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TOPICAL REVIEW

Decision Fusion for Stock Market Prediction: A Systematic Review

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ABSTRACT Stock market prediction based on machine or deep learning is an essential topic in the financial community. Typically, models with different structures or initializations provide different forecasts of the same response variable. In such cases, better prediction is often achieved by combining forecasts from multiple models rather than using a single model in isolation. This combination of forecasts from the base learners is known as decision fusion. Furthermore, although decision fusion is typical and essential for making the best possible use of multiple forecasts, few studies have systematically summarized the studies that apply this technique. Therefore, there is an urgent need for a literature review reflecting the application of decision fusion in this field. To this end, this study systematically reviewed research related to decision fusion for stock market prediction, focusing on the characteristics of base learners and decision fusion methods. Specifically, the research trend on this topic, which has shifted over the past two decades, is discussed. This review also presents future directions in applying decision fusion to stock market prediction, such as the fusion of forecasts with different data types, using new algorithms as base learners, and integrating sentiment analysis with decision fusion techniques.

INDEX TERMS Base learner, decision fusion, ensemble, machine learning, review, stock market prediction.

I. INTRODUCTION

Stock market prediction is essential to the financial community and helps develop effective security trading strategies [1]. Machine learning-based stock market forecasting usually involves applying a machine learning algorithm to learn a pattern from historical data and then predict the stock market's future. With rapidly increasing computing power over the past 20 years and the massive amount of data available from the Internet, machine learning algorithms have begun to show advantages in forecasting [2]. Li and Bastos [3] reviewed the latest research on stock market prediction using deep learning techniques from 2017 to 2020. They found that deep learning models also play a significant role in stock market forecasting.

Typically, given a response variable, different forecasts can be generated if the models used for prediction have different structures or the same structure but with random initialization. In such cases, better prediction is often achieved by combining multiple forecasts rather than by using a single model in isolation [4]. This "combining the wisdom of crowds" approach is known as ensemble learning, which involves training several base learners separately and combining their forecasts [5]. Ensemble learning applies decision fusion, or in other words, merges the "decisions" of several base learners into a single "decision" about the response variable [6]. Contextually, the term "fusion" means integrating data or knowledge from multiple sources [7] and can be classified into three types: data fusion, feature fusion, and decision fusion [8]. Therefore, this combination of multiple forecasts provided by base learners is also referred to as decision fusion [9], [10].

Fusion for stock market prediction involves several areas, such as artificial intelligence, data fusion techniques, and finance, and there is no fixed approach on how to use fusion techniques. Owing to the diversity of stock market forecasts, the choice of decision fusion method usually varies depending on the response variable and individual preferences.

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Nevertheless, the fundamental principle is that the final prediction should be generated based on the perceived situational knowledge [11]. If multiple forecasts are fully exploited, then more valuable predictions can be obtained at the decision level [12].

However, although decision fusion is typical and essential for making the best possible use of multiple forecasts [13], few studies have systematically summarized the studies that apply this technique. In this context, there is an urgent need for a literature review that presents research trends on this topic and provides clues to researchers who wish to apply decision fusion in their studies. Consequently, this paper presents a systematic review of research related to decision fusion for stock market prediction, considering relevant studies published in two scientific databases (Scopus and Web of Science). For each proposed model from the included studies, the focus was on the fundamental aspects of the decision fusion process, including the base learners and decision fusion methods. The main content is categorized based on whether the forecasting task is classification or regression.

The remainder of this paper is organized as follows. Section II analyzes the relevant review work and describes the review methodology. Section III provides an overview of the studies included in this review. Section IV summarizes the characteristics of the base learners in each forecasting model from the included studies. Section V extracts the fusion methods used at the decision level. Section VI provides an overall analysis of the included studies, categorizing the forecasting models based on their structures. Finally, this study provides some concluding remarks and highlights several directions for future research.

II. RELATED WORK AND RESEARCH METHODOLOGY

The first step in this study is to evaluate review studies related to decision fusion in the field of stock market prediction. Two leading databases of scientific papers, Web of Science and Scopus, were selected to search for related work. Furthermore, only articles with ''review'' or ''survey'' as keywords or partial abstracts were considered for discarding non-survey or non-review papers. Another filtering criterion was the presence of the words (''fusion'' or ''integration'' or ''aggregation'' or ''combination'') and (''stock market'' or ''financial market'') and (''forecast'' or ''prediction'') in the abstract or keywords. Eight articles were identified after the screening.

Table 1 presents a comparative analysis of relevant review studies under stock market prediction and fusion criteria. The columns indicate several aspects of each review paper, including the number of references and citations, primary concerns, and content related to fusion. These articles are helpful to the scientific community because the number of references for these studies exceeds 400; therefore, these studies present, to some extent, the latest research trends in stock market prediction.

As shown in Table 1, four reviews surveyed studies on forecasting stock market price or trend [15], [18]–[20]. In contrast, other reviews only include studies on forecasting stock market trends [14], [16]. On the other hand, two reviews have focused on broader areas, such as stock market price/trend and risk/return forecasting [21], and even predictions in areas from the stock market and e-commerce to corporate banking and cryptocurrency [17].

Most reviews mainly focused on the application of machine learning and deep learning techniques [14]–[17], [19]. This phenomenon can be attributed to the rapid increase in computing power in recent years, which has significantly affected the stock market prediction. Researchers have found that commonly used machine learning algorithms for effective prediction include artificial neural networks (ANNs), fuzzy-based techniques [14], and support vector machines (SVMs) [18]. Nosratabadi *et al.* [17] stated that deep learning algorithms, particularly long short-term memory (LSTM), convolutional neural networks (CNNs), and deep neural networks (DNNs), are the most applied techniques for analyzing financial time-series data. However, Pandurang and Kumar [15] and Bustos and Pomares-Quimbaya [16] reported that ''single-handed'' models, such as SVM and ANN, are not as efficient as other hybrid ensembles. This finding indicates that decision fusion is a promising approach for improving prediction.

Unfortunately, few reviews have considered decision fusion techniques. Instead, more attention was given to the raw datasets used in the included studies. Nti *et al.* [18] calculated the number of data sources and found that nearly 90% of studies favored a single data source. Moreover, Nalabala and Nirupamabhat [20] focused on data-mining techniques and sentiment analysis. They argued that analyzing and summarizing data with opinions is helpful for better predictions. Unlike the authors above, Thakkar and Chaudhari [21] focus on data and feature fusion techniques for stock market predictions. They argued that the unification of widespread classes given by various classification categories could be a contextual representation for future work.

Although most review articles do not focus primarily on fusion techniques, they still refer to ensemble models that employ decision fusion [14]–[19]. Other studies have also used ''fusion models'' to describe decision fusion [20], [21]. Therefore, it can be concluded from the comparative analysis of these reviews that researchers have realized the high-quality performance of ensemble or fusion models for stock market prediction.

Once similar studies were evaluated, the search equation was defined as searching for studies using decision fusion for stock market prediction. In this review, Web of Science and Scopus databases were searched. The search period was from the start of the database's record availability to October 27, 2021. As base learners and fusion methods are two fundamental aspects of the decision fusion process, this review answers the following research questions: (1) What are the characteristics of the base learners? This study examines the base learners required to constitute the overall forecasting model and classifies them according to their heterogeneity

TABLE 1. A comparative analysis of related review work under various criteria.

Author(s)	References	Citations	Forecasting domains	Primary concern	Fusion related
[14]	50	50	Stock market trend	ML and DL techniques	Ensemble
[15]	14	2	Stock market price/trend	ML and DL techniques	Ensemble
[16]	53	42	Stock market trend	ML and DL techniques	Ensemble
[17]	57	29	Financial forecasting	ML and DL techniques	Ensemble
[18]	122	77	Stock market price/trend	Technical and fundamental analysis	Ensemble
[19]	9	3	Stock market price/trend	ML and DL techniques	Ensemble
[20]	12	0	Stock market price/trend	Data mining, ML techniques, and sentiment analysis	Fusion model
[21]	110	23	Price/Trend/Risk/Return	Fusion techniques	Data and feature fusion

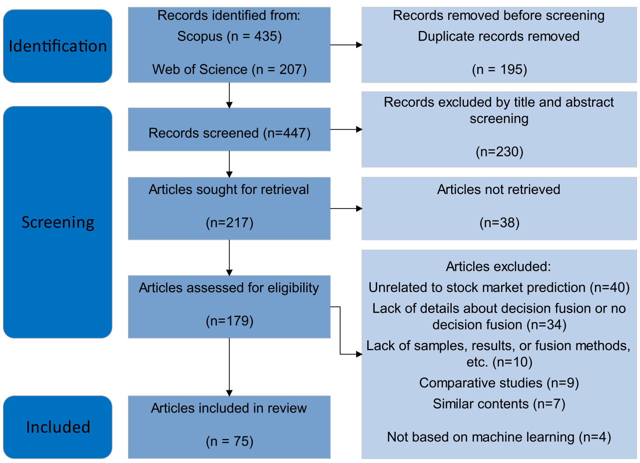

FIGURE 1. Flow diagram of the selection process.

TABLE 2. Major journal rankings.

Journal	Paper Count
Expert Systems with Applications	6
Applied Soft Computing Journal	5
Applied Intelligence	3
Fluctuation and Noise Letters	3
Complexity	2
Neurocomputing	2
North American Journal of Economics and Finance	2
Physica A: Statistical Mechanics and its Applications	2
Others in total	21

and forecasting tasks. (2) Which fusion methods are applied at the decision level? This study extracts the fusion methods used at the decision level for different forecasting tasks.

The following inclusion criteria were considered when selecting these studies: IC1: the included study predicted the stock market using machine learning or deep learning, and IC2: Decision fusion was used in the included study.

The search query included a set of keywords: TITLE-ABS-KEY ((((" decision" OR "decision level" OR "decision-level") AND ("fusion" OR "integration")) OR "group decision-making" OR "group decision making" OR "ensemble" OR "combination") AND ("stock market" OR "financial market" OR "stock exchange" OR "equity market" OR "share market" OR "financial price model" OR "financial volatility") AND ("forecast∗" OR "stock return" OR "predict∗" OR "forecast performance" OR "price model" OR "algorithm" OR "computational intelligence" OR "machine learning" OR "time series analysis" OR "big data")).

The selection process is illustrated in Fig. 1. The tool used for the title and abstract screening is Rayyan, a free web tool designed to help researchers working on systematic reviews, and the tool used for full-text screening and synthesis is NVivo. A total of 642 articles met the search criteria, and 195 duplicate articles were excluded. After screening by title and abstract, another 230 articles were excluded because decision fusion was not applied. Next, 38 articles were excluded because their full text could not be retrieved. After a thorough reading of the remaining articles, 104 studies were excluded for the following reasons:1) unrelated to stock market prediction (n=40); 2) lack of details about decision fusion or no decision fusion (n=34); 3) lack of samples, results, or fusion methods (n=10); 4) comparative studies (n=9); 5) similar content (n=7); and 6) not based on machine learning (n=4). After the selection process, seventy-five articles were included in this review.

III. OVERVIEW

This section provides an overview of the studies included in this review. Most of the included papers were published by indexed journals; the major journal rankings are listed in Table 2. Expert Systems with Applications, Applied Soft

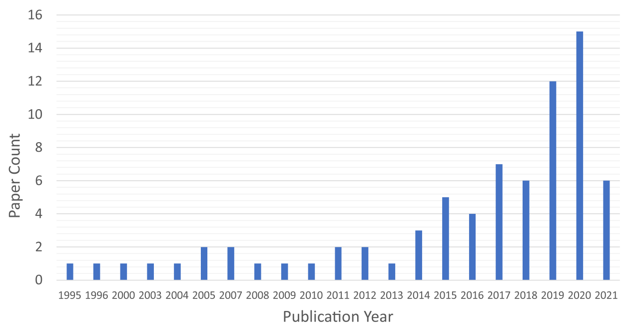

FIGURE 2. Number of publications per year.

Computing, Applied Intelligence and Fluctuation, and Noise Letters are the most relevant journals. The other reviewed papers have been presented at international conferences.

Fig. 2 provides an overview of the number of papers published in different years. The number of articles that met the selection criteria has increased annually, indicating the popularity of machine learning-based stock market prediction and decision fusion techniques. Fig. 3 shows the statistics of the datasets and the input attributes. The US stock market was the most investigated, well ahead of the stock markets in other countries. Next, datasets of various lengths were used, with periods between 5 and 10 years being the most popular. In addition, more than half of the studies focused on regression tasks, particularly for forecasting stock index prices, followed by binary and multi-class classification. For input attributes, a large proportion of the studies chose only historical trading data, followed by the combination of historical data and technical indicators. More details of each study are provided in Table 9 in the Appendix.

IV. CHARACTERISTICS OF BASE LEARNERS

Individual learners strategically grouped in an ensemble or fusion model are called the base learners [97]. The performance of an ensemble or fusion model depends heavily on the characteristics of the base learners, such as which algorithm each base learner employs or whether the base learners in a forecasting model are homogeneous or heterogeneous. The concept of heterogeneity of base learners is shown in Fig. 4. In this section, the included studies are divided into four groups based on base learners' heterogeneity and the category of forecasting tasks. The forecasts generated by the base learners are also discussed because they affect the selection of the fusion methods.

A. HOMOGENEOUS BASE LEARNERS

As shown in Fig. 4, the base learners in an ensemble or fusion model are described as homogeneous if they use the same algorithm. Table 3 summarizes the studies that applied homogeneous base learners for classification tasks. We found that ANN was the most commonly used algorithm, followed by decision trees, SVM, and LSTM. In addition to these algorithms, base learners can also be probabilistic neural networks (PNNs) [34], extreme learning machines (ELMs) [48], and deep belief networks (DBNs) [84].

TABLE 3. Homogeneous base learners for classification.

Base Learning Algorithm	Author(s)
ANN	[22], [33], [41], [42], [57], [58]
Decision Tree	[28], [40], [75], [96]
SVM	[43], [68], [93]
LSTM	[30], [88]
PNN	[34]
ELM	[48]
DBN	[84]

TABLE 4. Homogeneous base learners for regression.

Base Learning Algorithm	Author(s)
ANN	[47], [52], [53], [55], [66], [72], [78], [89], [91]
LSTM	[31], [60], [67], [80], [92]
Decision Tree	[25], [79]
SVR	[71], [74]
LRW	[61]
RVFL	[86]
ANFIS	[63]
NFS	[82]
EGARCH-BPNN	[54]
FNT	[35]
FNN	[38]
KNN	[59]
Random Forest	[95]
CNN-LSTM	[76]

Table 4 summarizes the studies that applied homogeneous base learners for regression tasks. Again, ANN was the most popular, followed by LSTM, decision trees, and support vector regression (SVR). Tables 3 and 4 show that ANN, decision trees, SVM, and LSTM are the most popular algorithms used by homogeneous base learners regardless of the forecasting task. Moreover, the base learner can be a hybrid algorithm such as an exponential autoregressive conditional heteroskedasticity backpropagation neural network (EGARCH-BPNN) [54] or CNN-LSTM [76].

B. HETEROGENEOUS BASE LEARNERS

Heterogeneous base learners refer to situations in which one ensemble or fusion model consists of a set of base learners,

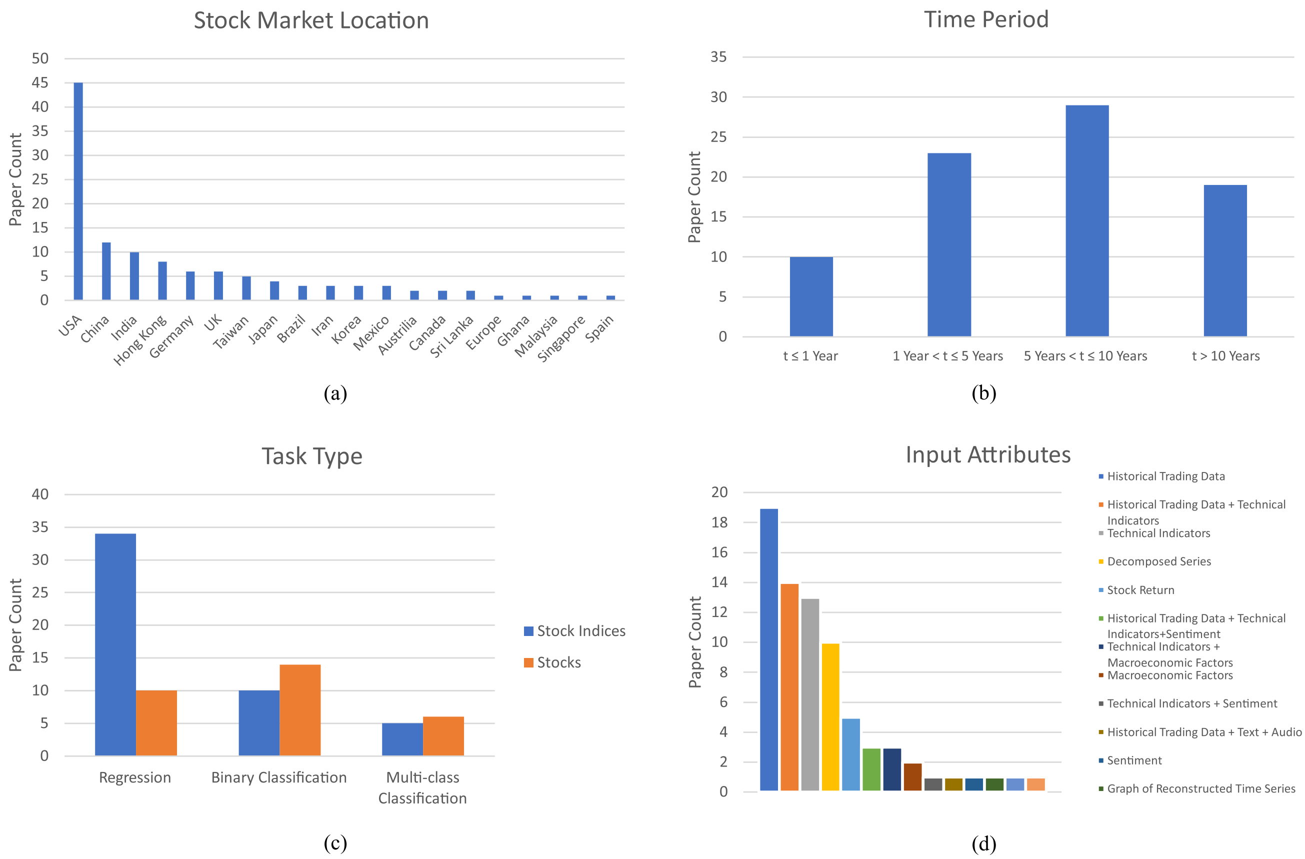

FIGURE 3. **Statistics of datasets and input attributes.**

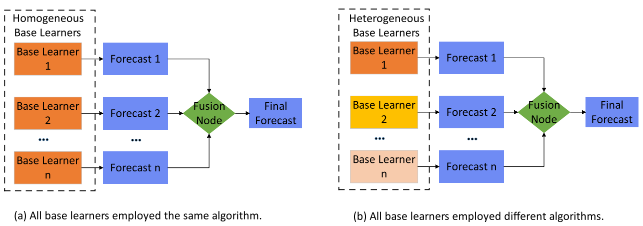

FIGURE 4. **Heterogeneity of base learners: a) Homogeneous base learners; b) Heterogeneous base learners.**

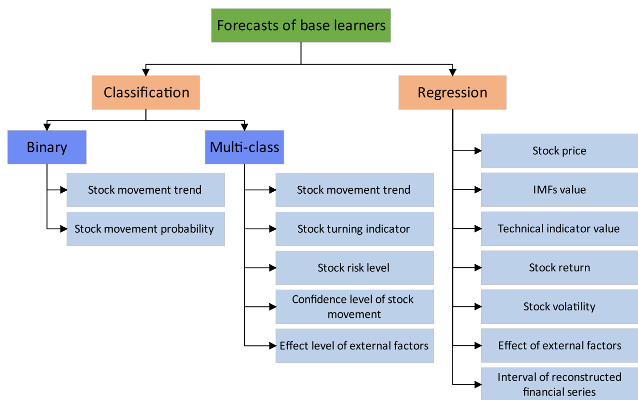

FIGURE 5. **Taxonomy of forecasts of base learners.**

each of which employs a different algorithm. The purpose of using different algorithms is to ensure ensemble diversity.

Table 5 summarizes studies that applied heterogeneous base learners for classification tasks. In addition to using traditional machine-learning algorithms, base learners can use non-machine learning methods, such as user knowledge [56] and speech and text encoders [77]. It is rare for the two forecasting models to employ the same set of base learners.

Table 6 summarizes the studies that employed heterogeneous base learners for regression tasks. Of the 75 articles reviewed, only one study did not provide details about base learners, but the authors mentioned cases in which the base learners were heterogeneous [94]. Apart from machine learning algorithms, non-machine learning methods, such as the Delphi method [51], have also been used.

C. FORECASTS OF BASE LEARNERS

Fig. 5 presents the taxonomy of forecasts generated by the base learners in the included studies. For binary classification, the forecasts of the base learners were mainly stock movement trends (e.g., up and down) and stock movement

TABLE 5. Heterogeneous base learners for classification.

Author(s)	Base Learning Algorithms
[27]	ANN, Decision Tree, Rule-Based Algorithms, SVM
[29]	MLP, Decision Table, Random Forest, Naïve Bayes, SVM
[32]	Random Forest, Gradient Boosting, SVM
[39]	MLP, Decision Tree, KNN, Linear Regression, Naïve Bayes, RBF Network, SVM
[44]	Adaptive Boosting, Gradient Boosting, KNN
[46]	ERT, LightGBM, Random Forest, XGBoost, GRU, LSTM, RNN, Bidirectional RNN
[49]	ANN, Random Forest, Gradient Boosting
[56]	ID3, Expert Knowledge, User Knowledge
[62]	3NN, MLP, RIPPER, LMT, Naïve Bayes, SMO
[64]	Decision Tree, KNN, Logistic Regression, SVM
[73]	ANN, Decision Tree, KNN
[77]	AAM, Speech and Text Encoders, SVM
[85]	ANN, Decision Tree, Random Forest, Genetic Programming, KNN, SVM

TABLE 6. Heterogeneous base learners for regression.

Author(s)	Base Learning Algorithms
[23]	ANN, DBNN, NFS, SVM
[24]	ANN, DBNN, MEP, NFS, SVM
[26]	BPNN, RNN, SVR
[36]	CNN, CNN-LSTM, LSTM
[37]	EEMD-OLS regression, Moving Average, Random Walk
[45]	MLP, GPR, Linear Regression, SVR
[50]	ANFIS, GARCH
[51]	ANN, Delphi method
[65]	FLANN, MLP, ARIMA, RBF network, SVM
[69]	Random Forest, KNN, Lasso, RidgeCv, SVR
[70]	ExtRa tree, SVR
[81]	DE-ELM, EEMD-DE-ELM
[83]	Various single Neural Networks
[87]	ANN, SVM
[90]	Dummy Regression, DTR, Random Forest, KNR, SVR

probability. In contrast, multi-class classification refers to forecasting stock turning indicators, the confidence level of stock movement, stock risk level, or stock movement (e.g., up, neutral, and down). Similarly, the regression forecasts are diverse and include future stock prices, stock returns, and volatility.

TABLE 7. Studies related to classification tasks.

Task	Forecasts of Base Learners	Author(s)
Binary	Stock movement trend (e.g., up and down)	[28], [29], [32], [39], [40], [41], [42], [43], [44], [46], [48], [62], [64], [68], [73], [75], [77], [84], [85], [88]
	Stock movement probability	[30], [49], [78], [93], [96]
Multi-class	Stock movement trend (e.g., up, neutral, and down)	[22], [34], [56]
	Stock turning indicator	[57], [58]
	Stock risk level	[27]
	Confidence level of stock movement	[33]
	Effect level of external factors	[56]

TABLE 8. Studies related to regression tasks.

Forecasts of Base Learners	Author(s)
Stock price	[23], [24], [25], [35], [36], [38], [45], [47], [51], [55], [53], [63], [65], [66], [69], [70], [72], [79], [80], [81], [83], [87], [89], [90], [91], [95]
IMFs value	[26], [31], [59], [60], [59], [60], [67], [74], [76], [86], [92]
Technical indicator value	[37], [71]
Stock return	[52], [82]
Stock volatility	[54], [50]
Effect of external factors	[50], [51], [78]
Interval of time series	[61]

Tables 7 and 8 summarize the studies by the forecasts of the base learners. Several studies have focused on binary classification, whereas only a few have considered multi-class classifications. However, most regression tasks refer to predicting stock prices or intrinsic mode function (IMFs) values. In addition, the final forecast can be the fusion result of different types of predictions, such as the fusion of stock movement trends and external factors [56], the fusion of stock prices and external factors [51], the fusion of stock movement probability and external factors [78], and the fusion of stock volatility and external factors [50].

V. DECISION FUSION METHODS

Admittedly, a better prediction can be obtained by fusing multiple forecasts of the base learners. However, the choice of the fusion method is also critical to the performance of the entire model. In addition, the selection of fusion methods often depends on whether the forecasting task is classification or regression. Figs. 6 shows the proposed taxonomies of the

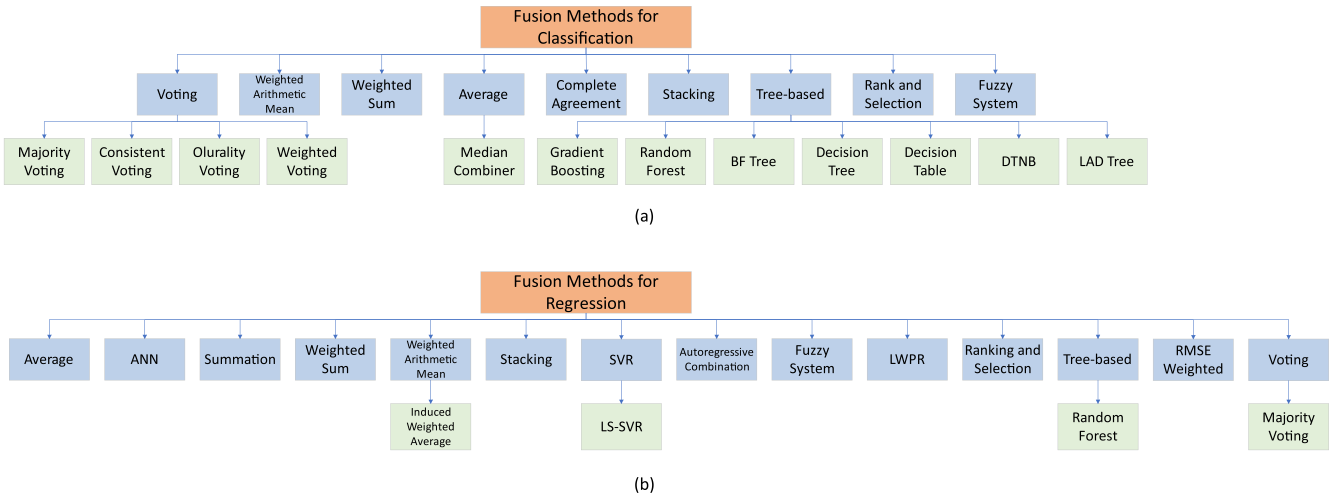

FIGURE 6. Taxonomy of decision fusion methods: a) methods for classification; b) methods for regression.

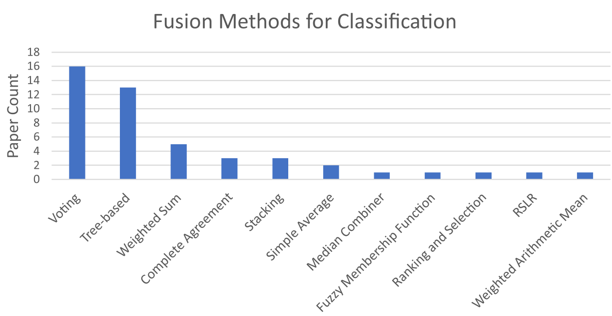

FIGURE 7. Fusion methods for classification.

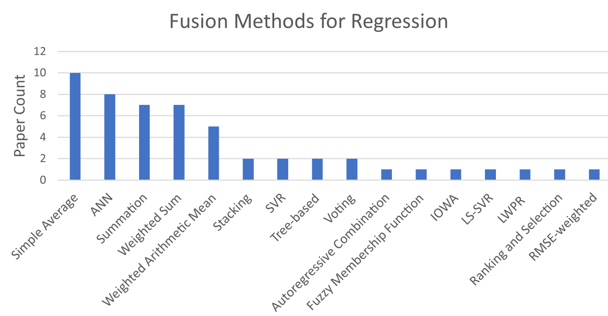

FIGURE 8. Fusion methods for regression.

fusion methods that the included studies used at the decision level for classification and regression.

A. FUSION METHODS FOR CLASSIFICATION

Fig. 7. shows the main methods used to fuse the classification results. Voting, especially majority voting, and tree-based methods are the two most commonly used methods. Other voting methods include accuracy-based voting [29], consistent voting [73], plurality voting [84], and weighted voting [39]. Here, the voting method makes a collective decision from several base learners[98].

The second most popular method for fusing classification results is the tree-based method, which involves first feeding forecasts of all base learners into a tree-based algorithm, then mapping each prediction to a neighborhood in the set of dependent variables, and then returning the mean neighborhood [99]. The most commonly used tree-based methods include gradient boosting [40], [75], [96] and random forest [28], [40], [75]. It is worth noting that Barak *et al.* [27] used five tree-based methods for decision fusion: the BF tree, decision table, decision tree, decision tree naïve Bayes (DTNB), and the LAD tree, with the decision table performing the best.

B. FUSION METHODS FOR REGRESSION

Fig. 8 shows the main decision fusion methods employed for regression. Interestingly, the simple average, or arithmetic average of all forecasts generated from the base learners, was used the most. This result was consistent with the findings of Genre *et al.* [100]. Here, a simple average can be perceived as a specific case of weighted arithmetic mean with equal weight for each component. Models that employ summation at the decision level refer to situations in which forecasts generated by all base learners must be summed. Therefore, each forecast of the base learner is a part of the final prediction. This type of model primarily refers to decomposition-based ensembles. The forecasts of the base learners are the future IMFs values, and the final prediction is the summation of all the predicted IMFs values [101]. More sophisticated methods, such as ANN and stacking (meta-learning), have also been employed to fuse regression forecasts [50]–[55], [78].

VI. OVERALL ANALYSIS

After analysis of the characteristics of base learners and the fusion methods, it is clear that the structures of the models proposed in the included studies follow several patterns. Based on their design, these forecasting models can be

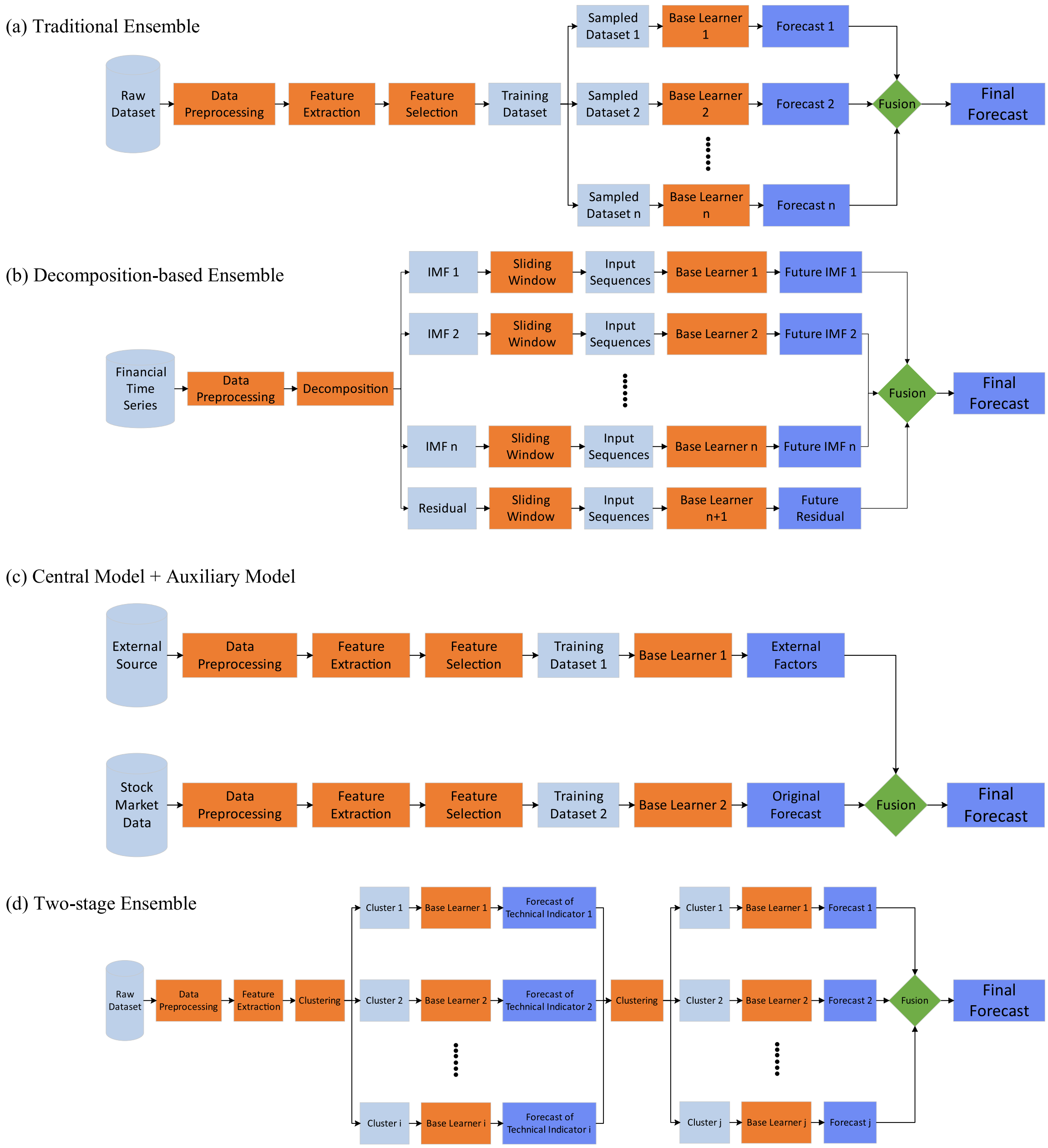

FIGURE 9. Data pipelines of decision fusion models.

roughly categorized into four types:1) traditional ensemble, 2) decomposition-based ensemble, 3) fusion models integrating auxiliary forecasting, and 4) two-stage ensemble.

Fig. 9 shows the data pipelines of the four types of decision fusion models. Most forecasting models fall under the category of traditional ensembles. This type of model typically has more than two base learners, each producing one forecast for the response variable. The traditional ensemble has been used for stock market prediction since 2000, and the number of relevant studies has increased annually. The second type of model was decomposition-based ensembles. This type of model was exclusive to the regression task and became popular only after 2015. The difference between traditional and decomposition-based ensembles is that the former's base learners produce complete forecasts of the response variable. The latter base learners only predict parts of the response variable, with the final forecast being the sum of these forecasts.

The third type of model is the fusion model combining central and auxiliary forecasts. The latter is often a forecast of the effect of external factors generated by either a machine learning model [50] or non-machine learning methods, such as the Delphi method [51] or expert knowledge [56]. The original forecast is refined at the decision fusion stage by integrating the effects of the external factors. This type of

TABLE 9. Bibliography of stock market prediction project. Not available (NA), Open (O), High (H), low (L), Close (C), Volume (V).

Author(s)	Tasks	Country/ Region	Period	Time Frame	Attributes	Base Learners	Fusion Methods	Performance Metrics	Baselines
Abdullah and Ganapathy [22]	Stock Trend	Malaysia	1991-1998	Daily	Differenced C with Sliding Window	ANN	Median Combiner	Hit Rate, Mean Return	Base Learners
Abraham and AuYeung [23]	Stock Index Price	India, USA	NA	Daily	O H L C	ANN, DBNN, NFS, SVM	Ranking and Selection, Weighted Sum	Correlation Coefficient, MAP, MAPE, RMSE	Base Learners, Different Fusion
Abraham *et al.* [24]	Stock Index Price	India, USA	NA	Daily	O H L C	ANN, DBNN, MEP, NFS, SVM	Weighted Sum	Correlation Coefficient, MAP, MAPE, RMSE	Base Learners, Different Optimization
Akhtar and Khursheed [25]	Stock Price	USA	NA	Daily	O H L V + Technical Indicators	Decision Tree	Average, Weighted Sum	Accuracy	Bagging, Boosting
Alhnaity and Abbod [26]	Stock Index Price	Japan, UK, USA	NA	Daily	C with Sliding Window	BPNN, RNN, SVR	Weighted Arithmetic Mean	MAE, MSE, R, RMSE, Standard Deviation	Base Learners, Different Fusion, Auto-regressive, BPNN, RNN, Simple Average, SVR
Barak *et al.* [27]	Stock Risk Level	Iran	2002-2012	Daily	Technical Indicators	ANN, Decision Tree, Rule-Based Algorithms, SVM	LAD Tree, BF Tree, Decision Tree, Decision Table, DTNB	Accuracy	Different Fusion, Other Studies
Basak *et al.* [28]	Stock Trend	USA	NA-2017	Daily	Technical Indicators	Decision Tree	XGBoost, Random Forest	Accuracy, Recall, Precision, Specificity, F-Score, Brier Score, AUC	Different Time Steps
Bautu *et al.* [29]	Stock Index Trend	USA	1969-1973	Daily	C with Sliding Window	MLP, Decision Table, Random Forest, Naïve Bayes, SVM	Weighted Sum, Majority Voting, Accuracy-based Voting	Accuracy, Specificity, Sensitivity, Mutual Information	Base Learners, Different Fusion
Borovkova and Tsiamas [30]	Stock Trend	USA	2014	Micro-second	Date + O H L C V + Technical Indicators	LSTM	Average, Weighted Arithmetic Mean	AUC	Different Fusion, Lasso, Ridge
Cao *et al.* [31]	Stock Index Price	China, Germany, Hong Kong, USA,	2007-2017	Daily	Decomposed Series with Sliding Window	LSTM	Summation	MAE, MAPE, RMSE	CEEMDAN-MLP, CEEMDAN-SVM, LSTM, SVM
Carta *et al.* [32]	Stock Index Trend	Germany, USA	2008-2018	Daily	Date + O H L C V + Technical Indicators with ICA	Random Forest, Gradient Boosting, SVM	Complete Agreement	Accuracy, Coverage, Equity Curve, Maximum Drawdown, Return Over Maximum Drawdown	Buy and Hold
Chakraborty *et al.* [33]	Stock Trend	Japan	NA	Daily	Technical Indicators	ANN	Voting	Accuracy	ANN
Chandrasekara *et al.* [34]	Stock Index Trend	Austrilia, Sri Lanka, USA	NA	Daily	C with Different Lags	PNN	Voting	Accuracy, Misclassification Percentage	Base Learners, Proposed model without MCUB
Chen *et al.* [35]	Stock Index Price	India, USA	NA	Daily	O H C	FNT	LWPR	Correlation Coefficient, MAP, MAPE, RMSE	Base Learners, Different Fusion
Chong *et al.* [36]	Stock Price	USA	2004-2018	Daily	Date + O H L C V	CNN, CNN-LSTM, LSTM	Average	RMSE	Random Forest, CNN, RNN
Dai and Zhu [37]	Stock Index Return	USA	1927-2017	Monthly	Technical Indicators + Macroeconomic Factors	EEMD-OLS regression, Moving Average, Random Walk	Summation	R^2	Wavelet Decomposition
Das *et al.* [38]	Stock Price	Singapore	1999-2010	Daily	C with Sliding Window	FNN	Weighted Arithmetic Mean	R^2, RMSE, Rules	DENFIS, RNFS
Dash *et al.* [39]	Stock Index Trend	India, USA	2015-2017	Daily	Technical Indicators	MLP, Decision Tree, KNN, Linear Regression, Naïve Bayes, RBF Network, SVM	Weighted Voting	Accuracy, F-score, G-mean, Precision, Recall, True Negative, True Positive	Different Fusion, Different Optimization
Deepika and Bhat [40]	Stock Trend	India	2019	Daily	Quantified Sentiment	Decision Tree	XGBoost, Random Forest	Accuracy, MAE, MAPE, RMSE	Different Fusion
Giacomel *et al.* [41]	Stock and Index Trend	USA	2008-2015	Daily	O H L C with Sliding Window	ANN	Complete Agreement	Hit Rate	Buy and Hold, Trivial Strategies
Giacomel *et al.* [42]	Stock and Index Trend	Brazil, USA	NA	15-minute, Daily	O H L C with Sliding Window	ANN	Complete Agreement	Hit Rate	Buy and Hold, Trivial Strategies
Gonzalez *et al.* [43]	Stock Index Trend	Brazil	1989-1998	Weekly	Technical Indicators	SVM	Majority Voting	Accuracy, p-value	Bagging, AdaBoost, Random Forest, SVM
Gyamerah *et al.* [44]	Stock Trend	Kenya	NA	Daily	Technical Indicators	Adaptive Boosting, Gradient Boosting, KNN	Stacking	Accuracy, Kappa, Out-of-bag Error, ROC	Base Learners
Hasan *et al.* [45]	Stock Price	Bangladesh	2015-2016	Daily	Date + O H L C V + Technical Indicators	MLP, GPR, Linear Regression, SVR	Average, Majority Voting, Weighted Arithmetic Mean	RMSE	Base Learners, Different Fusion, Different Time Steps
Jiang *et al.* [46]	Stock Index Trend	USA	2003-2019	Daily	Technical Indicators + Macroeconomic Factors	ERT, LightGBM, Random Forest, XGBoost, GRU, LSTM, RNN, Bidirectional RNN	Stacking	Accuracy, AUC, F-score	Base Learners, Different Optimization
Joao *et al.* [47]	Stock Price	USA	2009-2013	Daily	O H L C V	ANN	Average	Standard Deviation	MLP
Khuwaja *et al.* [48]	Stock Trend	Turkey	2011-2015	Hourly	Technical Indicators with Different Time Lags	ELM	Majority Voting	F-score, Precision, Recall	Base Learners, Random Approach
Krauss *et al.* [49]	Stock Trend	USA	1992-2015	Daily	Stock Return with Different Time Lags	ANN, Random Forest, Gradient Boosting	Average, Weighted Sum	Accuracy, Mean Return, Standard Deviation	Base Learners, Different Fusion

TABLE 9. ***(Continued.)*** **Bibliography of stock market prediction project. Not available (NA), Open (O), High (H), low (L), Close (C), Volume (V).**

Author(s)	Tasks	Country/ Region	Period	Time Frame	Attributes	Base Learners	Fusion Methods	Performance Metrics	Baselines
Kristjanpoller and Michell [50]	Stock Index Volatility	Brazil, Chile, Mexico	2001-2010	Daily	Macroeconomic Factors with Sliding Window	ANFIS, GARCH	ANN	MSE, MAPE	Base Learners, ANN-GARCH
Kuo *et al.* [51]	Stock Index Price	Taiwan	NA	Daily	Technical Indicators + Macroeconomic Factors	ANN, Delphi method	ANN	Dominant Rate, MSE	Base Learners
Lahmiri [52]	Stock Return	Morocco	2008-2011	Daily	Stock Return	ANN	ANN	MAE, MSE	ARMA
Lahmiri [53]	Stock Index Price	France, Germany, UK, USA	NA	Daily	Technical Indicators	ANN	ANN	MAE, MAPE, MARE, MSPE, MSRE, RMSE, RMSPE, RMSRE	Base Learners, ANN, SWT-NN
Lahmiri and Boukadoum [54]	Stock Index Volatility	USA	2011	1-minute, 5-minute	Stock Return with Sliding Window	EGARCH-BPNN	ANN	MAE, MSE	Base Learners
Lahmiri and Boukadoum [55]	Stock Index Price	Hong Kong, Korea, Taiwan	2000-2012	Daily	Decomposed Series	ANN	ANN	MAD, MAE, RMSE	ARMA
Lee and Kim [56]	Stock Index Trend	Korea	1988-1992	Weekly	Technical Indicators	ID3, Expert Knowledge, User Knowledge	Fuzzy Membership Function	F-score, t-test	Base Learners
Li *et al.* [57]	Stocks and Index Turning Point	UK, USA	NA	Daily	Turning Indicator with Sliding Window	ANN	Weighted Sum	Yule Coefficient, TpMSE, Total Profit, Rate of Return, p-value, Pearson's X2 Test, Information Content of the Forecast, Contingency Coefficient	Buy and Hold
Liang and Ng [58]	Stocks Turning Point	Hong Kong	2000-2010	Daily	Technical Indicators	ANN	Majority Voting, Weighted Sum	Rate of Return	Base Learners, Buy and Hold
Lin *et al.* [59]	Stock Index Price	USA	2006-2019	Daily	Decomposed Series with Sliding Window	KNN	Summation	MAPE, MASE, NMSE, POCID	Base Learners, Different Optimization
Lin *et al.* [60]	Stock Index Price	China, USA	2008-2019	Daily	Decomposed Series with Sliding Window	LSTM	Summation	MAE, MAPE, MSE, RMSE	BPNN, Elman Network, SVM, WAV
Liu *et al.* [61]	Stock Index Price	Hong Kong, Taiwan	1998-2006	Daily	Graph of Reconstructed Time Series	LRW	IOWA	Correlation Coefficient, MAPE, NSE, RMSE	Auto-regressive, FTSGA, INFS+ANFIS, INFS+SVR, Multi-order Fuzzy System
Livieris *et al.* [62]	Stock Trend	USA	2011	Weekly	O H L C + Technical Indicators	3NN, MLP, RIPPER, LMT, Naïve Bayes, SMO	Majority Voting	Accuracy, Specificity	Base Learners
Melin *et al.* [63]	Stock Index Price	Mexico, USA	2005-2009	Daily	C with Different Lags	ANFIS	Average, Weighted Arithmetic Mean	RMSE, t Student Test	Base Learners, Different Fusion
Moon *et al.* [64]	Stock Index Trend	Germany, Europe, Hong Kong, Korea, Japan, USA	2012-2015	Daily	Technical Indicators	Decision Tree, KNN, Logistic Regression, SVM	Majority Voting	AUC	Base Learners, Different Optimization
Nayak *et al.* [65]	Stock Index Price	India, Taiwan, UK, USA	2003-2016	Daily	C with Sliding Window	FLANN, MLP, ARIMA, RBF network, SVM	Weighted Sum	ARV, MAPE	Base Learners, Different Optimization
Nezhad and Bidgoli [66]	Stock Index Price	Iran, Taiwan, USA	NA	Daily	Price Changes with Sliding Window	ANN	Average, Weighted Arithmetic Mean	ARV, MAPE, POCID, Theil's U	Different Optimization, ANN, ARIMA, Other Studies
Niu *et al.* [67]	Stock Index Price	Hong Kong, UK, USA	2010-2019	Daily	Decomposed Series with Sliding Window	LSTM	Summation	CID, D stat, MAE, MAPE, RMSE	BPNN, CNN, ELM, LSTM, EMD-BPNN, EMD-CNN, EMD-ELM, EMD-LSTM, VMD-BPNN, VMD-CNN, VMD-ELM
Nti *et al.* [68]	Stock Trend	Ghana	2007-2019	Daily	O C + Technical Indicators	SVM	Majority Voting	Accuracy, AUC, MAE, RMSE	SVM Ensemble, Random Forest, ANN, Decision Tree
Padhi and Padhy [69]	Stock Index Price	Hong Kong, USA	NA	Daily	O + Technical Indicators	Random Forest, KNN, Lasso, RidgeCv, SVR	Stacking	MAE, MSE, RMSE, R^2	Attention-based LSTM
Pasupulety *et al.* [70]	Stock Price	India	2018-2019	Daily	O H L C V + Technical Indicators + Quantified Sentiment	ExtRa tree, SVR	Stacking	RMSE, R^2	Base Learners
Patel *et al.* [71]	Stock Index Price	India	2003-2012	Daily	H L C + Technical Indicators	SVR	ANN, SVR, Random Forest	MAE, MAPE, MSE, rRMSE	Different Fusion, Random Forest, ANN, SVR
Pulido *et al.* [72]	Stock Index Price	Mexico	2005-2009	Daily	C with Sliding Window	ANN	Fuzzy Membership Function	MSE, t Student Test	ANFIS Ensemble, NN Ensemble
Qian and Rasheed [73]	Stock Index Trend	USA	1969-1973	Daily	Stock Return with Sliding Window	ANN, Decision Tree, KNN	Stacking, Consistent Voting	Accuracy, Correlation Coefficient, Error Rate	Base Learners, Different Fusion, Different Combination of Base Learners
Qiu *et al.* [74]	Stock Price	UK, USA	NA	Daily	Decomposed Series with Sliding Window	SVR	SVR	MAPE, RMSE	Different Time Steps, EMD-ANN, EMD-SVR, ANN, SVR

TABLE 9. *(Continued.)* **Bibliography of stock market prediction project. Not available (NA), Open (O), High (H), low (L), Close (C), Volume (V).**

Author(s)	Tasks	Country/ Region	Period	Time Frame	Attributes	Base Learners	Fusion Methods	Performance Metrics	Baselines
Qolipour *et al.* [75]	Stock Trend	Iran	NA	Daily	Date + O H L C V + Technical Indicators	Decision Tree	Gradient Boosted Tree, Random Forest	Accuracy, AUC, Precision, Recall	Base Learners, Different Fusion
Rezaei *et al.* [76]	Stock Index Price	Germany, Japan, USA	2010-2019	Daily	Decomposed Series with Sliding Window	CNN-LSTM	Summation	MAE, MAPE, RMSE	EMD-LSTM, CNN-LSTM, DTR, LSTM, SVR
Sawhney *et al.* [77]	Stock Index Volatility	USA	2017	Daily	C + Text Features + Audio Features	AAM, Speech and Text Encoders, SVM	Weighted Sum	F-score, MSE, R^2, Mathew's Correlation Coefficient	Other Studies
Senanayake [78]	Stock Index Price	Sri Lanka	NA	Daily	Macroeconomic Factors	ANN	ANN	MSE	NA
Sharma and Juneja [79]	Stock Index Price	Canada, India	2006-2015	Daily	O H L V + Technical Indicators	Decision Tree	LSBoost	MAE, MAPE, MSE, rRMSE	SVR
Sun *et al.* [80]	Stock Index Price	China, USA	2015-2017	Daily	C with Sliding Window	LSTM	Weighted Sum	Directional Symmetry, MAPE	AdaBoost-ELM, AdaBoost-MLP, AdaBoost-SVR, ARIMA, ELM, LSTM, MLP, SVR
Tang *et al.* [81]	Stock Index Price	China, USA	NA	Daily	Decomposed Series with Sliding Window	DE-ELM, EEMD-DE-ELM	Summation	MAE, MAPE, RMSE	EEMD-DE-ELM, EEMD-VMD-DE-ELM, VMD-DE-ELM, VMD-Res.-DE-ELM, ELM
Vlasenko *et al.* [82]	Stock Return	USA	NA	Daily	C with Sliding Window	NFS	Average	RMSE, SMAPE	Base Learners, Different Combination of Base Learners, BSNN, RBM, SVM
Wang and Wu [83]	Stock Index Price	China	2005-2006	Daily	O H L C + Technical Indicators	Various Single Neural Networks	LS-SVR	Correlation Coefficient, MAPE, RMSE, Trend Accuracy	Simple Regression Ensemble
Wang *et al.* [84]	Stock Index Trend	China	2012-2015	Daily	Technical Indicators + Quantified Sentiment	DBN	Plurality Voting	Accuracy, AUC, F-score, Precision, Recall	Base Learners, ANN Ensemble, SVM Ensemble, Random Forest, ANN, LSTM, RNN, SVM
Winkler *et al.* [85]	Stocks and Index Trend	Spain	2003-2013	Daily	Technical Indicators	ANN, Decision Tree, Random Forest, Genetic Programming, KNN, SVM	Majority Voting	Accuracy, Classification Confidence, Coverage	Different Time Steps
Wu *et al.* [86]	Stock Index Price	China	1990-2020	Daily	Decomposed Series with Sliding Window	RVFL	RMSE-weighted	Directional Statistic, Diebold–Mariano Test, MAPE, RMSE	ICEEMDAN-BPNN, ICEEMDAN-LS-SVR, ICEEMDAN-RW, BPNN, LS-SVR, RW
Wu *et al.* [87]	Stock Index Price	Canada, India, USA	NA	Daily	C with Sliding Window	ANN, SVM	Weighted Sum	RMSE	Base Learners
Xie *et al.* [88]	Stock Index Trend	China	2012-2017	Daily	O H L C V + Technical Indicators	LSTM	Voting	Accuracy, AUC, F-score, Precision, Recall	Base Learners, Different Combination of Base Learners
Xu *et al.* [89]	Stock Index Price	USA	NA	Daily	C	ANN	Average	MAE, MAPE, RMSE	Base Learners, Bagging
Xu *et al.* [90]	Stock Price	China	2008-2019	Daily	C + Technical Indicators	Dummy Regression, DTR, Random Forest, KNR, SVR	Average	MAE, MAPE, MSE, rRMSE	SVR-SVR, SVR-RF (Random Forest)
Yang *et al.* [91]	Stock Index Price	China	NA-2016	Daily	O H L C V + Technical Indicators	ANN	Average	Accuracy, Relative Error	Base Learners
Yang *et al.* [92]	Stock Index Price	Austrilia, Germany, Hong Kong, USA	NA-2020	Daily	Decomposed Series with Sliding Window	LSTM	Weighted Sum	MAE, R^2, RMSE	BARDR, KNR, LSTM, SVR
Zhang *et al.* [93]	Stock Trend	China, USA	2010-2015	Daily	Technical Indicators	SVM	Ranking and Selection	Accuracy, G-mean	BPNN, SVM
Zheng *et al.* [94]	ETF Trend	USA	2002-2010	Daily	Stock Return	NA	RSLR	Annualized Sharpe Ratio, Cumulative Daily Return, Daily Average, Daily Volatility, Median Return, Normalized Cumulative Absolute Error	Different Optimization
Zhong *et al.* [95]	Stock Index Price	USA	NA	Daily	O C + Technical Indicators + Quantified Sentiment	Random Forest	Autoregressive Combination	Absolute Deviation	Base Learners
Zhou *et al.* [96]	Stock Index Trend	China, USA	NA	Daily	O H L C V + Technical Indicators + Quantified Sentiment + Text Count	Decision Tree	Gradient Boosted Tree	Hit Rate, F-score, Precision, Recall	GBDT, TPOT, ANN, Logistic Regression, SVM

fusion model can be seen as an early version of the model using decision fusion for stock market prediction because it mainly appeared in the 1990s. Finally, a two-stage ensemble was recently reported in which the forecast from the first-stage ensemble was used as the input feature for the second-stage ensemble [90]. The distribution of the various decision fusion models according to the publication year is shown in Fig. 10.

Furthermore, based on the analysis in Section IV, for each forecasting model, the forecasts of the base learners always

TABLE 10. List of abbreviations.

3NN	3-Nearest Neighbor
AAM	Attention Alignment Mechanism
ANFIS	Adaptive Network-Based Fuzzy Inference System
ANN	Artificial Neural Networks
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
ARV	Average Relative Variance
AUC	Area Under the Curve
BARDR	Bayesian ARD Regression
BPNN	Back-propagation Neural Network
BSNN	Bipolar Sigmoid Neural Network
CID	Complexity-invatiant Distance
CNN	Convolutional Neural Networks
DBN	Deep Belief Networks
DBNN	Difference Boosting Neural Network
DE	Differential Evolution
DENFIS	Dynamic Evolving Neuro-Fuzzy Inference System
DL	Deep Learning
DNN	Deep Neural Networks
DTNB	Decision Tree Naïve Bayes
DTR	Decision Tree Regression
EEMD	Ensemble Empirical Mode Decomposition
EGARCH	Exponential Autoregressive Conditional Heteroskedasticity
ELM	Extreme Learning Machines
EMD	Empirical Mode Decomposition
ERT	Extreme Randomized Trees
FLANN	Functional Link Artificial Neural Network
FNN	Fuzzy Neural Network
FNT	Flexible Neural Tree
FTSGA	Fuzzy Time Series with Genetic Algorithm
GAN	Generative Adversarial Network
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GBDT	Gradient Boosted Decision Trees
GNN	Graph Neural Network
GPR	Gaussian Process Regression
GRU	Gated Recurrent Units
ICA	Independent Component Analysis
ID3	Iterative Dichotomiser 3
IMF	Intrinsic Mode Function
INFS	Integrated Nonlinear Feature Selection
IOWA	Induced-Ordered Weighted Averaging
KNN	K-Nearest Neighbor

TABLE 10. *(Continued.)* List of abbreviations.

KNR	K-Nearest Neighbors Regression
LightGBM	Light Gradient Boosting Machine
LMT	Logistic Model Tree
LRW	Local Random Walk
LS-SVR	Least-Squares Support Vector Regression
LWPR	Local Weighted Polynomial Regression
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAP	Maximum Absolute Percentage Error
MAPE	Mean Absolute Percentage Error
MARE	Mean Absolute Relative Error
MASE	Mean Absolute Scaled Error
MCUB	Multi-Class Undersampling Based Bagging
MEP	Multi-Expression Programming
ML	Machine Learning
MLP	Multilayer Perceptron
MSE	Mean Square Error
MSPE	Mean Squared Percentage Error
MSRE	Mean Squared Relative Error
NFS	Neuro-Fuzzy System
NMSE	Normalized Mean Square Error
NSE	Nash–Sutcliffe Efficiency Coefficient
OLS	Ordinary Least Squares
PNN	Probabilistic Neural Networks
POCID	Prediction of Change in Direction
R	Cross Correlation Coefficient
RBF	Radial Basis Function
RBM	Restricted Boltzmann Machine
RIPPER	Repeated Incremental Pruning To Produce Error Reduction
RMSE	Root Mean Square Error
RMSPE	Root Mean Squared Percentage Error
RMSRE	Root Mean Squared Relative Error
RNFS	Rough-Set Neuro Fuzzy System
RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristic
rRMSE	relative Root Mean Squared Error
RSLR	Regularized Sequential Linear Regression
RVFL	Random Vector Functional Link
RW	Random Walk
SMAPE	Symmetric Mean Absolute Percent Error
SMO	Sequential Minimum Optimization
SVM	Support Vector Machines

TABLE 10. ***(Continued.)*** **List of abbreviations.**

SVR	Support Vector Regression
SWT	Stationary Wavelet Transform
TPOT	Tree-Based Pipeline Optimization Tool
VMD	Variational Mode Decomposition
WAV	Wavelet Neural Network
XGBoost	extreme Gradient Boosting

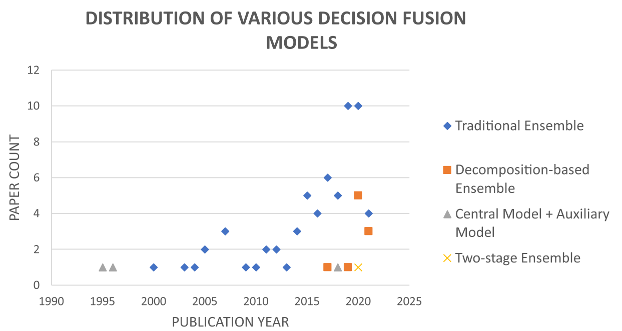

FIGURE 10. **Distribution of decision fusion models.**

had the same data type. Even when these forecasts target different response variables, their data type remains the same, implying that the fusion methods that appeared in this review can only deal with forecasts with the same data type.

VII. CONCLUSION

This study presents a systematic review of the literature related to decision fusion for stock market prediction. It analyzes two essential aspects of the decision fusion process: the base learners and fusion methods. To this end, 75 studies were selected and examined in detail.

A forecasting model that applies decision fusion can consist of only homogeneous base learners, such as ANN, decision trees, SVM, and LSTM, or heterogeneous base learners employing various algorithms. Two studies that used the same set of heterogeneous base learners were rare. For binary classification, the forecasts of the base learners included stock movement trends or stock movement probabilities. In contrast, for multi-class classification, the forecasts of base learners include stock turning indicators, the confidence level of stock movement, stock risk level, or stock movement (e.g., up, neutral, and down). Regression forecasts of base learners mainly refer to future stock prices, stock returns, and stock volatility.

Meanwhile, a forecasting model can employ different methods to fuse the forecasts of base learners. The data type of forecasts is a critical factor in selecting fusion methods. In general, voting and tree-based methods are the two most common fusion methods for classification, while simple averages and ANN are the most commonly used fusion methods for regression.

Decision fusion techniques for stock market predictions have been developing rapidly. Researchers have shifted their attention from the fusion of machine learning forecasts with non-machine learning forecasts in the 1990s to traditional ensembles since 2000 and recently to decomposition-based ensembles.

This study had several limitations. First, relevant articles not included in the selected databases may have been omitted. Second, although the definition of keywords used for the literature search covers many studies, we may have missed some studies that used less common linguistic terms. However, to our knowledge, this review covers most forecasting models that have applied decision fusion. In addition, the findings presented in this review would also be insightful for other financial prediction problems such as cryptocurrency price or exchange rate prediction. Most importantly, these findings will help newcomers keep on the right track when they want to build a model that intends to produce a better prediction by combining multiple forecasts.

Finally, for each forecasting model, the forecasts generated by the base learners always had the same data type. Considering the diversification of forecasts in the stock market and the necessity of decision fusion, the unification of broad classes or even the fusion of forecasts with different data types is a new challenge for stock market prediction in the future. In addition, developing an ensemble with base learners using other algorithms, such as the jump-diffusion model, generative adversarial network (GAN), graph neural network (GNN), and capsule network, can be a future direction for researchers. Furthermore, only a few studies on sentiment-aware prediction have applied decision fusion. The potential of integrating sentiment analysis and decision fusion techniques to improve stock market predictions can be further exploited in future studies.

APPENDIX

See Table 9 and Table 10.

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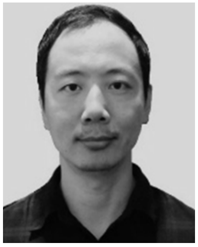

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