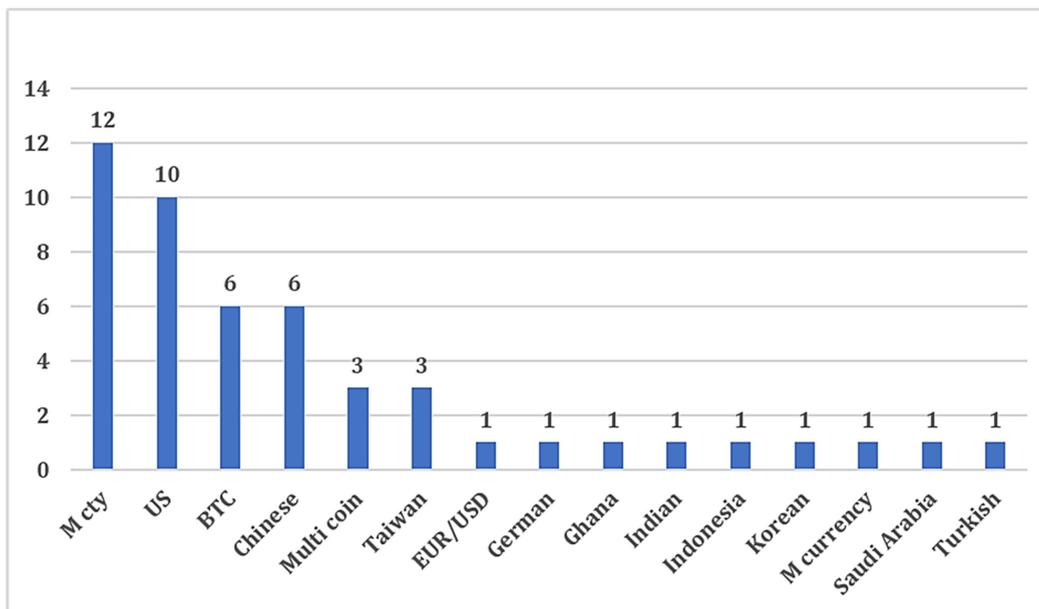


FIGURE 4. Summary of financial markets.

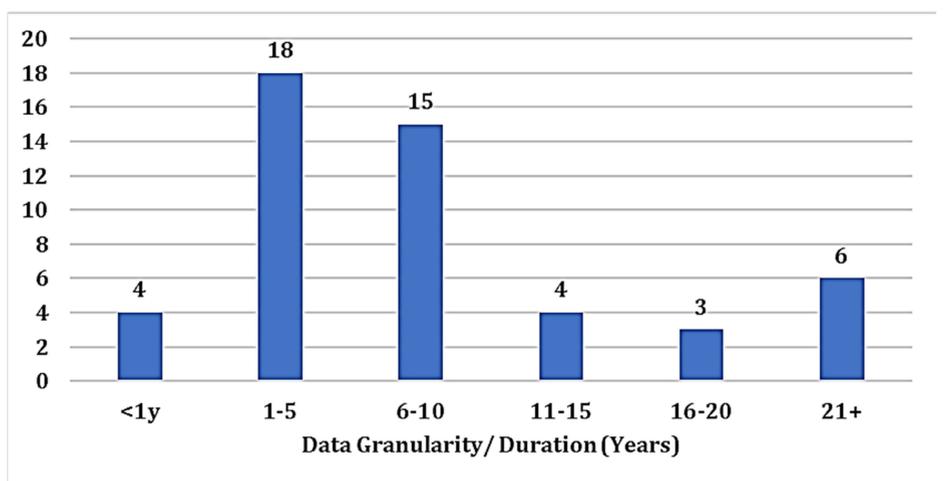


FIGURE 5. Data granularity and duration.

TABLE 6. Summary of data granularity.

Granularity	Frequency	Percentage
Daily	47	92%
15-min	1	2%
5-min	1	2%
1-min	2	4%

its predictive output, as shown in Table 8 and Figure 13. Only four studies adopted a multi-class or -output approach, wherein the emphasis lay in predicting both trend and price or price-change concurrently.

V. APPLICATIONS AND IMPLICATIONS OF AI IN FINANCIAL MARKETS

The finance sector is at a pivotal moment in the AI boom and has undergone seismic shifts in recent years, largely due to the rapid growth and adoption of AI technologies, including

large language models (LLMs). Technology disruption and consumer shifts are laying the basis for the adoption of new technology for financial business models, and the COVID-19 pandemic and its financial and economic effects have accelerated these trends. AI has proven invaluable in the financial markets as it empowers not only organizations but also individuals to optimize processes and identify potential risks. A few application areas, but not a complete list, of AI including practical implications of such techniques in the financial predictive domain are described in the next subsections.

A. APPLICATIONS

1) INVESTMENT ADVISOR

The utilization of intelligent algorithms to provide investors with decision-making information based on their risk

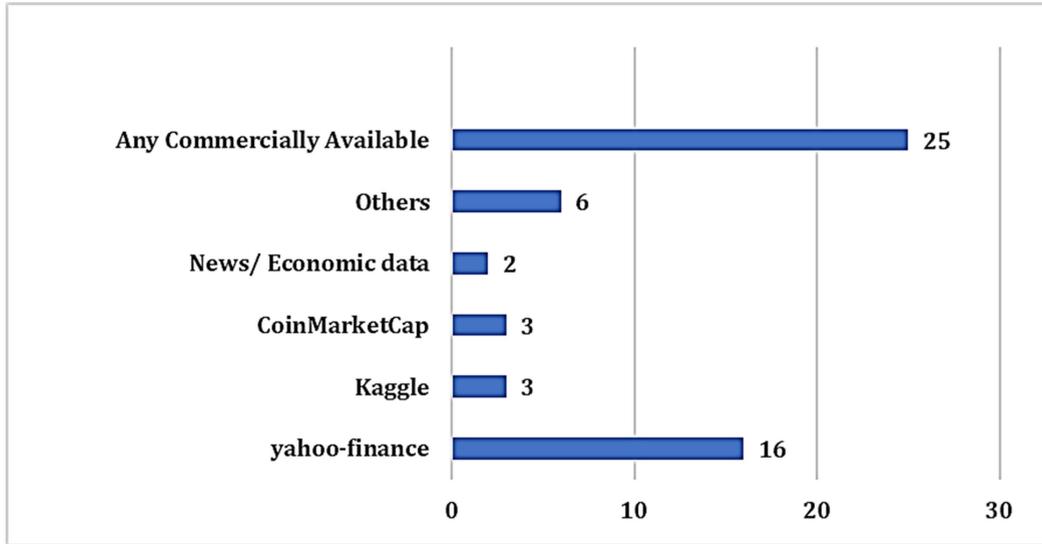


FIGURE 6. Summary of dataset sources.

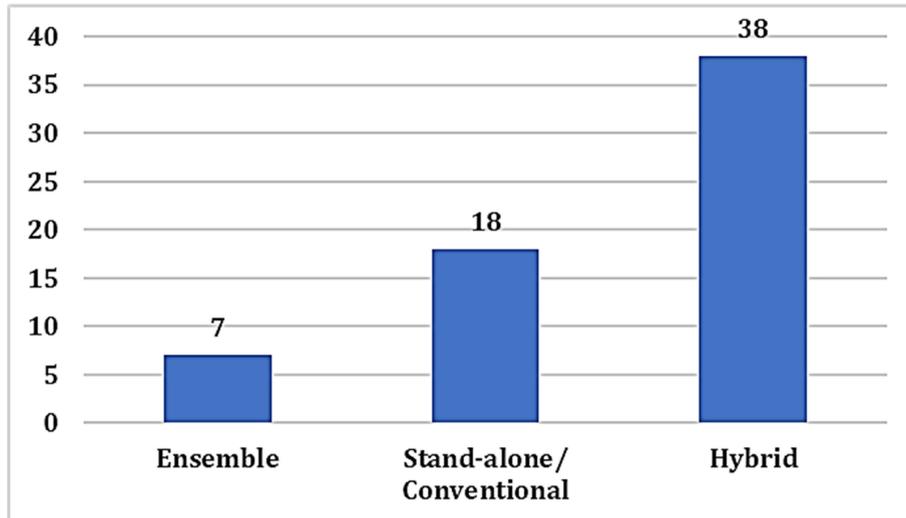


FIGURE 7. Types of predictors implemented.

preferences, investment income requirements, and investment styles is the fundamental concept behind AI-driven investment advisory services. Such systems offer dynamic asset portfolio suggestions that adapt to the ever-changing financial market conditions. Intelligent investment advisors excel not only in investment allocation and transaction execution but also in assisting investors in managing their emotional biases. This field represents one of the most extensive applications of AI technology within the financial sector [74].

In 2008 driven by Wall Street’s enthusiasm for AI and big data, AI investment banking in asset management emerged as a growing market demand for wealth management. The U.S. market now boasts several mature smart investment platforms, including Vanguard Fund, Charles Schwab, Betterment, and Wealthfront. In contrast, intelligent investment banking entered the Chinese market in 2014,

initially driven by Internet companies and subsequently adopted by major commercial banks and financial institutions. Traditional financial institutions hold an advantage in terms of their established customer networks, product resources, and industry experience. Major players like China Merchants Bank, Industrial Bank, Ping An Bank, Everbright Bank, and Industrial and Commercial Bank of China have launched intelligent investment platforms [75].

2) PERSONALIZED WEALTH MANAGEMENT

AI-powered technologies enable personalized financial planning, analyzing data, and recognizing patterns to provide customized investment strategies, discern risks, and optimize portfolio performance. With interactive platforms, individuals can easily share their financial objectives, income, and expenses, which serves as the foundation for the

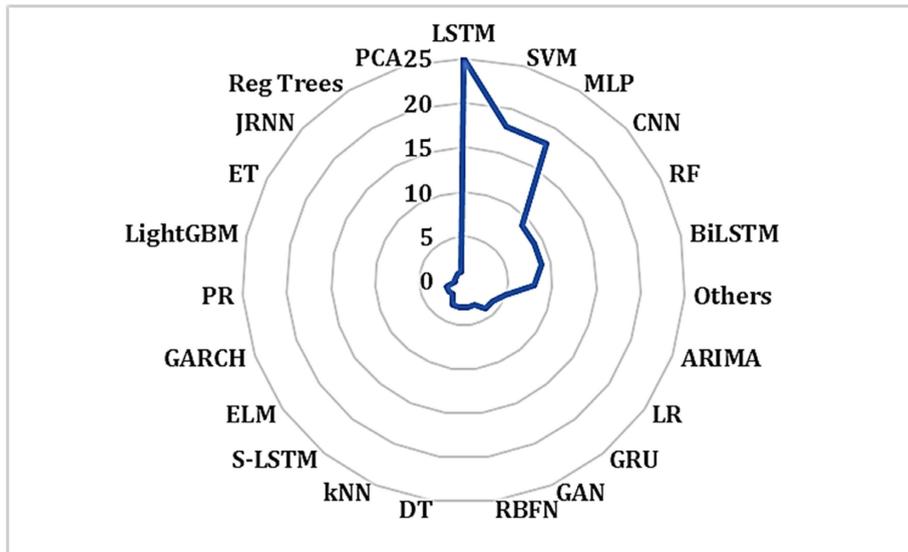


FIGURE 8. Most commonly implemented predictors.

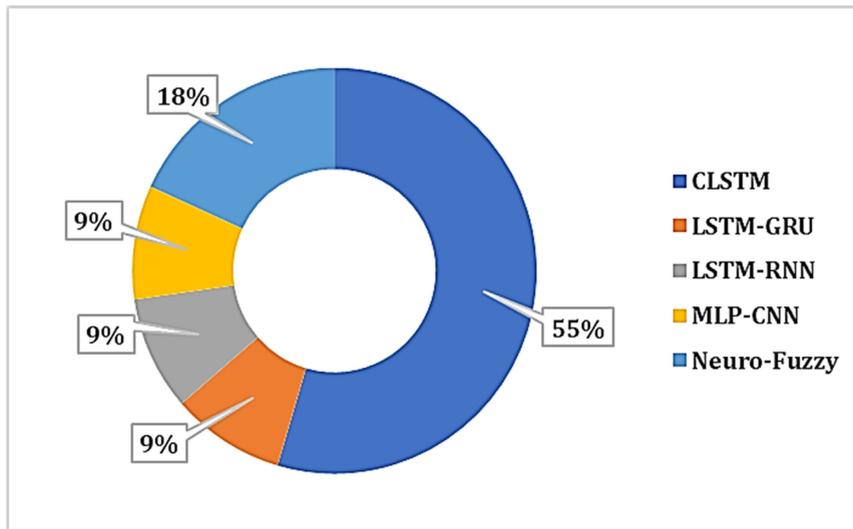


FIGURE 9. Summary of hybrid predictors.

AI algorithm to create a financial plan that meets their specific needs. AI-based automated financial advisory offers a well-organized analysis of financial data, risk profiles, objectives, and preferences. Such systems provide services such as onboarding and profiling of clients for better decision-making or advice; real-time portfolio construction and management; communication and reporting; and rebalancing based on market data and financial goals [76]. They also assess risk tolerance and adjust investment portfolios accordingly to strike a balance between risk and potential returns. Analyzing user behavior and emotional responses to market fluctuations allows insights from the field of behavioral finance and prevents irrational investment decisions. Continuous monitoring of financial markets, economic indicators, and individual portfolio performance enables real-time adjustments to optimize returns, and strategies to minimize tax liabilities and manage risks.

3) RISK MANAGEMENT

The advent of Internet finance has heightened the demand for the development of intelligent risk control systems. Effective financial risk management serves to mitigate losses and maximize profits, relying extensively on information-driven decision-making wherein AI has assumed a critical role in risk management tasks [77]. Intelligent risk control systems, comprising neural networks, knowledge maps, ML, data analysis, and other AI algorithms, have evolved into comprehensive risk management frameworks. These systems encompass market surveys, market evaluation, and market greed-fear factors. They significantly enhance process efficiency by training on historical data, processing multi-dimensional structured and unstructured data, and monitoring and identifying black swan events. Customer experience is further enriched by iterative refinement of the model.

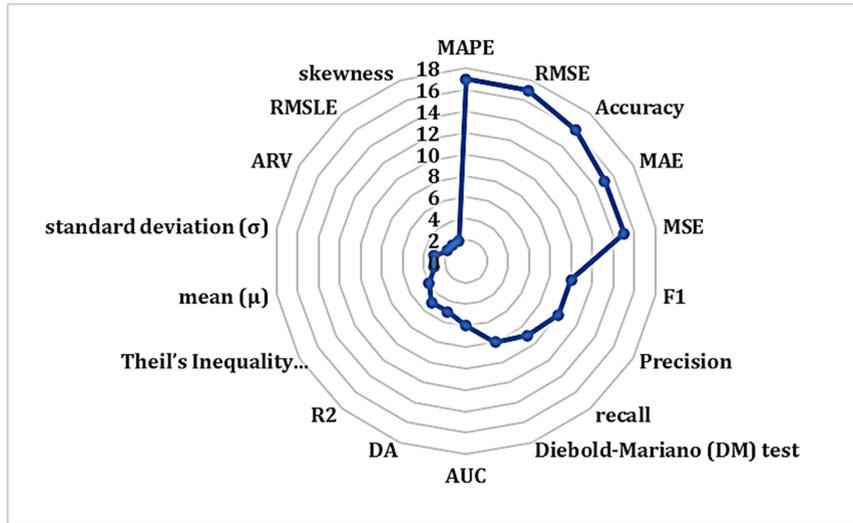


FIGURE 10. Most common performance metrics.

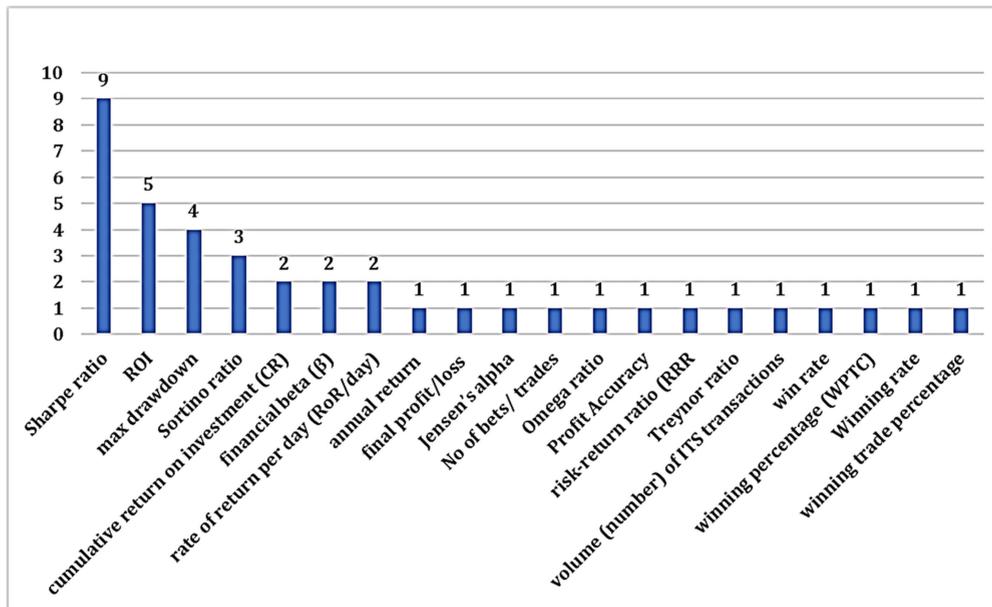


FIGURE 11. Most common profitability metrics.

Additionally, AI systems are used to oversee the operations and financial performance of financial institutions and publicly listed companies. The Securities and Exchange Commission of the United States (SEC) employs AI to analyze unstructured data submitted by registration applicants, predict applicant behavior from multiple dimensions, and assess information against risk levels [75].

4) ALGO-AI TRADING

Algorithmic trading, characterized by the execution of transactions based on predefined rules derived from historical data, forms a significant aspect of contemporary financial markets. These rules draw insights from sources such as

charts, indicators, technical analyses, and fundamental stock attributes. For instance, an algorithm can be devised to purchase a specific asset when its price reaches a predetermined low and sell it when the price attains a predetermined high, based on the occurrence of a pre-determined condition, status, or assumption for a particular asset. This has revolutionized the majority of contemporary financial transactions, with trade execution times reduced to nanoseconds.

According to Wall Street, algorithmic trading comprises more than 60% of the total equity trading activity in the United States. Projections indicate that the global algorithmic trading industry is poised for a consistent growth rate of 8.53% in the next five years (2023-28). Notably, the Asia Pacific region is expected to show rapid expansion,

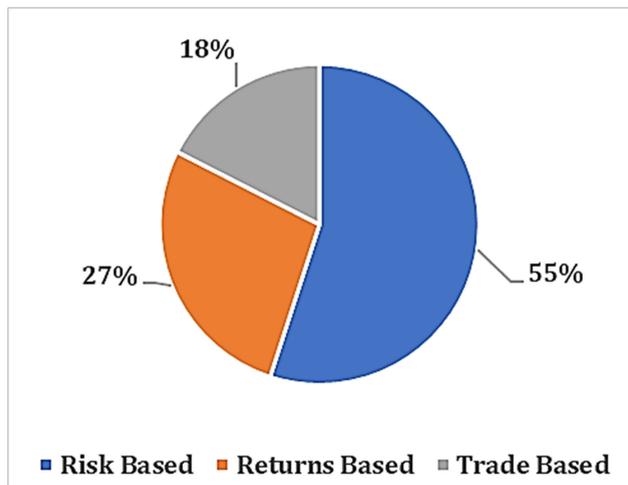


FIGURE 12. Summary of profitability metrics based on risk, return, or trade/ bets.

while North America is to continue its dominance as the largest market in terms of size [78]. These algorithms are expected to become increasingly sophisticated, incorporating AI to adapt to diverse trading patterns. The future may see algorithmic trading evolve further into AI applications capable of real-time analysis of vast and varied data sources.

5) HIGH-FREQUENCY TRADING

Algorithmic trading led to the development of High-frequency trading (HFT), characterized by the rapid mechanical buying and selling of substantial volumes of stocks and shares. HFT is an evolving category within algorithmic trading and is anticipated to emerge as a dominant form of trading in the future. AI is particularly useful for this as it leverages models and methods from various disciplines, including statistics, algorithms, artificial intelligence, and control theory. It focuses on the development of computationally efficient algorithms to derive predictive models from extensive datasets, affecting trade execution and alpha generation (performance of asset or portfolio of assets).

6) AI MANAGED PORTFOLIOS: CASE STUDY

The rise of exchange-traded funds (ETFs) has reshaped portfolio investment, as most ETFs are index funds, they incur a low expense ratio because they are not actively managed (just passively managed). An index fund is much simpler to run since it does not require security selection and can be done largely by computer. An example is the AI-powered equity exchange-traded fund (AIEQ), which leverages IBM's artificial intelligence, Watson, for fund management which consistently outperforms the S&P 500 [76]. The democratization of information and the increasing complexity of the investment landscape have driven the shift towards data-driven, AI-based approaches [74], which has led to the replacement of human advisors in actively managed equity funds. For instance, BlackRock, the world's largest asset manager, has initiated the replacement of human

stock-pickers with a fully automated AI engine, called Aladin [76].

B. IMPLICATIONS

1) EXPLAINABILITY

The transparency of AI systems in the financial sector is vital. AI models are often considered "black boxes" [79], making it challenging to assess the appropriateness of their decisions and potentially exposing organizations or individuals to vulnerabilities such as biased data, unsuitable modeling techniques, or incorrect decision-making [80]. However, stronger explainability could enable external manipulation of algorithms, posing risks to the financial predictive system [81]. Generally, there is a trade-off between model flexibility which refers to its capacity to approximate different functions and is directly related to the number of parameters of the model and its explainability. AI models are more flexible and accurate but are less explainable [82].

2) BIAS

Human bias can permeate AI systems during design and training such as the choice of inclusion or exclusion of features in the model is influenced by various psychological, social, emotional, and cultural factors. Biases may also arise from data collection, such as using incomplete or unrepresentative data, or from prevailing prejudices [83], [84]. Thus, the data pre-processing stage becomes essential for clean data particularly feature selection techniques. However, it has to be employed with caution, given that bias may arise as an unintended consequence during development and implementation. bias mitigation and detection become part of their operational risk management in any financial predictive system. Robust bias mitigation and detection mechanisms are essential parts of operational risk management to address these challenges and ensure the reliability of AI-driven financial systems.

3) ROBUSTNESS

Maintaining AI system robustness is crucial, particularly in safeguarding against cyber threats and safeguarding performance from false signals during market shifts or black swan events. AI models are reasonably able to incorporate evolving data trends without significant loss in prediction accuracy, however, models may struggle to adapt during rapid structural changes in data environments, leading to a deterioration in predictive accuracy. The misalignment of AI-generated risk assessments observed during the COVID-19 pandemic is a good illustration because they were not originally trained for such an event. Strategies for managing these risks are essential to ensure the reliability of AI-driven financial systems [85], [86], [87].

4) STABILITY OF FINANCIAL PREDICTIVE SYSTEMS AND FINANCIAL MARKETS

The widespread adoption of AI in the financial sector could be transformational, and its impact on financial stability is

TABLE 7. Trading/ investment strategies implemented in selected studies.

Study	Trading Strategy	Comments
[30]	Long-Short	Tri-state – Buy-Hold-Sell
[33]	Long-Short	Tri-state – Buy-Hold-Sell
[34]	Long-Short	Buy-Sell and additional rules like maturity date and target price also apply
[48]	Long and Short	with stop loss
[52]	Long only	-
[66]	Long and Long-Short	-
[69]	Portfolio Optimization	Based on: Stock specific & Universal
[70]	Stock pair-wise strategy	
[71]	Trading Agents	zero/minimal, computational, neuro-fuzzy

TABLE 8. Summary of predictive outputs.

Trading Strategy	Frequency	Comments
Price	25	
Trend	17	
Portfolio optimization	1	
Returns	1	
Volatility	1	
Volatility and trend	1	Multi-output
Trend and price-change	1	Multi-output
Trend and price	2	Multi-output
Risk	1	

yet to be fully assessed. With carefully designed and tested algorithms to limit risks and performance issues, such systems may bring increased efficiencies; better assessment and management of pricing and risks; and improved regulatory compliance all of which will improve financial stability. But new systemic risks will also be introduced like potential single points of failure in algorithmic trading, uniformity (herding) and out-of-sample risks from data concentration, increased procyclicality, and risks associated with AI’s response to inaccurate assessment of black swan events. Consequently, achieving a balance between AI automation and human intervention is crucial for the stability of financial systems.

5) DIGITAL DIVIDE BETWEEN ADVANCED AND DEVELOPING ECONOMIES

Currently, the deployment and benefits of AI are mostly limited to advanced economies and a few emerging markets thus, rapid advancements could worsen the digital divide between advanced and developing economies. However, developing economies could also reap significant benefits from these technologies, such as improved access to credit through reduced costs of credit risk assessments [88]. Due to inadequate investment, limited access to research, and a scarcity of human capital, some economies are lagging. To bridge this gap, it is important to create a policy framework that can be achieved through four main policy pillars: investing in infrastructure, promoting a business-friendly environment, investing in skills, and establishing risk management frameworks [89].

6) REPLACEMENT OF HUMAN RESOURCE

These trends raise concerns about the potential displacement of human advisors by robo-advisors, which could result

in significant unemployment. However, the data on performance from AI-managed portfolios remains limited. The academic community is still evaluating the implications of AI trading for market volatility and risk. Moreover, while AI investment advisors offer cost-effectiveness and efficiency personal interactions and human judgment remain crucial at certain stages of investing. A hybrid approach, where AI and humans coexist, may represent a sustainable future for the finance industry, potentially reshaping higher education toward the integration of data science (FinTech) applications that harmonize AI and human expertise.

VI. GAPS AND FUTURE DIRECTIONS

A. RQ6: WHAT ARE THE GAPS IDENTIFIED AND PROPOSED FUTURE WORKS IN THE EXPLORED STUDIES?

From the analyses made in previous subsections and the information obtained through Table 5, Table 6, Table 7, and Table 8, it is possible to visualize the most used tools for this review, and the research trend over the years, besides mentioning several possible gaps to be explored in future works.

Although this systematic research does not limit publication year, after carrying out the inclusion and exclusion criteria, the remaining articles date from 2018 to 2023, showing that studies involving DL with technical analysis for the stock market are relatively recent. There has been a steady increase in the number of papers in this research area since 2018. The best years are 2022 and 2021. Only four studies have been published in 2023, however, this SLR considered studies up to 14 May 2023, as shown in Figure 14. Among the selected studies, there is no paper from IEEE or ACM in the years 2018, 2022, and 2023. Moreover, the number of studies gradually increased in the Springer digital library since 2018. It can be inferred that researchers’ interest in Springer publications is increasing particularly for hybrid, ensemble, and multi-class problems, as displayed in Figure 15.

Only three digital libraries are searched. Out of the selected studies, 84% are selected from the Springer digital library, whereas from IEEE and ACM digital libraries, only 12% and 4% respectively have been selected, as shown in Figure 17.

Based on the 51 studies, the top journals in the field are Financial Innovation (8), Neural Computing Applications (6), Journal of Big Data (4), Soft Computing (4), Applied Intelligence (3), and Computational Economics (3), as per

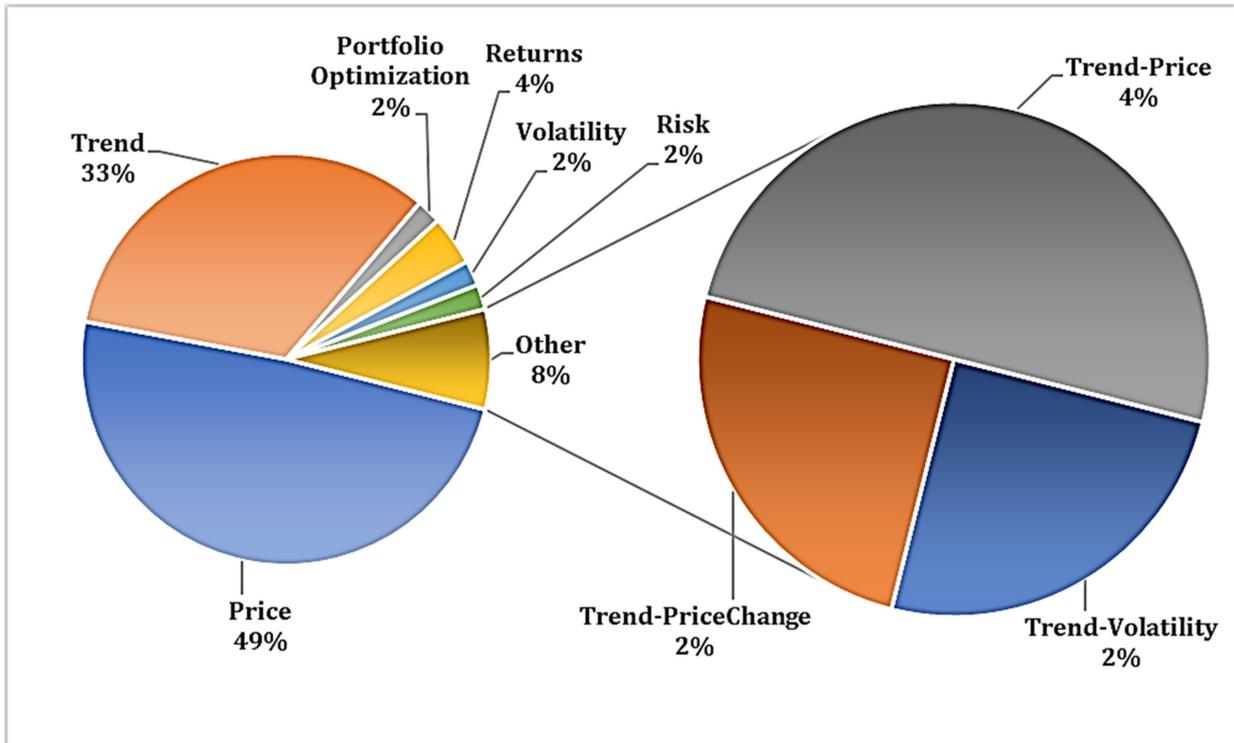


FIGURE 13. Type of predictive output.

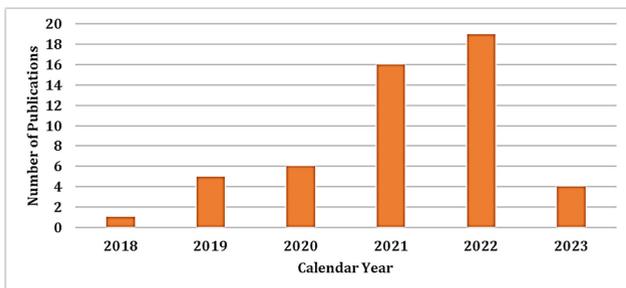


FIGURE 14. Year-wise publications.

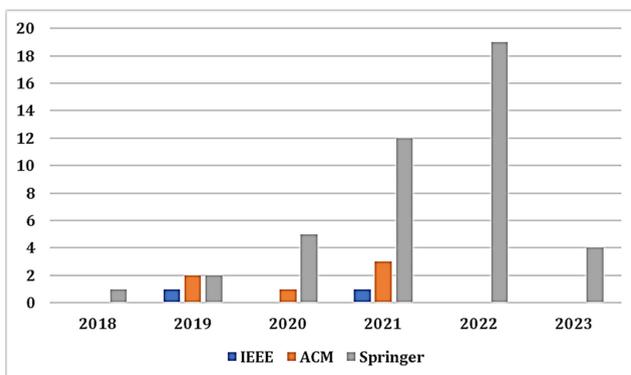


FIGURE 15. Selected studies based on year and digital library.

Figure 16. Although 51x studies have been selected, only two groups of authors have published two papers each, whereas other authors have published only one paper. This implies that researchers are more focused on predictors as a research area

and not on predictive applications of AI/ ML techniques in financial markets, particularly prediction or trading.

B. GAPS, LIMITATIONS, AND FUTURE WORKS

Based on the analyses conducted in the preceding sections, a full reading of studies, and the insights derived from research questions, it becomes possible to discern the evolving research trends over the years. Furthermore, several potential research gaps emerge, paving the way for future investigations.

1) LONG AND SHORT-TERM TRADING

Distinct differences exist between long- and short-time horizons in cryptocurrency trading:

- i) Long-term trading offers the potential for higher profits but also entails a greater need for risk management when holding positions over weeks or months. Given the extended holding periods associated with long-term strategies, risk control becomes mandatory, as risk exposure escalates proportionally. This necessitates the employment of risk-based evaluation metrics in conjunction with performance metrics.
- ii) Conversely, shorter prediction horizons entail higher costs and lower risks, emphasizing cost considerations in strategy design. Short-term trading allows for the application of automated algorithmic trading when holding periods are less than a week. This entails the employment of profitability and performance metrics

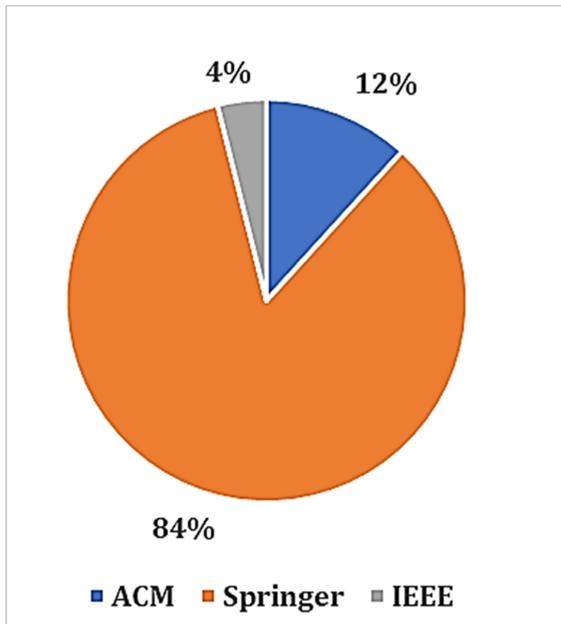


FIGURE 16. Selected papers based on journals.

to offset and provide opportunities to at least break even the cost-benefit curve of financial trading.

- iii) Additionally, long-term trading involves tracing trends and utilizing simple technical indicators in market analysis, whereas short-term trading relies on small positions to limit overall risk. Nonetheless, market noise and the short duration of transactions may introduce stress in short-term trading.
- iv) Researchers can differentiate between long-term and short-term trading in the cryptocurrency domain by employing wavelet technology to analyze bubble regimes and considering hypotheses such as price explosiveness for short- and long-term research. Exploring trading signal extraction, time-series research, portfolio management applications, the relationship between significant market crashes and minor price drops, derivative pricing in the cryptocurrency market, and other related areas present promising avenues for further research.

2) TRADING STRATEGY AND TRANSACTIONAL COSTS

Among the twelve publications reviewed, only nine studies incorporated investment or trading strategy, employing simple trading strategy in almost all the cases to validate the prediction system.

- i) The trading strategies employed in these works are predominantly straightforward and encompass three primary approaches:
 - a) The trading system executes long positions based on forecasting and maintains them until a shift to short positions is indicated,
 - b) The system acquires assets and holds the positions for a predetermined duration, and
 - c) In addition to the long strategy, the system is equipped to engage in short positions and

subsequently adjust them to realize profits or mitigate losses. The utilization of such techniques is paramount, considering the inherent noise and chaotic nature of financial series data, which can surpass loss limits and lead to significant financial damages.

- ii) It is essential to consider trading fees and transaction costs when formulating trading strategies, as these are often overlooked when calculating ROI. This can potentially harm traders with higher costs when executing trades, particularly in the case of high-frequency trading (HFT). Moreover, these expenses, although lower for Bitcoin compared to retail foreign exchange markets, can vary among different financial assets, exchanges, and crypto coins. Incorporating these costs into the trading strategy built upon trend or price predictions can ensure that they do not undermine the gains derived from the ability to moderately forecast short-term market movements.

3) AI MODELS

A majority of studies focused on employing the LSTM network, renowned for its suitability in time series forecasting, owing to its capacity to retain memory and address the gradient vanishing issue. Specifically, 25 studies solely implemented this technique. However, if hybrid models, all of which incorporate the recurrent network, are considered, an additional 11 articles should be accounted for, totaling 36 works and representing 70.6% of the examined publications. The results of hybrid and ensemble approaches are better than traditional or stand-alone employment of AI techniques. Conducting a comprehensive comparative study, as a future avenue for research, among various hybrid and ensemble predictors can yield more conclusive and superior results, with particular emphasis on reducing execution times and model complexity.

4) MULTI-OUTPUT AND MULTI-CLASS PROBLEMS

The predominant focus in existing literature has been on evaluating models based on their performance metrics rather than profitability metrics. Furthermore, the majority of studies (92%) have employed single-class or single-output predictive models. Thus,

- i) This approach has resulted in the design of simplistic trading strategies that rely solely on binary or three-way signals (up-down-hold). Consequently, future research endeavors can explore the utilization of multi-class or multi-output models to assess their performance and profitability in comparison to single-class or single-output models. Additionally, trading strategies can be devised that leverage multiple signals derived from such models to make more intricate decisions.
- ii) Hyperparameter tuning techniques are employed to refine the parameters of AI models, thereby enhancing their performance. In this SLR, various studies implement AI techniques for effective feature engineering

Figure 17: Selected Papers based on Journals

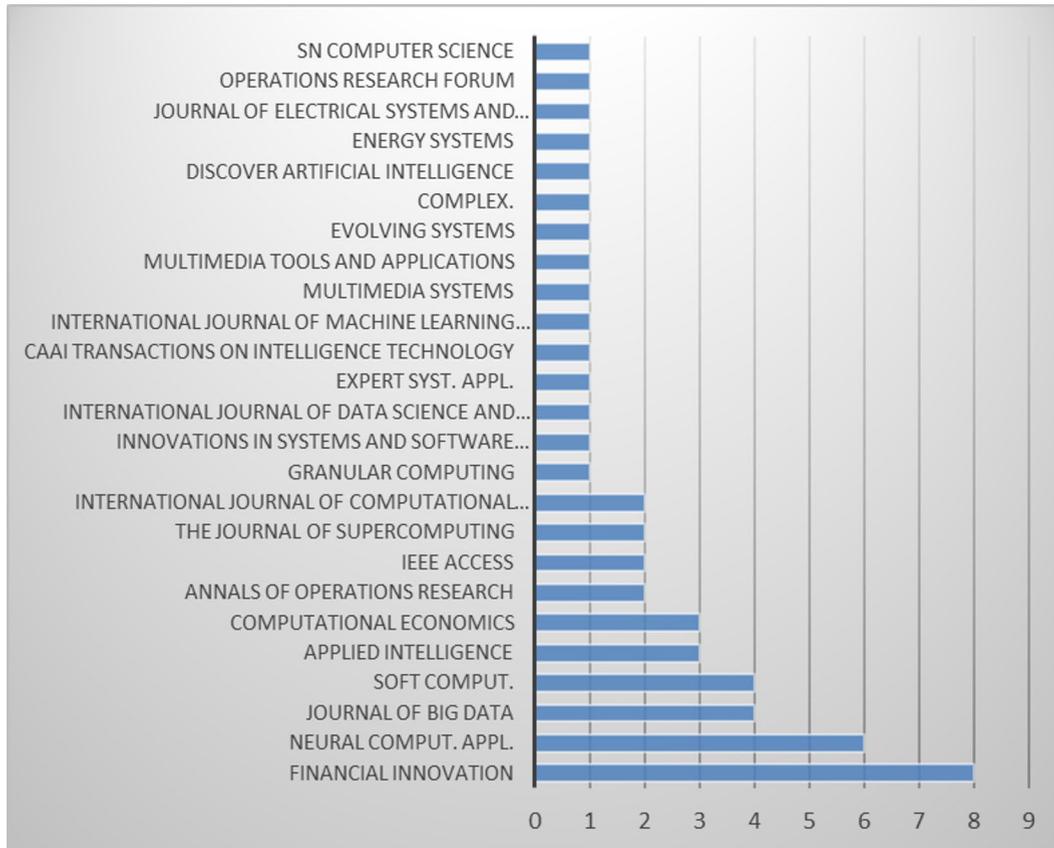


FIGURE 17. Papers selected from digital libraries.

before model training, contributing to the overall performance improvement of AI models. Similarly, the adoption of multi-class and multi-output approaches offers another avenue for hyper-tuning of financial predictive systems to further improve performance and profitability, independent of the underlying AI model. Consequently, optimizing the entire financial predictive system to operate at its optimal capacity. These areas warrant further investigation and hold significant potential for research advancement.

5) NON-ECONOMIC FEATURES

Despite the models' ability to achieve better performance, it is crucial to acknowledge that markets are influenced by numerous variables, including geopolitical decisions and global news, which can result in sudden market movements. This limitation poses a challenge for AI-based market forecasting, as designing a system capable of comprehending every variable proves challenging. Developing a reliable predictive model for real-world implementation may necessitate incorporating multiple data points and features.

6) OTHER AREAS

- i) **Feature Extraction and Selection:** Most of the studies that employed hybrid models, used feature extraction or selection through statistical, ML, or AI

techniques to optimize the dataset before training, validation, or testing the model. Advancements in feature extraction and selection techniques can contribute to reducing model complexity and execution time, enabling timely predictions and offering opportunities for better employment in HFT environments.

- ii) **Model Generalizations through a comparative study of different financial markets and assets:** Exploring other markets to assess model generalization, reducing dimensionality in TIs, and varying the number of TIs can be potential areas for investigation.

VII. CONCLUSION

This article conducted a review of academic literature on financial time series forecasting utilizing hybrid. This systematic review provides an updated overview of financial market prediction literature, focusing on works conducted between 2018 and 2023 that explore forecasting across various financial markets and assets. Employing a rigorous research methodology, 51 studies are selected subsequent analyses and discussions centered around four primary perspectives: financial markets and assets, AI techniques, evaluation metrics, and investment or trading strategy.

Yahoo Finance and stock markets emerged as the most popular sources of datasets for financial market forecasting. Among the predictor techniques, hybrid and ensemble

models favorably integrated LSTM and its variants, as well as SVM and MLP. The extensive use of the LSTM is observed due to its memory storage capabilities and ability to mitigate the vanishing gradient problem. Hybrid models incorporating LSTM, technical indicators, and other AI techniques for feature engineering demonstrate more robust results, indicating potential avenues for future research.

A particular aspect related to the validation of financial trading systems based on trading strategy is lacking, as only nine of the studies incorporated them, often utilizing simple logic. Sophisticated strategies are essential for long-term forecasts due to increased risk and asset volatility. Another aspect worth mentioning is that a small portion of articles (21.5%) assessed profitability, while the rest focused on performance evaluation. Another area of research can be a multi-output and multi-class prediction, which can have a great impact on the trading strategy stage of financial predictive systems and can be hyper-tuned independent of the underlying predictive AI model.

This review acknowledges certain limitations and outlines future directions. The review identified gaps that warrant further investigation, such as hybrid models incorporating qualitative and quantitative data, intelligent and adaptive trading strategies, performance metrics with a positive correlation to profitability, implementation of risk management techniques, and others. In future research areas, firstly, it exclusively encompasses journal articles, potentially overlooking other flavors of academic literature. Future research can broaden the search scope to include conference papers, thesis dissertations, and other relevant literary works. Secondly, the inclusion of only three digital libraries restricts the range of studies considered, necessitating the incorporation of additional libraries such as Hindawi, ScienceDirect, or Scopus to enhance the review's comprehensiveness. Furthermore, exploring the applicability of natural language processing (NLP) techniques in fundamental analysis of financial markets vis-à-vis market hypotheses and theories represents a promising avenue for future research.

APPENDIX A SPECIFIC SEARCH STRINGS USED IN DIGITAL LIBRARIES

A. IEEE

(
("Abstract": "Financial Market" OR "Crypto Market"
OR "Crypto Exchange" OR "Crypto Currency" OR
"Stock Market" OR "Stock Exchange" OR "Commodities
Exchange" OR "Commodities Market" OR "Crypto" OR
"Commodities" OR "Stocks" OR "Forex") OR ("Docu-
ment Title": "Financial Market" OR "Crypto Market"
OR "Crypto Exchange" OR "Crypto Currency" OR
"Stock Market" OR "Stock Exchange" OR "Commodities
Exchange" OR "Commodities Market" OR "Crypto" OR
"Commodities" OR "Stocks" OR "Forex") OR ("Author
Keywords": "Financial Market" OR "Crypto Market"
OR "Crypto Exchange" OR "Crypto Currency" OR
"Stock Market" OR "Stock Exchange" OR "Commodities

Exchange" OR "Commodities Market" OR "Crypto" OR
"Commodities" OR "Stocks" OR "Forex")) AND ((
("Abstract": "Multi-Class" OR "Multi Class" OR "Hybrid
Models" OR "Technical Analysis" OR "Multi Class" OR
"Hybrid CNN" OR "Hy-brid RNN" OR "K-line" OR "K
line" OR "Candle sticks" OR "Tech-nical Indicators") OR
("Document Title": "Multi-Class" OR "Multi Class" OR
"Hybrid Models" OR "Technical Analysis" OR "Multi
Class" OR "Hybrid CNN" OR "Hybrid RNN" OR "K-
line" OR "K line" OR "Candle sticks" OR "Technical
Indicators") OR ("Author Keywords": "Multi-Class" OR
"Multi Class" OR "Hybrid Models" OR "Technical Anal-
ysis" OR "Multi Class" OR "Hybrid CNN" OR "Hybrid
RNN" OR "K-line" OR "K line" OR "Candle sticks"
OR "Technical Indicators")) AND ((("Abstract": "CNN"
OR "Convolutional Neural Network" OR "RNN" OR
"Recurrent Neural Network" OR "MLP" OR "Multi Layer
Per-cep-tron" OR "Technical Analysis" OR "Technical
Indicators" OR "TA") OR ("Document Title": "CNN"
OR "Convolutional Neural Network" OR "RNN" OR
"Recurrent Neural Network" OR "MLP" OR "Multi
Layer Perceptron" OR "Technical Analysis" OR "Technical
Indicators" OR "TA") OR ("Author Keywords": "CNN"
OR "Convolutional Neural Network" OR "RNN" OR
"Recurrent Neural Network" OR "MLP" OR "Multi
Layer Perceptron" OR "Technical Analysis" OR "Technical
Indica-tors" OR "TA") OR ("Abstract": "TI" OR "LSTM"
OR "Long Short Term Memory" OR "GRU" OR "Gated
Recurrent Unit" OR "Volume Indicators" OR "Momentum
Indicators" OR "Fibonacci" OR "Fibonacci Retracement")
OR ("Document Title": "TI" OR "LSTM" OR "Long Short
Term Memory" OR "GRU" OR "Gated Recurrent Unit"
OR "Volume Indi-cators" OR "Momentum Indicators" OR
"Fibonacci" OR "Fibonacci Retracement") OR ("Author
Keywords": "TI" OR "LSTM" OR "Long Short Term
Memory" OR "GRU" OR "Gated Recurrent Unit"
OR "Volume Indi-cators" OR "Momentum Indicators"
OR "Fibonacci" OR "Fibonacci Retracement")) AND
((("Abstract": "Prediction" OR "Profitable Prediction"
OR "Trend" OR "Trend Prediction" OR "Trend Signal
Prediction" OR "Trend Signal Prediction" OR "Trend
Signal" OR "Trend Signal" OR "Profitabil-ity") OR
("Document Title": "Prediction" OR "Profitable Predic-
tion" OR "Trend" OR "Trend Prediction" OR "Trend
Signal Prediction" OR "Trend Signal Prediction" OR
"Trend Signal" OR "Trend Signal" OR "Profitability")
OR ("Author Keywords": "Prediction" OR "Profitable
Prediction" OR "Trend" OR "Trend Prediction" OR "Trend
Signal Prediction" OR "Trend Signal Prediction" OR
"Trend Signal" OR "Trend Signal" OR "Profitability"))
AND (("Abstract": "Evaluation Metrics" OR "Perfor-
mance Metrics" OR "Profitability Metrics" OR "Accu-
racy" OR "ROI" OR "Return on Investment" OR
"MDD" OR "Maximum Draw Down") OR ("Document
Title": "Evaluation Metrics" OR "Performance Metrics"
OR "Profitability Metrics" OR "Accuracy" OR "ROI"

OR “Return on Investment” OR “MDD” OR “Maximum Draw Down”) OR (“Author Keywords”:“Evaluation Metrics” OR “Performance Metrics” OR “Profitability Metrics” OR “Accuracy” OR “ROI” OR “Return on Investment” OR “MDD” OR “Maximum Draw Down”)

B. ACM

(Title:(“Financial Market” OR “Crypto Market” OR “Crypto Exchange” OR “Crypto Currency” OR “Stock Market” OR “Stock Exchange” OR “Commodities Exchange” OR “Commodities Market” OR “Crypto” OR “Commodities” OR “Stocks” OR “Forex”) AND Title:(“Multi-Class” OR “Multi Class” OR “Hybrid Models” OR “Technical Analysis” OR “Multi Class” OR “Hybrid CNN” OR “Hybrid RNN” OR “K-line” OR “K line” OR “Candle sticks” OR “Technical Indicators”) AND Title:(“CNN” OR “Convolutional Neural Network” OR “RNN” OR “Recurrent Neural Network” OR “MLP” OR “Multi Layer Perceptron” OR “Technical Analysis” OR “Technical Indicators” OR “TA” OR “TI” OR “LSTM” OR “Long Short Term Memory” OR “GRU” OR “Gated Recurrent Unit” OR “Volume Indicators” OR “Momentum Indicators” OR “Fibonacci” OR “Fibonacci Retracement”) AND Title:(“Prediction” OR “Profitable Prediction” OR “Trend” OR “Trend Prediction” OR “Trend Signal Prediction” OR “Trend Signal Prediction” OR “Trend Signal” OR “Trend Signal” OR “Profitability”) AND Title:(“Evaluation Metrics” OR “Performance Metrics” OR “Profitability Metrics” OR “Accuracy” OR “ROI” OR “Return on Investment” OR “MDD” OR “Maximum Draw Down”))

OR

(Abstract:(“Financial Market” OR “Crypto Market” OR “Crypto Exchange” OR “Crypto Currency” OR “Stock Market” OR “Stock Exchange” OR “Commodities Exchange” OR “Commodities Market” OR “Crypto” OR “Commodities” OR “Stocks” OR “Forex”) AND Abstract:(“Multi-Class” OR “Multi Class” OR “Hybrid Models” OR “Technical Analysis” OR “Multi Class” OR “Hybrid CNN” OR “Hybrid RNN” OR “K-line” OR “K line” OR “Candle sticks” OR “Technical Indicators”) AND Abstract:(“CNN” OR “Convolutional Neural Network” OR “RNN” OR “Recurrent Neural Network” OR “MLP” OR “Multi Layer Perceptron” OR “Technical Analysis” OR “Technical Indicators” OR “TA” OR “TI” OR “LSTM” OR “Long Short Term Memory” OR “GRU” OR “Gated Recurrent Unit” OR “Volume Indicators” OR “Momentum Indicators” OR “Fibonacci” OR “Fibonacci Retracement”) AND Abstract:(“Prediction” OR “Profitable Prediction” OR “Trend” OR “Trend Prediction” OR “Trend Signal Prediction” OR “Trend Signal Prediction” OR “Trend Signal” OR “Trend Signal” OR “Profitability”) AND Abstract:(“Evaluation Metrics” OR “Performance Metrics” OR “Profitability Metrics” OR “Accuracy” OR “ROI” OR “Return on Investment” OR “MDD” OR “Max-

imum Draw Down”) OR (Keyword:(“Financial Market” OR “Crypto Market” OR “Crypto Exchange” OR “Crypto Currency” OR “Stock Market” OR “Stock Exchange” OR “Commodities Exchange” OR “Commodities Market” OR “Crypto” OR “Commodities” OR “Stocks” OR “Forex”) AND Keyword:(“Multi-Class” OR “Multi Class” OR “Hybrid Models” OR “Technical Analysis” OR “Multi Class” OR “Hybrid CNN” OR “Hybrid RNN” OR “K-line” OR “K line” OR “Candle sticks” OR “Technical Indicators”) AND Keyword:(“CNN” OR “Convolutional Neural Network” OR “RNN” OR “Recurrent Neural Network” OR “MLP” OR “Multi Layer Perceptron” OR “Technical Analysis” OR “Technical Indicators” OR “TA” OR “TI” OR “LSTM” OR “Long Short Term Memory” OR “GRU” OR “Gated Recurrent Unit” OR “Volume Indicators” OR “Momentum Indicators” OR “Fibonacci” OR “Fibonacci Retracement”) AND Keyword:(“Prediction” OR “Profitable Prediction” OR “Trend” OR “Trend Prediction” OR “Trend Signal Prediction” OR “Trend Signal Prediction” OR “Trend Signal” OR “Trend Signal” OR “Profitability”) AND Keyword:(“Evaluation Metrics” OR “Performance Metrics” OR “Profitability Metrics” OR “Accuracy” OR “ROI” OR “Return on Investment” OR “MDD” OR “Maximum Draw Down”))

C. SPRINGER LINK

(“Financial Market” OR “Crypto Market” OR “Crypto Exchange” OR “Crypto Currency” OR “Stock Market” OR “Stock Exchange” OR “Commodities Exchange” OR “Commodities Market” OR “Crypto” OR “Commodities” OR “Stocks” OR “Forex”) AND (“Multi-Class” OR “Multi Class” OR “Hybrid Models” OR “Technical Analysis” OR “Multi Class” OR “Hybrid CNN” OR “Hybrid RNN” OR “K-line” OR “K line” OR “Candle sticks” OR “Technical Indicators”) AND (“CNN” OR “Convolutional Neural Network” OR “RNN” OR “Recurrent Neural Network” OR “MLP” OR “Multi Layer Perceptron” OR “Technical Analysis” OR “Technical Indicators” OR “TA” OR “TI” OR “LSTM” OR “Long Short Term Memory” OR “GRU” OR “Gated Recurrent Unit” OR “Volume Indicators” OR “Momentum Indicators” OR “Fibonacci” OR “Fibonacci Retracement”) AND (“Prediction” OR “Profitable Prediction” OR “Trend” OR “Trend Prediction” OR “Trend Signal Prediction” OR “Trend Signal Prediction” OR “Trend Signal” OR “Trend Signal” OR “Profitability”) AND (“Evaluation Metrics” OR “Performance Metrics” OR “Profitability Metrics” OR “Accuracy” OR “ROI” OR “Return on Investment” OR “MDD” OR “Maximum Draw Down”)

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