Financial Forecasting with Machine Learning and Large Language Models: A Survey

Abstract

This survey explores the integration of advanced computational techniques in financial forecasting, emphasizing the transformative impact of machine learning (ML), large language models (LLMs), and hybrid models. These technologies enhance predictive accuracy and decision-making processes, addressing the complexities of modern financial markets. The survey highlights the role of deep learning in improving predictive capabilities, underscoring the need for customized architectures tailored to specific financial contexts. The integration of diverse techniques, including natural language processing and optimization algorithms, provides a comprehensive framework for analyzing large datasets and optimizing financial outcomes. Advancements in neural network architectures and the application of LLMs in sentiment analysis and market trend prediction demonstrate the potential of these technologies to revolutionize financial forecasting. The survey also discusses the optimization of hybrid models and model fusion, which leverage the strengths of individual methodologies to improve forecasting accuracy. Additionally, the exploration of new methodologies and applications continues to drive innovation, offering opportunities to address evolving challenges in financial markets. The integration of alternative data sources and the development of interpretable AI models are crucial for ensuring transparency and trust in financial forecasting systems. Overall, the survey reinforces the importance of integrating advanced technologies in financial forecasting, highlighting their role in achieving superior financial outcomes and supporting diverse demographics, including low-wage workers, in managing their financial health. As the financial landscape evolves, the adoption of cutting-edge technologies remains essential for maintaining a competitive edge and achieving long-term success in the financial sector.

1 Introduction

1.1 Multidisciplinary Domain Overview

The multidisciplinary domain of financial forecasting integrates diverse computational techniques across sectors such as finance, legal, and life sciences [1]. Large language models (LLMs) and Transformer-based models have been effectively employed to enhance time series forecasting, particularly in volatile markets like cryptocurrencies [2]. The complexity of stock market predictions necessitates advanced methodologies beyond traditional approaches [3], underscoring the crucial role of machine learning (ML) and deep learning (DL) techniques in electronic markets [4].

Natural language processing (NLP) techniques further enrich financial forecasting by analyzing multilingual financial news, addressing the global market's linguistic diversity [5]. The use of psycholinguistic variables from news articles exemplifies the interdisciplinary approach essential in this field [6]. Additionally, the fusion of Vision-Language models with traditional time-series methodologies represents an innovative strategy to improve forecasting accuracy [7].
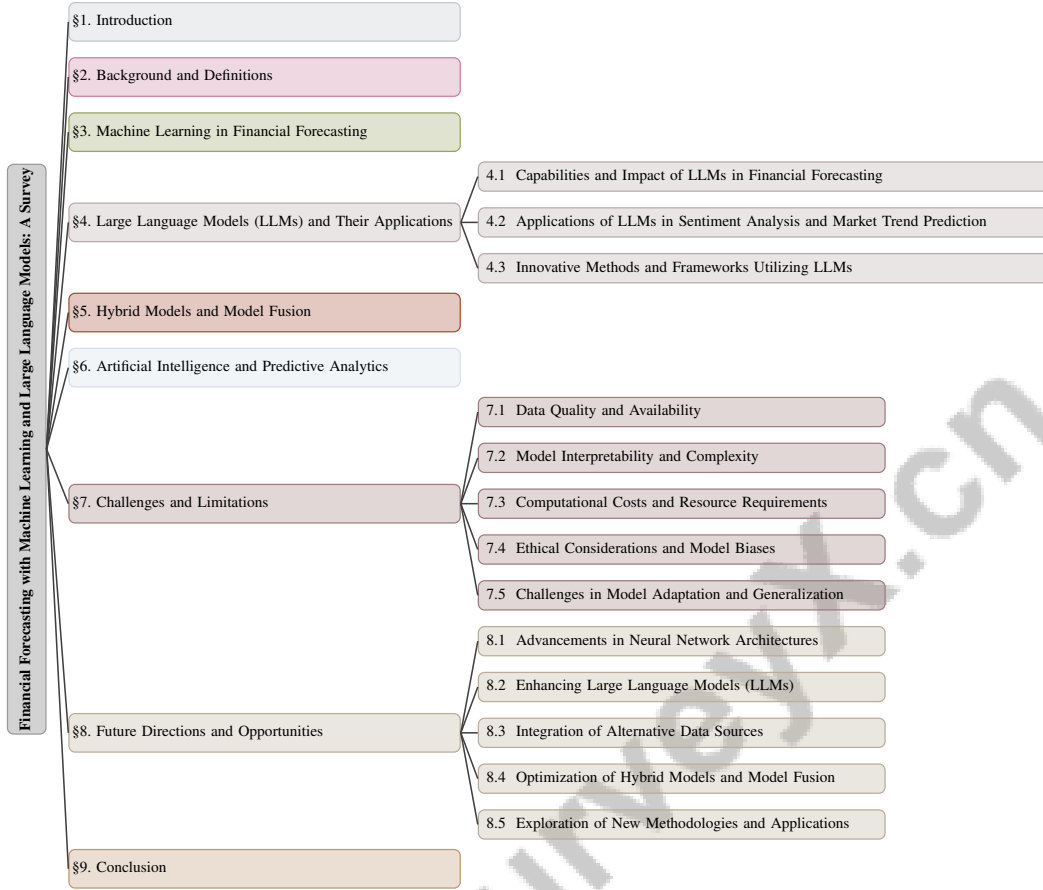
Figure 1: chapter structure

Generative AI and Evolutionary Algorithms play a significant role in large-scale multi-objective optimization, highlighting the complexity inherent in financial forecasting [8]. The organization and structuring of natural language-based financial forecasting (NLFF) techniques and applications clarify the breadth of this multidisciplinary domain [9].

In quantitative finance, asset price prediction remains a challenging yet vital task for both practitioners and academics [10]. Research is categorized into financial forecasting, banking applications, and corporate finance, each utilizing distinct methodologies [11]. The integration of LLMs and optimization algorithms extends beyond finance, influencing areas such as robotics and drug design, further emphasizing the interdisciplinary nature of these technologies [12].

Effective utilization of diverse data streams is crucial for informed investment decisions in the fast-paced financial sector [13]. As financial planning grows increasingly complex, traditional algorithms struggle with nuanced scenarios, paving the way for sophisticated AI and ML solutions [14]. The ongoing advancements in ML methods for financial time series forecasting reflect the demand for robust forecasts in the era of Big Data [15].

1.2 Significance in Quantitative Finance

The integration of advanced technologies in quantitative finance is vital for enhancing predictive accuracy and optimizing decision-making. ML and DL methods have transformed financial forecasting, where even marginal improvements in predictive performance can yield significant financial benefits [16]. Traditional statistical models often inadequately capture complex, non-linear dependencies in financial data, necessitating the adoption of sophisticated methodologies like deep learning [7]. Techniques such as CLIP-LSTM exemplify innovative approaches that enhance forecasting accuracy [7].

Incorporating NLP techniques into financial forecasting not only improves predictive models but also provides deeper insights into market behavior, underscoring the importance of these technologies [9]. Moreover, decision-focused methodologies, particularly in portfolio optimization, highlight the relevance of advanced technologies in informed financial decision-making [17].

Cluster-based regression techniques further illustrate the significance of advanced methodologies in financial forecasting. By identifying clusters and estimating cluster-specific regression parameters, these techniques enhance output predictions and decision-making [18]. The challenge of accurately predicting stock movements based on various factors extracted from news articles emphasizes the need for integrating advanced technologies for improved forecasting [19].

The continuous evolution of the financial landscape necessitates the adoption of cutting-edge technologies to maintain a competitive edge and achieve superior outcomes. These advancements are crucial not only for high-income investors but also for providing personalized financial guidance to underserved demographics, including the approximately 30% of the U.S. workforce engaged in low-wage jobs who often live paycheck to paycheck. By leveraging innovative data mining techniques for small-scale transaction analysis, advancements aim to enhance financial planning tools, such as WageGoal, which primarily serves low-income individuals. This targeted approach addresses the financial instability faced by diverse segments of the population, facilitating improved budgeting and cash flow management tailored to their unique challenges [11, 20].

1.3 Structure of the Survey

The survey is systematically organized to provide a comprehensive exploration of financial forecasting utilizing machine learning, large language models (LLMs), hybrid models, and artificial intelligence. It begins with an introduction to the multidisciplinary domain, emphasizing the integration of diverse computational techniques and their significance in quantitative finance. This is followed by a background section defining core concepts and terminologies relevant to financial forecasting, including machine learning, LLMs, hybrid models, AI, and predictive analytics.

Subsequent sections focus on specific methodologies and their applications: "Machine Learning in Financial Forecasting" discusses various ML algorithms, neural networks, and advanced regression techniques; "Large Language Models and Their Applications" explores the capabilities and impact of LLMs, particularly in sentiment analysis and market trend prediction; and "Hybrid Models and Model Fusion" examines the conceptual framework and advantages of model combinations, supported by case studies.

The survey further discusses the integration of AI and predictive analytics in financial forecasting, emphasizing decision-making improvements through AI techniques and interpretable models. Challenges and limitations associated with these technologies, such as data quality, model interpretability, and ethical considerations, are addressed in a dedicated section.

Finally, the survey concludes with future directions and opportunities, exploring advancements in neural network architectures, enhancements in LLMs, and the integration of alternative data sources. Each section is meticulously crafted to build upon existing literature and provide insights into the evolving landscape of financial forecasting.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Core Concepts in Financial Forecasting

The integration of machine learning (ML) and artificial intelligence (AI) is pivotal in enhancing the predictive accuracy and decision-making processes within financial forecasting. Traditional methods, such as technical and fundamental analyses, often fall short in addressing market complexities [21]. Advanced computational techniques, including deep learning models, demonstrate their transformative potential, as evidenced by applications in predicting indices like KOSPI 200 [21]. Distinguishing between predictive tasks and causal inference is critical for financial planning, particularly in stock prediction, where ML algorithms are assessed based on their ability to forecast performance using quarterly data [22, 23]. The high-dimensional and unstructured nature of financial data necessitates sophisticated preprocessing and model selection strategies to enhance prediction reliability [10, 24].

Optimization algorithms and large language models (LLMs) are essential in algorithm design and model optimization, forming the foundation of effective financial forecasting [12]. Enhancing interpretability through natural language explanations in time series models increases understanding and trustworthiness [25]. However, single-agent systems in financial LLM applications present inefficiencies in prioritizing critical memory events for optimized trading [13]. The volatility of stock markets underscores the need for interpretable decision-making models tailored to diverse investor needs [26]. Traditional linear models often fail to capture non-linear relationships in high-dimensional datasets, necessitating advanced methodologies adept at handling non-Gaussian returns [27]. Research continues to focus on improving forecasting accuracy and efficiency, particularly in churn prediction and credit risk assessment [28].

Predicting stock market volatility using sentiment scores from financial news highlights the importance of integrating diverse data sources and methodologies [29]. Addressing these core concepts and challenges is vital for advancing financial forecasting and improving prediction reliability in economic and financial time series data. Supervised ML methods, including linear and nonlinear models such as penalized regressions, neural networks, and ensemble methods, play a crucial role in this domain [15]. Accurate prediction of mean-reverting financial time series, often affected by noise, requires robust methods to capture long-term trends [30].

The correlation of news events with stock price movements and the application of sentiment analysis to understand market dynamics emphasize the influence of news sentiment on stock prices. Utilizing natural language processing techniques to predict financial market dynamics from textual data remains challenging [9]. Predicting future stock market directions based solely on historical price data necessitates innovative methodologies [7]. Additionally, predicting outputs based on input data varying across different clusters underscores the significance of tailored regression parameters in financial forecasting [18]. The challenge of utilizing high-dimensional data complicates the training of recurrent neural networks (RNNs) due to exponential parameter growth [31]. Finally, predicting mid-price movement in financial time series, particularly from limit order books, involves understanding complex market behaviors [32]. These core concepts and challenges highlight the evolving landscape of financial forecasting and the necessity for continuous methodological and application innovation.

In recent years, the integration of machine learning techniques into financial forecasting has transformed the landscape of predictive analytics. This evolution is characterized by a variety of approaches and methodologies that enhance the precision and reliability of market predictions. To illustrate this transformation, Figure 2 presents a comprehensive overview of the hierarchical structure of machine learning applications in financial forecasting. This figure highlights key techniques, models, and innovations across three main categories: Machine Learning and Its Role in Finance, Neural Networks and Deep Learning Models, and Advanced Regression and Tensor Models. Each category is meticulously detailed with specific methods and their applications, showcasing the diverse and dynamic nature of financial market predictions. By examining these categories, we can better understand the multifaceted approaches that contribute to the efficacy of financial forecasting in contemporary markets.

3 Machine Learning in Financial Forecasting

3.1 Machine Learning and Its Role in Finance

Machine learning (ML) is integral to financial forecasting, offering sophisticated techniques to navigate the complexities of dynamic and non-stationary financial markets [4]. Methods such as Random Forest, Support Vector Machines (SVM), Multi-Layer Perceptron, and Gradient Boosting effectively discern intricate patterns, thereby enhancing stock price prediction accuracy. Neural network architectures, notably Convolutional Neural Networks (CNNs), excel in identifying complex patterns often missed by conventional methods [4]. The Wasserstein Deep Learning Model (WDL) further refines predictions by incorporating class distances, leading to more accurate forecasts [33]. Long Short-Term Memory (LSTM) networks, particularly when integrated with other architectures, demonstrate the efficacy of hybrid approaches in financial forecasting [6].

Innovative frameworks like LLMFactor utilize Sequential Knowledge-Guided Prompting (SKGP) to extract relevant factors from news articles impacting stock prices, merging natural language processing with ML for market trend predictions [19]. The TT-RNN model simplifies recurrent

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neural networks' parameter complexity while maintaining the multi-modal structure of financial data, enhancing both generalization and interpretability [31]. HeMLGOP, employing a heterogeneous neural architecture, addresses prediction tasks and imbalanced data challenges, showcasing ML's adaptability in financial contexts [32]. Transformer-based models, such as TradingGPT, further highlight ML's role in classifying time series data and predicting sharp market movements [34].

As illustrated in Figure 3, the categorization of machine learning techniques and frameworks in financial forecasting underscores the primary forecasting techniques, innovative frameworks, and decision-making models that enhance financial prediction and decision-making processes. The development of interpretable decision-making models that incorporate technical indicators and ML techniques provides transparent investment signals, catering to diverse investor needs and enhancing confidence in financial decision-making [16]. As financial markets evolve, the adoption of ML techniques remains vital for navigating market dynamics and achieving superior forecasting outcomes, enriching ML applications in finance through various perspectives, including connectionist and portfolio management [9]. The integration of ML with optimization and quantum-enhanced methods, alongside exploring Gaussian Processes for mean-reverting time series, represents the cutting edge of innovation in this domain [7].

3.2 Neural Networks and Deep Learning Models

Method Name	Model Types	Integration Techniques	Performance Enhancement
LSTM[35]	Lstm Networks	Hyperparameter Tuning	Feature Selection
LSTM+ANN[3]	Lstm, Ann	Stacking Approach	Linear Regression Meta-model
TT-RNN[31]	Tt-RNN	Tensor Decomposition	Dimensionality Reduction
HeMLGOP[32]	Heterogeneous Architecture	Nonlinear Transformations	Adaptively Map
DPLS[27]	Deep Neural Network	Projection-based Dimensionality	Outlier Detection Methods
ODC[36]	-	Tensor Decomposition	Outlier Detection

Table 1: Summary of neural network and deep learning methodologies applied in financial forecasting, highlighting various model types, integration techniques, and performance enhancement strategies. The table provides a comparative overview of methods such as LSTM, LSTM+ANN, TT-RNN, HeMLGOP, DPLS, and ODC, detailing their unique approaches to improving forecasting accuracy and adaptability.

Table 1 presents a comprehensive comparison of neural network and deep learning models utilized in financial forecasting, emphasizing their integration techniques and performance enhancement strategies. Neural networks and deep learning models are pivotal in financial forecasting, adept at capturing intricate patterns in high-dimensional datasets. Long Short-Term Memory (LSTM) networks are particularly effective for sequential data, making them ideal for time series forecasting in finance [35]. Their predictive capabilities are enhanced through integration with other architectures, such as Artificial Neural Networks (ANN), improving stock price forecasting accuracy [3]. Deep learning models, including Multi-Layer Perceptrons (MLP) and CNNs, demonstrate superior performance in financial series prediction by leveraging their capacity to process large datasets and adapt to the dynamic nature of financial markets [4]. Attention networks, which achieve notable hit ratios, further emphasize relevant input features, enhancing forecasting outcomes [21].

Novel architectures, such as deep-embedded networks that combine categorical variable embeddings with deep learning methods, improve prediction accuracy in business analytics [37]. The Tensor-Train Recurrent Neural Network (TT-RNN) employs tensor decomposition to reduce parameter complexity while enhancing interpretability, showcasing the adaptability of neural networks in financial contexts [31]. The HeMLGOP algorithm illustrates an adaptive neural architecture that progressively constructs a neural network for predicting financial time series while addressing class imbalance, highlighting the capacity of neural networks to tackle diverse forecasting challenges [32]. Projection-based dimensionality reduction techniques, such as Deep Partial Least Squares (DPLS), enhance neural networks by projecting firm characteristics and asset returns onto a subspace of latent factors, facilitating nuanced financial predictions [27].

Comparative studies indicate that neural forecasting models utilizing deep learning techniques significantly outperform traditional statistical benchmarks in adaptability and accuracy [38]. The adaptability of these models is further enhanced by outlier detection techniques, such as the PKDE method, which effectively identifies anomalous data points, surpassing traditional methods [36]. The ongoing evolution of neural network architectures, coupled with advancements in optimization

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algorithms and the integration of ML techniques into time series forecasting, underscores the critical role of deep learning in finance. These developments, along with the superior performance of models like MLPs and Linear Regression in achieving higher R² values and lower RMSE, reinforce the significance of neural networks and deep learning models in achieving exceptional forecasting outcomes [39].

3.3   Advanced Regression and Tensor Models

Advanced regression techniques and tensor models are crucial in enhancing financial forecasting by capturing complex, multi-dimensional relationships within financial data. The Cluster-Based Regression Using Variational Inference (CBR-VI) method exemplifies this by identifying clusters in input data and estimating cluster-specific regression parameters, significantly improving predictive accuracy [18]. This approach accommodates the diverse and dynamic nature of financial markets. Tensor models, such as those incorporating recursive autoencoders, provide sophisticated frameworks for processing financial data sequences, creating compact, lower-dimensional representations that encapsulate essential contextual information [40]. These models effectively address the high-dimensionality and non-linearity of financial datasets, offering improved insights and predictive capabilities.

The integration of Wasserstein loss in time series forecasting enhances point estimation accuracy compared to traditional cross-entropy loss, thereby refining the performance of financial forecasting models [33]. This methodological innovation highlights the importance of tailored loss functions in optimizing model performance for financial applications. Dynamic methods like HeMLGOP demonstrate the potential of architectures that adapt based on data, effectively capturing complex relationships and mitigating biases from imbalanced classes [32]. Such adaptability is crucial in financial forecasting, where market conditions and data distributions can change rapidly.

These advanced regression and tensor models significantly contribute to financial forecasting by providing robust frameworks capable of handling the intricacies of financial data. The integration of advanced text-mining technologies enhances prediction accuracy and reliability, enabling informed decision-making processes. By leveraging innovative deep learning models and interpretable AI techniques, financial analysts can analyze vast amounts of unstructured data, including market news and earnings calls, leading to improved forecasting of stock movements and investment recommendations. These advancements not only bolster investor confidence but also ensure that predictions align closely with actual market outcomes, critical in a domain where misinterpretation costs can be substantial [29, 11, 40, 41, 26].

4   Large Language Models (LLMs) and Their Applications

The integration of Large Language Models (LLMs) is crucial in modern financial forecasting, serving as advanced tools for enhancing predictive accuracy and decision-making. This section examines the transformative role of LLMs in financial forecasting, highlighting their impact on predictive precision and market dynamics understanding.

4.1   Capabilities and Impact of LLMs in Financial Forecasting

LLMs revolutionize financial forecasting by blending qualitative insights with quantitative analytics, enhancing accuracy and interpretability. This is visually represented in Figure 4, which illustrates the hierarchical categorization of the capabilities and impacts of LLMs in financial forecasting. The figure highlights three main areas: the integration of qualitative and quantitative insights, enhancements in predictive accuracy, and the development of adaptive and robust models. Each category is supported by specific methodologies and innovations from recent research, showcasing LLMs' diverse applications in financial contexts.

LLMs excel at processing extensive textual data, extracting sentiment and psycholinguistic features that affect market behavior. Unlike traditional sentiment analysis, LLMs dynamically adjust predictions based on event-induced insights [42]. Models like TradingGPT employ layered memory systems to categorize information, essential for nuanced analysis in volatile markets [13]. Their integration in multi-objective optimization enhances decision variable understanding, demonstrating versatility in complex tasks [8].

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Recursive autoencoders within LLM architectures outperform traditional methods in predicting stock movements post-disclosures, bridging qualitative expert knowledge with quantitative analytics [40, 34]. LLM advancements improve generalization and multi-task performance, crucial in multilingual contexts for diverse linguistic environments [43, 44]. LLMFactor offers clearer market dynamics insights, enhancing forecasting accuracy [19].

Dynamic adaptive optimization (DAO) modules adjusting loss weights enhance model convergence and performance over static methods [45]. LLMs outperform smaller models in complex reasoning and in-context learning tasks [46]. Their potential in modeling market agents towards competitive equilibria underscores their role in understanding market dynamics [47]. LLMs provide comprehensive uncertainty estimates, robust against noise, often surpassing simpler models [30]. Continued research promises further refinement for effective deployment in finance.

4.2 Applications of LLMs in Sentiment Analysis and Market Trend Prediction

LLMs, such as ChatGPT, significantly enhance sentiment analysis and market trend prediction in finance. Their ability to process complex natural language inputs is pivotal for extracting sentiment from textual data, crucial for market movement predictions [48]. Utilizing neural network models with word and character-level encoders, LLMs classify numerals in financial tweets, providing market sentiment insights [49].

LLMs excel in bilingual financial tasks, facilitating cross-linguistic comparisons and market dynamics comprehension [44]. By merging text-based key factors with numerical data, LLMs dynamically update to reflect the latest market information, enhancing trend prediction accuracy [50]. Comparative surveys of models like GPT-3, GPT-4, and BERT emphasize the importance of model selection for specific sentiment analysis tasks [51]. DAO modules applied to financial text datasets improve LLM performance by adjusting loss weights during training, enhancing convergence and accuracy in trend prediction [45].

LLMs in experimental market environments, such as double auction simulations, provide insights into their behavior against market equilibrium benchmarks, demonstrating their capacity to model complex interactions [47]. These applications illustrate LLMs' transformative impact on sentiment analysis and market trend prediction, offering robust tools for navigating financial market complexities.

As shown in Figure 5, LLMs are foundational in AI, offering transformative applications in sentiment analysis and market trend prediction. The first figure categorizes language modeling techniques, highlighting LLMs' pivotal role. The second figure illustrates LLM training processes, such as pretraining and transfer learning. The third figure tracks research growth on LLMs, reflecting rapid advancement and interest. These visual aids underscore LLMs' significance in enhancing sentiment analysis and market trend prediction, providing insights into their development and expanding influence [51, 52, 43].

4.3 Innovative Methods and Frameworks Utilizing LLMs

Innovative LLM methods and frameworks have advanced financial forecasting by enhancing interpretability, reducing costs, and improving decision-making. Wimmer et al. use CLIP models to process stock data as images and text, enhancing predictive performance through multimodal integration [7]. Dynamic memory mechanisms like LDM2 update state-action tuples, improving forecast accuracy by adapting to market conditions. Graph Laplacian matrices in the Graph-Regularized Tensor Regression (GRTR) framework enhance model interpretability and performance by embedding economic relationships into modeling, addressing high-dimensional data challenges [53, 31, 27].

Quantized LLMs with efficient memory footprints lower deployment costs, expanding accessibility in financial forecasting, where qualitative and quantitative data integration is crucial [34, 50, 43, 54]. A taxonomy categorizing hallucination mitigation techniques offers insights into improving LLM output reliability in financial decision-making [34, 50, 55, 56]. Tailored approaches for refining LLMs for domain-specific tasks further illustrate their versatility.

Arithmetic-GPT, a model pretrained for arithmetic tasks, exemplifies targeted LLM applications to improve decision-making accuracy. Integrating LLMs into financial processes enhances contextual trade-offs and provides customized explanations for stakeholders. Frameworks like LLMFactor use Sequential Knowledge-Guided Prompting (SKGP) for extracting stock movement factors and

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converting qualitative insights into quantifiable metrics. By dynamically updating reports and merging with numerical data, LLMs offer timely analyses that outperform traditional models in financial forecasting, improving decision-making effectiveness [19, 50].

The DAO module, as a plug-and-play component, significantly enhances LLM adaptability. It facilitates sentiment analysis by adjusting task weights based on data characteristics, addressing multi-task learning challenges. Empirical studies show substantial model performance improvements, demonstrating LLM frameworks' potential to adapt and optimize across applications [8, 45, 34, 12, 50]. These methods and frameworks underscore LLMs' transformative potential in financial forecasting, paving new research and application avenues.

As shown in Figure 6, LLMs like GPT-4 are pivotal in AI, driving innovation in NLP. The figure presents deep learning models in NLP, highlighting modern frameworks' complexity. Few-shot learning with GPT-4 demonstrates its versatility. This section lists models, including Falcon-40b-4bit and Llama-2-13b, illustrating diverse methodologies to enhance performance with minimal data. These examples underscore innovative methods and frameworks leveraging LLMs to advance language understanding and generation [52, 57].

5   Hybrid Models and Model Fusion

Hybrid models in financial forecasting integrate diverse computational techniques to enhance predictive accuracy and adaptability in dynamic markets. They combine various methodologies to address the complexities of financial markets, offering a robust approach by leveraging strengths and mitigating weaknesses. The following subsection explores the conceptual framework of hybrid models, detailing their role in improving prediction and adaptability.

5.1   Conceptual Framework of Hybrid Models

Hybrid models in financial forecasting integrate diverse computational techniques to improve predictive accuracy and adaptability. By combining methodologies, these models leverage strengths while mitigating weaknesses, offering a robust forecasting approach. A prime example is the integration of text mining and machine learning for stock price prediction, which combines qualitative insights from textual data with quantitative modeling [6].

The framework includes multi-agent systems with layered memory architectures, as seen in TradingGPT, which enhances decision-making and trading strategies through agent collaboration [13]. This highlights the importance of memory management in adaptive forecasting models responding to market changes.

Innovations like the NLFF method showcase hybrid models' versatility by integrating sentiment analysis and event extraction to boost forecasting accuracy [5]. Similarly, Text2TimeSeries dynamically adjusts predictions based on real-time events, enhancing outcomes [42].

The FinSen dataset, combining sentiment analysis with temporal attributes, and the novel Focal Calibration Loss enrich the hybrid framework by structuring model calibration and boosting accuracy [29]. Additionally, LLMs identify and encode patterns like money laundering activities, translating expert intuition into quantifiable insights [34].

The multifaceted design of hybrid models in financial forecasting integrates various techniques to address market complexities. By combining methodologies, hybrid models enhance predictive capabilities and adaptability, outperforming traditional approaches and capturing non-linear dynamics in financial time series. Event-driven insights from large language models provide a nuanced understanding of non-numeric factors influencing market trends, making hybrid models essential for real-time decision-making in the evolving financial landscape [42, 38].

5.2   Applications and Case Studies

Hybrid models significantly enhance financial forecasting by integrating diverse methodologies for improved predictive accuracy and adaptability. A notable application is the combination of Long Short-Term Memory (LSTM) networks with Artificial Neural Networks (ANN) for financial time series prediction. Tested on 860 million trading records from SP 500 companies, the LSTM+ANN

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model outperformed traditional models like CNN, RNN, and ARIMA, demonstrating superior performance in capturing complex, non-linear dependencies [3].

A case study highlights the integration of sentiment analysis with quantitative models for stock price forecasts using advanced Large Language Models (LLMs). Combining qualitative insights from securities firms' reports with numerical data creates contextually rich datasets, significantly outperforming traditional models in financial forecasting despite challenges in reproducibility and explainability [19, 50, 42]. By leveraging textual data from financial news and social media, hybrid models enhance market prediction accuracy by integrating sentiment scores with traditional indicators.

Hybrid models are also effective in portfolio optimization, combining machine learning techniques with optimization algorithms for optimal asset allocation. These models use historical price data, economic indicators, and investor sentiment, integrating techniques like Sequential Knowledge-Guided Prompting (SKGP) and SHAP-based explainability. This approach identifies critical stock movement drivers, enhances investment strategy interpretability, and adapts to market changes, improving investor confidence and portfolio performance [19, 26].

In risk management, hybrid models integrating traditional statistical techniques with advanced machine learning, including text mining and neural networks, predict credit risk and default likelihood. Leveraging extensive financial data, including textual information from earnings reports and market sentiment, these models enhance predictive accuracy and robustness for informed decision-making in dynamic environments [11, 38, 16, 17]. By integrating machine learning with traditional risk assessment, these models offer enhanced predictive capabilities for better risk management and decision-making.

Recent research emphasizes hybrid models' adaptability and efficacy in financial forecasting, integrating numerical time series with textual information from news events for enhanced predictive accuracy and robustness. Advancements like N-HiTS, N-BEATS neural forecasting models, LLMFactor, and Text2TimeSeries showcase their ability to manage financial market complexities and non-linear dynamics, supporting real-time decision-making and making hybrid models critical in modern financial analysis [19, 22, 38, 11, 42].

In Figure 7, hybrid models and model fusion are exemplified through practical applications and case studies. The "Transformer Recurrent Decoder Architecture" figure illustrates the integration of transformer and recurrent neural network components for optimized token generation and processing, highlighting the power of combining model architectures for robust language processing. The "Schematic of Sections" figure demonstrates hybrid models' application in organizing and synthesizing complex information, particularly in generative AI and creativity. The "Prompts and Techniques for Hallucination Mitigation in Large Language Models" figure provides insight into hybrid models' role in improving large language models' reliability by mitigating hallucinations, categorizing techniques used at different stages of language generation. These examples demonstrate hybrid models' transformative potential and model fusion across various applications, paving the way for more intelligent and adaptable AI systems [48, 51, 55].

5.3 Innovative Hybrid Methodologies

Innovative hybrid methodologies in financial forecasting integrate advanced computational techniques to enhance predictive performance and accuracy. The LLMFactor framework exemplifies this by improving factor extraction related to stock price movements, surpassing traditional sentiment or keyphrase-based methods [19]. This demonstrates the potential of combining large language models (LLMs) with quantitative analytics for actionable financial insights.

Integrating LLMs with machine learning algorithms has led to sophisticated hybrid models capable of processing and analyzing complex financial datasets. These models use LLMs' advanced natural language processing capabilities to analyze and integrate qualitative data from financial news and reports. By transforming subjective insights into quantifiable features, these models enhance market dynamics' contextual understanding, enabling more accurate financial forecasting and decision-making. This integration addresses multimodal information challenges and leverages real-time updates and background knowledge for a robust stock movement prediction framework [19, 50, 34]. By combining qualitative insight with quantitative data analysis, hybrid models offer comprehensive and accurate market predictions.

Real-time data processing capabilities in hybrid forecasting models enable dynamic adjustments based on market conditions, enhancing prediction accuracy and relevance. Incorporating numerical data and textual insights from news events provides a comprehensive understanding of market influences. Using causal feature selection and sentiment analysis, these models align probabilistic forecasts with actual outcomes, improving decision-making for investors and stakeholders in the financial sector [19, 29, 50, 42, 26]. This adaptability is crucial in volatile financial environments where rapid changes impact market trends and investment strategies.

Overall, innovative hybrid methodologies significantly advance financial forecasting by strategically integrating diverse computational techniques. Combining LLMs with advanced machine learning techniques provides a sophisticated approach to analyzing and forecasting financial markets. This is achieved by integrating qualitative insights from securities firms' reports with quantitative data, creating contextually rich information sets that enhance prediction accuracy. For example, the LLMFactor framework uses Sequential Knowledge-Guided Prompting to identify and explain stock movement factors, moving beyond traditional sentiment analysis. These approaches have shown improved performance over conventional time-series models, though challenges like reproducibility and explainability remain [19, 50].

In Figure 8, innovative hybrid methodologies are exemplified through diverse model and technique integration, advancing various domains. The first example compares simple and CoT-based error detection methods in GPT-4 and Claude 2.1, highlighting different approaches' efficacy in identifying errors with detailed detection rates. The second example uses a Venn diagram to explore the intersection of Natural Language Processing (NLP) and Financial Forecasting, underscoring shared and unique elements within each field, like "Embedding," "Word," and "Parsing," demonstrating how NLP technique fusion enhances financial forecasting capabilities. These examples illustrate hybrid models' potential to leverage multiple methodologies' strengths, fostering innovation and improved performance in complex tasks [58, 11].

6 Artificial Intelligence and Predictive Analytics

6.1 AI Techniques in Financial Forecasting

AI techniques play a crucial role in enhancing predictive accuracy and navigating market complexities in financial forecasting. As illustrated in Figure 9, key AI techniques include the Graph Regularized Tensor Regression (GRTR) method, which integrates domain knowledge via graph regularization, effectively mitigating overfitting and revealing significant relationships within financial data [53]. The Multi-objective Co-evolution Framework (MOCF) further optimizes feature selection and neural architecture amid market disruptions, enhancing forecasting performance [59]. Additionally, the figure highlights the combination of Long Short-Term Memory (LSTM) networks with Artificial Neural Networks (ANN), an approach that adeptly addresses non-linear dependencies, thereby improving stock price prediction accuracy [3].

Advanced normalization techniques, such as Bilinear Input Normalization (BiN), enhance parameter optimization alongside neural networks, aligning multivariate financial time-series data to improve model precision [60]. AI models further benefit from informed feature selection and hyperparameter tuning in LSTM networks, significantly boosting stock price prediction accuracy. Reinforcement learning methods optimize savings and investment strategies, maximizing the probability of achieving diverse financial objectives [14]. Additionally, employing Wasserstein loss in time series forecasting refines point estimation accuracy, showcasing the efficacy of tailored loss functions in AI models [33].

Moreover, variational inference for estimating regression parameters in cluster-based models enhances accuracy by tailoring models to specific market regimes [18]. Collectively, these AI techniques underscore the transformative potential of advanced computational methods in improving financial forecasting accuracy and reliability.

6.2 Interpretable AI Models

Interpretable AI models are vital in finance, where transparency and accountability are paramount. These models offer clear insights into decision-making processes, fostering trust among financial practitioners. Explainable AI (XAI) techniques, such as SHAP (SHapley Additive exPlanations) and

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LIME (Local Interpretable Model-agnostic Explanations), demystify complex AI models, making them accessible to users without deep technical expertise [16]. Interpretability is crucial in applications like credit scoring and risk assessment, where understanding predictive factors is essential for regulatory compliance and customer trust. By elucidating the variables driving predictions, interpretable AI models enable financial institutions to justify their decisions and mitigate potential data biases [18].

Attention mechanisms in neural networks enhance interpretability by highlighting relevant input features contributing to model outputs. This not only improves model transparency but also boosts predictive performance by focusing on the most informative data aspects [21]. The synergy of interpretability and predictive accuracy is particularly valuable in high-stakes financial contexts, where decisions have significant economic repercussions.

Advancing interpretable AI models represents a crucial research frontier, driven by the growing demand for transparency and accountability in decision-making. These models enhance investor confidence and profitability by providing insights into factors influencing financial forecasts, as evidenced by innovative approaches like SHAP-based explainability techniques and deep learning frameworks that improve predictive accuracy and feature extraction from complex financial data [19, 11, 40, 41, 26]. By addressing challenges in traditional equity research and forecasting systems, interpretable AI models foster stakeholder trust and facilitate informed investment decisions in a rapidly evolving market environment.

6.3 Integration of Text Mining and Predictive Analytics

The integration of text mining techniques with predictive analytics has revolutionized financial forecasting by extracting insights from unstructured textual data, such as financial news, reports, and social media posts. This approach enhances predictive capabilities by incorporating qualitative data, providing a comprehensive understanding of market dynamics. Text mining methods, including natural language processing (NLP) and sentiment analysis, systematically extract and quantify sentiment and psycholinguistic features from extensive textual datasets, facilitating the analysis of relationships between public sentiment and market dynamics [11, 19, 42, 9].

Advanced language models, particularly Large Language Models (LLMs), have further improved the integration of text mining and predictive analytics by enhancing sentiment analysis and trend prediction capabilities. LLMs excel at interpreting intricate language patterns, extracting nuanced insights from textual data, and converting qualitative insights from domain experts into quantifiable features that improve predictive accuracy. By integrating textual information from daily securities reports with numerical data, LLMs create contextually rich datasets that enable informed decision-making in financial analytics [50, 34]. This integration is particularly effective in multilingual contexts, facilitating cross-linguistic comparisons and improving market forecast accuracy.

Combining text mining with machine learning algorithms enables the development of hybrid models that leverage both qualitative and quantitative data, resulting in robust and adaptable forecasting models responsive to changing market conditions. For instance, frameworks incorporating real-time sentiment analysis into predictive models allow for timely and accurate market predictions, providing a competitive edge in fast-paced financial environments [42].

The integration of text mining techniques with predictive analytics signifies a substantial advancement in financial forecasting, enhancing predictive performance through diverse data sources and methodologies. This approach not only improves market prediction accuracy by utilizing advanced techniques such as Sequential Knowledge-Guided Prompting and deep learning models but also offers insights into factors influencing market behavior, including the impact of earnings conference calls and financial disclosures on stock movements. By employing large language models to extract and analyze relevant data, this method clarifies the complexities driving stock price fluctuations, ultimately enhancing decision-making for investors and stakeholders [19, 41, 40, 26].

7 Challenges and Limitations

Addressing the challenges and limitations in financial forecasting requires a detailed examination of factors affecting predictive model efficacy. Data quality and availability are paramount, influencing prediction reliability and the success of forecasting endeavors. The following subsections delve

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into the complexities of data quality and availability, model interpretability, computational costs, ethical considerations, and model adaptation challenges, highlighting the primary obstacles faced by researchers and practitioners.

7.1 Data Quality and Availability

Financial forecasting is significantly constrained by data quality and availability, which directly affect model accuracy and reliability. Financial datasets often present high dimensionality and noise, complicating model selection and requiring robust statistical foundations for machine learning methods. These datasets frequently exhibit non-stationarity and fat tails, leading to unreliable predictions with traditional methods [31]. Imbalanced data distributions further introduce biases favoring majority classes [32].

The use of outdated algorithms and legacy language models can impede advancements in natural language processing, affecting prediction quality and market dynamics capture. This limitation is evident in methods like LLMFactor, which may face challenges in prediction accuracy due to data representation inconsistencies [47]. The scarcity of high-quality data, especially news articles misaligned with market movements, exacerbates these issues. Traditional models often rely on historical numerical data without adequately integrating non-numeric factors like economic news or market sentiment, undermining forecast robustness. While innovative datasets like FinSen and methodologies incorporating large language models (LLMs) aim to enhance predictive accuracy, inconsistencies in text-based forecasting methods raise concerns about reliability, emphasizing the need for comprehensive models that account for financial markets' dynamic nature [16, 26, 29, 42]. Current benchmarks often fail to assess prediction consistency, a critical factor for model reliability.

Processing noisy social media data and the lack of standardized evaluation metrics further highlight the need for improved data quality and availability. Managing large datasets presents significant challenges, necessitating scalable solutions for training LLMs and advanced machine learning applications. As LLMs evolve, their performance increasingly depends on access to diverse datasets, emphasizing innovative methodologies to handle large-scale data processing complexities [52, 51, 34, 37, 1]. Addressing these challenges requires innovative approaches that enhance data quality, improve model robustness, and integrate diverse data sources to capture market dynamics. Advanced frameworks like LLMFactor and ECC Analyzer utilize LLMs and innovative extraction techniques to bolster forecasting models' reliability and effectiveness, providing clearer insights and fostering greater stakeholder confidence in investment decisions [19, 41, 26].

7.2 Model Interpretability and Complexity

Model interpretability and complexity are pivotal in developing and deploying financial forecasting models. The complexity of financial markets often necessitates sophisticated models with numerous parameters, complicating interpretation and increasing overfitting risks [61]. Balancing model accuracy with transparency and explainability presents significant challenges.

Models like Convolutional Neural Networks (CNNs) are highly sensitive to parameter settings, affecting performance and complicating result interpretability [62]. This sensitivity underscores the importance of careful parameter tuning and model selection to ensure robustness and interpretability. Additionally, the high computational demands of training these complex models require rigorous statistical validation to prevent overfitting and ensure generalization to unseen data [15].

Maintaining interpretability while utilizing complex models is further complicated by analyzing high-dimensional financial datasets, often requiring advanced techniques such as SHAP-based explainability and LLMs for actionable insights. These methods enhance prediction clarity and investor confidence by elucidating the factors influencing forecasts, addressing market volatility, and improving decision-making processes for stakeholders [41, 26]. This necessitates a trade-off between complexity and interpretability, as simpler models may offer greater transparency but at the cost of reduced predictive power.

Researchers increasingly focus on methods that enhance interpretability without sacrificing performance. Techniques such as model simplification, interpretable machine learning frameworks, and incorporating domain knowledge into model design are being explored to improve transparency and usability in financial forecasting. These initiatives are essential for effectively applying complex

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models in finance, facilitating clear, actionable insights by integrating qualitative and quantitative data, ultimately enhancing decision-making processes and addressing challenges related to data context and model explainability [11, 50].

7.3 Computational Costs and Resource Requirements

The computational costs and resource requirements of advanced financial forecasting models pose significant challenges, particularly regarding deploying LLMs and complex machine learning architectectures. A core obstacle is the substantial memory overhead required to maintain multiple models and the high costs of training these models, especially when they are not open-source [54]. This issue is exacerbated by the need to process vast amounts of data, necessitating considerable computational power and storage capacity.

Deploying LLMs in financial forecasting often involves significant resource allocation due to their size and complexity. Models like GPT-3 and GPT-4 demand substantial computational resources for training and inference, creating barriers to accessibility for many organizations. High costs associated with necessary hardware and electricity often limit usage to well-funded entities like major tech companies, constraining deployment in smaller research labs and startups and impacting broader adoption across sectors like healthcare, finance, and education [2, 48, 57, 51].

Moreover, the high computational demands of training deep learning models, such as CNNs and LSTMs, contribute to the resource-intensive nature of financial forecasting. Implementing these models necessitates significant computational resources, specifically high-performance GPU and CPU capabilities, leading to elevated operational costs and energy consumption, posing challenges for organizations with limited budgets or infrastructure. While these models can enhance predictive accuracy and decision-making, their deployment must be carefully considered regarding resource allocation and sustainability [51, 48, 12, 37].

Efforts to mitigate these challenges include developing more efficient algorithms and employing model compression techniques to reduce memory and computational requirements. Advancements in cloud computing and distributed processing offer promising solutions for large-scale financial forecasting by providing scalable resources to manage the vast amounts of data generated in the financial sector. These technologies enable sophisticated text-mining applications leveraging LLMs to extract valuable insights from unstructured data, enhancing predictive accuracy and addressing financial analytics complexities [11, 41].

To facilitate widespread adoption of advanced forecasting models in finance, addressing computational costs and resource requirements is essential, especially given the growing complexity of financial data and the need for efficient processing methods like machine learning and neural network models such as N-HiTS and N-BEATS. These models show promise in enhancing predictive accuracy and adapting to intricate financial time series dynamics, underscoring the necessity of optimizing resource utilization for effective implementation across various financial applications [11, 22, 38].

7.4 Ethical Considerations and Model Biases

Ethical considerations and model biases present critical challenges in deploying financial forecasting models that utilize advanced technologies like LLMs and AI. The novelty of LLMs and their data collection strategies can limit quantifying their economic value, raising concerns about applicability and fairness in real-world financial contexts [56]. These models can generate biased or harmful content, posing significant ethical risks, especially in sensitive financial decision-making processes [43].

The interpretability of LLMs remains a pressing issue, as understanding decision-making processes is crucial for ensuring transparency and accountability in financial forecasting [52]. The lack of clarity in model outputs can lead to mistrust among users and stakeholders, highlighting the need for frameworks that enhance interpretability in AI-driven financial models [51].

Furthermore, potential biases inherent in AI technologies are a significant concern. These biases can stem from training data that may not fully represent diverse financial market conditions or the complexity of human decision-making processes [63]. This can result in models perpetuating existing inequalities or making inaccurate predictions, underscoring the importance of developing methods to identify and mitigate biases in financial forecasting models [24].

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The ethical implications of deploying LLMs and AI in finance extend beyond model biases to encompass broader societal impacts, such as potential job displacement and reinforcement of systemic inequalities. Addressing these ethical challenges requires a multifaceted approach, including developing robust ethical guidelines, implementing bias detection and correction mechanisms, and ongoing research to explore optimal scaling and deployment of LLMs responsibly and equitably [52].

The ethical considerations and inherent biases in financial forecasting models necessitate diligent scrutiny and proactive strategies to ensure these advanced technologies promote fairness and societal benefit. This is particularly important given the increasing reliance on machine learning and text-mining techniques in finance, which can inadvertently perpetuate existing inequalities if not carefully managed. Tailored financial forecasting solutions for underserved populations, such as low-wage workers, are essential to ensure equitable access to financial planning tools. Therefore, addressing these ethical concerns and biases is critical for fostering transparency and inclusivity in the financial sector [11, 20, 22, 26].

7.5 Challenges in Model Adaptation and Generalization

The adaptation and generalization of financial forecasting models across contexts present significant challenges due to the inherent complexity and variability of financial data. Financial markets are dynamic, with frequent shifts in trends and patterns that can render models trained on historical data less effective in new or evolving conditions. This variability necessitates models that are robust and capable of adapting to diverse scenarios [24].

One primary challenge in model adaptation is the high dimensionality of financial data, which can lead to overfitting if models are not carefully regularized. Overfitting occurs when a model learns noise in the training data rather than underlying patterns, resulting in poor generalization to new data. Techniques like cross-validation and regularization are essential to mitigate this risk, albeit computationally intensive, especially in large-scale financial datasets [15].

Another challenge is the presence of non-stationarity in financial time series, where statistical properties such as mean and variance change over time. This non-stationarity complicates model generalization, requiring models capable of adapting to these changes to maintain predictive accuracy. Advanced methodologies like adaptive learning algorithms and time-varying parameter models address these issues but add complexity to model development [31].

Integrating diverse data sources, such as textual information from news articles and social media, adds complexity to model adaptation, particularly in finance and sentiment analysis, where the interplay between numerical data and non-numeric factors can dramatically influence outcomes. This challenge is compounded by the need to process vast amounts of information generated daily, necessitating advanced techniques to effectively incorporate and analyze varied data inputs for accurate predictions and insights [11, 1, 51, 42]. While these data sources provide valuable insights, they also introduce additional noise and variability that models must account for, requiring effective integration of qualitative data with quantitative financial indicators to enhance forecasting accuracy without compromising robustness.

Moreover, the need for models to generalize across different financial contexts, such as varying economic conditions or regulatory environments, necessitates a flexible approach to model design. This includes incorporating domain-specific knowledge and dynamically adjusting model parameters in response to new information. Developing hybrid models that combine machine learning with traditional financial theories offers a promising avenue for achieving this flexibility [19].

8 Future Directions and Opportunities

The field of financial forecasting is undergoing rapid transformation due to innovative methodologies and technologies. Key areas of growth include the evolution of neural network architectures, such as N-HiTS and N-BEATS, which excel in adapting to the complex, non-linear dynamics of financial markets. These models enhance forecast accuracy and robustness, facilitating real-time decision-making and offering advantages over traditional methods. By leveraging deep learning techniques that extend classical neural networks with additional hidden layers, the capacity to extract relevant features from complex financial data is significantly enhanced, highlighting these innovations' critical role in modern financial analytics [11, 40, 26, 38].

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8.1 Advancements in Neural Network Architectures

Recent advancements in neural network architectures have significantly impacted financial forecasting by capturing intricate data patterns. Future research will likely prioritize the scalability of novel methods like Cluster-Based Regression Using Variational Inference (CBR-VI), potentially extending beyond finance [18]. Additionally, curriculum learning techniques can refine model accuracy and adaptability, improving predictive performance in financial contexts. Innovations such as the HeML-GOP architecture show promise for enhancing learning efficiency, with future inquiries exploring its application across various financial prediction tasks [32]. The integration of multimodal data sources, exemplified by frameworks like ECCAnalyzer, highlights the potential for combining diverse data types to bolster prediction performance, with future research refining these techniques and exploring additional sources [51, 11, 40, 34, 41].

The potential of Large Language Models (LLMs) in financial forecasting is underscored by ongoing research into sophisticated architectures that could improve predictive performance. Enhancing LLM robustness in optimization tasks and integrating domain knowledge are crucial areas for future exploration. Advancing robust validation methods tailored for non-stationary environments is essential for ensuring predictive analytics' reliability, particularly in finance and healthcare. Systematically encoding nuanced insights into quantifiable features can address challenges posed by varying data distributions, improving machine learning applications' overall robustness [51, 11, 40, 34, 41].

Structured methodologies for building analytical models lay the groundwork for future advancements in financial forecasting. Identifying valuable use cases for deep learning and improving model interpretability are essential for facilitating its adoption in business analytics. Refining sentiment analysis methodologies and developing integrated forecasting systems utilizing diverse indicators, including textual data from news and reports, are critical avenues for future research. This approach aims to enhance predictive accuracy by leveraging advanced text-mining techniques and large language models, capturing nuanced sentiments and contextual factors influencing market dynamics [11, 19, 9, 42].

The ongoing advancement of neural network architectures, particularly their adaptability to market changes and integration with sophisticated computational techniques, offers transformative potential for financial forecasting. Recent studies emphasize addressing data incompatibility during market crises and highlight the superior predictive capabilities of models like N-HiTS and N-BEATS in capturing complex financial time series dynamics. Innovative methodologies such as curriculum learning and interpretable AI models enhance predictive accuracy and reliability, empowering financial stakeholders with robust decision-making tools. These developments collectively promise to significantly improve financial forecasting, providing precise and trustworthy models tailored to the evolving needs of the sector [32, 38, 59, 64, 26].

8.2 Enhancing Large Language Models (LLMs)

The future trajectory of Large Language Models (LLMs) in financial forecasting is poised for substantial advancements, focusing on enhancing contextual understanding by integrating multimodal inputs, enabling processing and synthesis from diverse sources like textual, numerical, and visual data. This integration improves financial forecast accuracy, with adaptive learning capabilities and behavioral economics integration significantly enhancing economic simulations for nuanced market predictions [47].

Further improvements in model predictive capabilities and explainability can be achieved by incorporating alternative data sources and employing advanced natural language processing techniques, allowing LLMs to integrate a broader range of information, such as social media sentiment and economic indicators, providing a holistic view of market dynamics. The exploration of economic impacts driven by LLM transformations represents another promising research avenue, uncovering novel applications and benefits in various financial contexts [46].

Enhancing the classification and understanding of fine-grained numerals, such as product or version numbers, can bolster LLMs' capacity to analyze and interpret financial documents and datasets, facilitating critical quantitative insights extraction for more accurate financial forecasting and actionable decision-making. Integrating structured numerical data with qualitative insights from expert knowledge produces a comprehensive market dynamics understanding. Recent studies demonstrate that such advancements outperform traditional time-series models while providing clearer stock

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movement explanations, leading to more informed investment strategies [34, 50, 19, 49]. Exploring hybrid models that combine LLMs with other machine learning techniques could further optimize predictive accuracy and robustness.

Enhancing LLM interpretability is critical for building trust and ensuring ethical AI use in financial forecasting. Developing guidelines for responsible AI deployment and exploring energy-efficient training methods are vital to minimize the environmental impact of LLMs. Improving memory retrieval processes and enabling LLMs to reason with limited data are ripe for exploration, significantly enhancing efficiency in data-constrained scenarios by systematically integrating expert insights into quantifiable features, thereby improving predictive analytics and decision-making accuracy across various fields [50, 34, 43, 51].

Finally, optimizing the Any-Precision LLM method to address specific application requirements and enhancing the summarization of complex multimodal data are crucial for maximizing LLM utility in financial forecasting. These efforts aim to enhance LLM applications in financial analysis significantly by integrating qualitative insights with quantitative data, resulting in forecasting solutions that are more accurate, interpretable, and efficient. Addressing challenges related to multimodal information fusion, as seen in frameworks like LLMFactor, enables the extraction of key factors influencing stock movements and converting qualitative insights into quantifiable metrics, leading to contextually relevant predictions that outperform traditional time-series models and improve risk assessment and decision-making processes in finance [19, 50, 34].

8.3 Integration of Alternative Data Sources

Integrating alternative data sources in financial forecasting presents a promising avenue for enhancing prediction accuracy and robustness. As the financial landscape becomes increasingly complex, reliance on traditional data sources may be insufficient to capture the full spectrum of market dynamics. Future research should focus on expanding dataset compendiums to address data availability gaps and explore new trends in data utilization for machine learning applications [1]. This expansion involves incorporating diverse data types, including social media sentiment, web search trends, and satellite imagery, which can provide unique insights into market behaviors and investor sentiment.

The integration of alternative models alongside these new data sources can further enhance prediction capabilities [39]. By leveraging the strengths of different models, such as deep learning algorithms and ensemble methods, researchers can develop more robust forecasting systems capable of handling financial market complexities. Including diverse news sources, as suggested by Feuerriegel et al., can improve the robustness and applicability of predictive models by providing broader context for understanding market movements [40].

Moreover, enhancing the quality of factors extracted from various textual sources is crucial for improving result reproducibility and ensuring forecast reliability [19]. This involves refining natural language processing techniques and developing sophisticated algorithms to accurately interpret and incorporate qualitative data into forecasting models.

The integration of alternative data sources, such as text-mining technologies and neural forecasting models, presents substantial opportunities to enhance financial forecasting accuracy by leveraging diverse information inputs and addressing financial market complexities [11, 16, 38]. By embracing a wider array of data inputs and innovative modeling approaches, researchers can develop comprehensive and reliable predictive systems that better reflect the multifaceted nature of financial markets.

8.4 Optimization of Hybrid Models and Model Fusion

Optimizing hybrid models and model fusion in financial forecasting involves strategically combining diverse computational techniques to enhance predictive accuracy and robustness. Hybrid models leverage the strengths of individual methodologies, such as machine learning, natural language processing, and traditional statistical approaches, to create a comprehensive forecasting framework. A key aspect of optimizing hybrid models is effectively integrating various data sources, including structured financial data, unstructured textual information, and alternative data inputs, capturing the multifaceted nature of financial markets [19].

One promising optimization approach is using ensemble methods, which combine predictions from multiple models to improve overall accuracy and reduce overfitting risk. By aggregating different models' outputs, ensemble techniques can mitigate individual model biases and enhance forecast robustness. Additionally, applying advanced machine learning algorithms, such as deep learning and reinforcement learning, can further refine hybrid models by enabling them to learn complex patterns and adapt to dynamic market conditions [31].

Integrating Large Language Models (LLMs) within hybrid frameworks offers significant potential for improving the interpretability and contextual understanding of financial forecasts. LLMs can process and analyze large volumes of textual data, extracting sentiment and psycholinguistic features that inform market predictions. By incorporating these qualitative insights into quantitative models, hybrid systems can provide a more nuanced and accurate representation of market dynamics [34].

Furthermore, developing novel optimization strategies, such as dynamic adaptive optimization, can enhance hybrid model performance by adjusting parameters in real-time based on changing market conditions. This adaptability is crucial in volatile financial environments, where rapid shifts in trends require flexible and responsive models [45].

The optimization of hybrid models and model fusion in finance represents a critical research area, offering significant potential to improve forecasting accuracy and reliability. By harnessing diverse computational techniques—including advanced text mining, deep learning, and sentiment analysis—and integrating various data sources such as earnings conference calls and global financial news, researchers can create sophisticated predictive models. These models are designed to capture the intricate dynamics of modern financial markets while enhancing forecast accuracy and interpretability, ultimately enabling stakeholders to make more informed investment decisions [29, 11, 40, 41, 26].

8.5 Exploration of New Methodologies and Applications

Exploring new methodologies and applications in financial forecasting is pivotal for advancing the field and addressing the evolving complexities of financial markets. Future research should focus on integrating additional variables and applying existing benchmarks to a broader range of forecasting tasks, enhancing the robustness and generalizability of predictive models [29]. Optimizing computational efficiency, exploring alternative kernel functions, and further validating with real-world financial data are essential for improving forecasting methods' applicability [30].

Incorporating additional features, alternative neural network architectures, and real-time data sources can significantly enhance financial models' predictive capabilities [35]. Training foundational time series models from scratch using innovative loss functions, such as Wasserstein loss, and enhancing probabilistic forecasting capabilities are promising future research directions [33]. Furthermore, empirically testing frameworks that translate expert intuition into quantifiable insights, refining encoding techniques, and integrating multimodal data are crucial for developing comprehensive forecasting systems [34].

Building domain-specific resources, developing online predictive models, and establishing comprehensive evaluation metrics are vital for enhancing the reliability and comparability of forecasting results [9]. Applying benchmarks to diverse financial text sources and incorporating transaction costs into trading simulations can provide realistic assessments of model performance [16]. Additionally, exploring the application of the CLIP-LSTM method across different markets and datasets will validate its robustness and adaptability [7].

Expanding score functions and developing more adaptive initial model weights can enhance frameworks like BPDS, offering opportunities for new methodologies in financial forecasting [17]. Enhancing models such as TT-RNN in various market conditions and exploring their applications to different financial forecasting problems are also promising areas for future exploration [31]. These efforts aim to advance financial forecasting by introducing innovative methodologies and applications that address the complex and dynamic nature of financial markets.

9   Conclusion

The survey highlights the pivotal role of advanced technologies, such as machine learning, large language models (LLMs), and hybrid models, in transforming financial forecasting. These tech-

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nologies significantly improve predictive accuracy and decision-making, effectively navigating the complexities of modern financial markets. The use of deep learning to enhance predictive capabilities underscores the need for specialized architectures tailored to distinct financial scenarios. Moreover, the integration of diverse computational techniques, including natural language processing and optimization algorithms, provides a comprehensive framework for analyzing large datasets and optimizing financial outcomes.

The advancements in neural network architectures and the utilization of LLMs for sentiment analysis and market trend prediction illustrate the revolutionary potential of these technologies in financial forecasting. Their ability to process and integrate data from multiple sources enhances the reliability and robustness of predictive models. Additionally, the optimization of hybrid models through model fusion leverages the strengths of individual methodologies to improve forecasting accuracy.

The continuous exploration of innovative methodologies and applications drives progress in the field, offering solutions to the dynamic challenges of financial markets. The inclusion of alternative data sources and the development of interpretable AI models are essential for maintaining transparency and trust in financial forecasting systems.

The survey underscores the importance of incorporating advanced technologies in financial forecasting, highlighting their role in achieving superior financial outcomes and supporting diverse demographics, including low-wage workers, in managing financial health. As the financial landscape continues to evolve, embracing cutting-edge technologies is essential for sustaining a competitive edge and ensuring long-term success in the financial sector.

References

[1] Paul Bilokon, Oleksandr Bilokon, and Saeed Amen. A compendium of data sources for data science, machine learning, and artificial intelligence, 2023.

[2] Aleksandr Simonyan. Breakgpt: Leveraging large language models for predicting asset price surges, 2024.

[3] Fang Liu, Shaobo Guo, Qianwen Xing, Xinye Sha, Ying Chen, Yuhui Jin, Qi Zheng, and Chang Yu. Application of an ann and lstm-based ensemble model for stock market prediction, 2024.

[4] Christian Janiesch, Patrick Zschech, and Kai Heinrich. Machine learning and deep learning. *Electronic Markets*, 31(3):685–695, 2021.

[5] Sahar Arshad, Nikhar Azhar, Sana Sajid, Seemab Latif, and Rabia Latif. Cross-lingual news event correlation for stock market trend prediction, 2024.

[6] B. Shravan Kumar, Vadlamani Ravi, and Rishabh Miglani. Predicting indian stock market using the psycho-linguistic features of financial news, 2019.

[7] Christopher Wimmer and Navid Rekabsaz. Leveraging vision-language models for granular market change prediction, 2023.

[8] Gaurav Singh and Kavitesh Kumar Bali. Enhancing decision-making in optimization through llm-assisted inference: A neural networks perspective, 2024.

[9] Frank Z Xing, Erik Cambria, and Roy E Welsch. Natural language based financial forecasting: a survey. *Artificial Intelligence Review*, 50(1):49–73, 2018.

[10] Philip Ndikum. Machine learning algorithms for financial asset price forecasting. *arXiv preprint arXiv:2004.01504*, 2020.

[11] Aaryan Gupta, Vinya Dengre, Hamza Abubakar Kheruwala, and Manan Shah. Comprehensive review of text-mining applications in finance. *Financial Innovation*, 6:1–25, 2020.

[12] Sen Huang, Kaixiang Yang, Sheng Qi, and Rui Wang. When large language model meets optimization, 2024.

[13] Yang Li, Yangyang Yu, Haohang Li, Zhi Chen, and Khaldoun Khashanah. Tradinggpt: Multi-agent system with layered memory and distinct characters for enhanced financial trading performance, 2023.

[14] Shareefuddin Mohammed, Rusty Bealer, and Jason Cohen. Embracing advanced ai/ml to help investors achieve success: Vanguard reinforcement learning for financial goal planning, 2021.

[15] Ricardo P Masini, Marcelo C Medeiros, and Eduardo F Mendes. Machine learning advances for time series forecasting. *Journal of economic surveys*, 37(1):76–111, 2023.

[16] Linyi Yang, Yingpeng Ma, and Yue Zhang. Measuring consistency in text-based financial forecasting models, 2023.

[17] Emily Tallman and Mike West. Predictive decision synthesis for portfolios: Betting on better models, 2024.

[18] Udai Nagpal and Krishan Nagpal. Cluster-based regression using variational inference and applications in financial forecasting, 2023.

[19] Meiyun Wang, Kiyoshi Izumi, and Hiroki Sakaji. Llmfactor: Extracting profitable factors through prompts for explainable stock movement prediction, 2024.

[20] Wenyu Zhang, Raya Horesh, Karthikeyan N. Ramamurthy, Lingfei Wu, Jinfeng Yi, Kryn Anderson, and Kush R. Varshney. Financial forecasting and analysis for low-wage workers, 2018.

[21] Sangyeon Kim and Myungjoo Kang. Financial series prediction using attention lstm, 2019.

[22] Helmut Wasserbacher and Martin Spindler. Machine learning for financial forecasting, planning and analysis: Recent developments and pitfalls, 2021.

[23] Yuxuan Huang, Luiz Fernando Capretz, and Danny Ho. Machine learning for stock prediction based on fundamental analysis, 2022.

[24] Marcin P. Joachimiak, Mark A. Miller, J. Harry Caufield, Ryan Ly, Nomi L. Harris, Andrew Tritt, Christopher J. Mungall, and Kristofer E. Bouchard. The artificial intelligence ontology: Llm-assisted construction of ai concept hierarchies, 2024.

[25] Taha Aksu, Chenghao Liu, Amrita Saha, Sarah Tan, Caiming Xiong, and Doyen Sahoo. Xforecast: Evaluating natural language explanations for time series forecasting, 2024.

[26] Sahar Arshad, Seemab Latif, Ahmad Salman, and Rabia Latif. Enhancing profitability and investor confidence through interpretable ai models for investment decisions, 2024.

[27] Matthew F. Dixon, Nicholas G. Polson, and Kemen Goicoechea. Deep partial least squares for empirical asset pricing, 2022.

[28] Sohum Thakkar, Skander Kazdaghli, Natansh Mathur, Iordanis Kerenidis, André J. Ferreira-Martins, and Samurai Brito. Improved financial forecasting via quantum machine learning, 2024.

[29] Wenhao Liang, Zhengyang Li, and Weitong Chen. Enhancing financial market predictions: Causality-driven feature selection, 2024.

[30] Narayan Tondapu. Enhancing mean-reverting time series prediction with gaussian processes: Functional and augmented data structures in financial forecasting, 2024.

[31] Yao Lei Xu, Giuseppe G. Calvi, and Danilo P. Mandic. Tensor-train recurrent neural networks for interpretable multi-way financial forecasting, 2021.

[32] Dat Thanh Tran, Juho Kanniainen, Moncef Gabbouj, and Alexandros Iosifidis. Data-driven neural architecture learning for financial time-series forecasting. *arXiv preprint arXiv:1903.06751*, 2019.

[33] Andrei Chernov. Fine-tuning a time series foundation model with wasserstein loss, 2024.

[34] Phoebe Jing, Yijing Gao, Yuanhang Zhang, and Xianlong Zeng. Translating expert intuition into quantifiable features: Encode investigator domain knowledge via llm for enhanced predictive analytics, 2024.

[35] Nisarg Patel, Harmit Shah, and Kishan Mewada. Enhancing financial data visualization for investment decision-making, 2023.

[36] Firuz Kamalov and Ikhlaas Gurrib. Machine learning-based forecasting of significant daily returns in foreign exchange markets. *International Journal of Business Intelligence and Data Mining*, 21(4):465–483, 2022.

[37] Mathias Kraus, Stefan Feuerriegel, and Asil Oztekin. Deep learning in business analytics and operations research: Models, applications and managerial implications, 2019.

[38] Mohit Apte and Yashodhara Haribhakta. Advancing financial forecasting: A comparative analysis of neural forecasting models n-hits and n-beats, 2024.

[39] Asef Yelghi, Aref Yelghi, and Shirmohammad Tavangari. Artificial intelligence in financial forecasting: Analyzing the suitability of ai models for dollar/tl exchange rate predictions, 2024.

[40] Stefan Feuerriegel and Ralph Fehrer. Improving decision analytics with deep learning: The case of financial disclosures, 2018.

[41] Yupeng Cao, Zhi Chen, Qingyun Pei, Nathan Jinseok Lee, K. P. Subbalakshmi, and Papa Momar Ndiaye. Ecc analyzer: Extract trading signal from earnings conference calls using large language model for stock performance prediction, 2024.

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[42] Litton Jose Kurisinkel, Pruthwik Mishra, and Yue Zhang. Text2timeseries: Enhancing financial forecasting through time series prediction updates with event-driven insights from large language models, 2024.

[43] Humza Naveed, Asad Ullah Khan, Shi Qiu, Muhammad Saqib, Saeed Anwar, Muhammad Usman, Naveed Akhtar, Nick Barnes, and Ajmal Mian. A comprehensive overview of large language models. *arXiv preprint arXiv:2307.06435*, 2023.

[44] Xiao Zhang, Ruoyu Xiang, Chenhan Yuan, Duanyu Feng, Weiguang Han, Alejandro Lopez-Lira, Xiao-Yang Liu, Sophia Ananiadou, Min Peng, Jimin Huang, and Qianqian Xie. Dólares or dollars? unraveling the bilingual prowess of financial llms between spanish and english, 2024.

[45] Hongcheng Ding, Xuanze Zhao, Shamsul Nahar Abdullah, Deshinta Arrova Dewi, Zixiao Jiang, and Xiangyu Shi. Dynamic adaptive optimization for effective sentiment analysis fine-tuning on large language models, 2024.

[46] Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, et al. A survey of large language models. *arXiv preprint arXiv:2303.18223*, 2023.

[47] Jingru Jia and Zehua Yuan. An experimental study of competitive market behavior through llms, 2024.

[48] Frank Joublin, Antonello Ceravola, Joerg Deigmoeller, Michael Gienger, Mathias Franzius, and Julian Eggert. A glimpse in chatgpt capabilities and its impact for ai research, 2023.

[49] Chung-Chi Chen, Hen-Hsen Huang, Yow-Ting Shiue, and Hsin-Hsi Chen. Numeral understanding in financial tweets for fine-grained crowd-based forecasting. In *2018 IEEE/WIC/ACM International Conference on Web Intelligence (WI)*, pages 136–143. IEEE, 2018.

[50] Hoyoung Lee, Youngsoo Choi, and Yuhee Kwon. Quantifying qualitative insights: Leveraging llms to market predict, 2024.

[51] Muhammad Usman Hadi, Rizwan Qureshi, Abbas Shah, Muhammad Irfan, Anas Zafar, Muhammad Bilal Shaikh, Naveed Akhtar, Jia Wu, Seyedali Mirjalili, et al. A survey on large language models: Applications, challenges, limitations, and practical usage. *Authorea Preprints*, 3, 2023.

[52] Rajvardhan Patil and Venkat Gudivada. A review of current trends, techniques, and challenges in large language models (llms). *Applied Sciences*, 14(5):2074, 2024.

[53] Yao Lei Xu, Kriton Konstantinidis, and Danilo P. Mandic. Graph-regularized tensor regression: A domain-aware framework for interpretable multi-way financial modelling, 2022.

[54] Yeonhong Park, Jake Hyun, SangLyul Cho, Bonggeun Sim, and Jae W. Lee. Any-precision llm: Low-cost deployment of multiple, different-sized llms, 2024.

[55] S. M Towhidul Islam Tonmoy, S M Mehedi Zaman, Vinija Jain, Anku Rani, Vipula Rawte, Aman Chadha, and Amitava Das. A comprehensive survey of hallucination mitigation techniques in large language models, 2024.

[56] Jochen Wulf and Juerg Meierhofer. Towards a taxonomy of large language model based business model transformations, 2023.

[57] Yilin Gao, Sai Kumar Arava, Yancheng Li, and James W. Snyder Jr au2. Improving the capabilities of large language model based marketing analytics copilots with semantic search and fine-tuning, 2024.

[58] Tianyu Cao, Natraj Raman, Danial Dervovic, and Chenhao Tan. Characterizing multimodal long-form summarization: A case study on financial reports, 2024.

[59] Faizal Hafiz, Jan Broekaert, and Akshya Swain. Evolution of neural architectures for financial forecasting: A note on data incompatibility during crisis periods, 2023.

[60] Dat Thanh Tran, Juho Kanniainen, Moncef Gabbouj, and Alexandros Iosifidis. Bilinear input normalization for neural networks in financial forecasting, 2021.

[61] Andrea Bucci. Realized volatility forecasting with neural networks. *Journal of Financial Econometrics*, 18(3):502–531, 2020.

[62] Alexiei Dingli and Karl Sant Fournier. Financial time series forecasting-a deep learning approach. *International Journal of Machine Learning and Computing*, 7(5):118–122, 2017.

[63] Jian-Qiao Zhu, Haijiang Yan, and Thomas L. Griffiths. Language models trained to do arithmetic predict human risky and intertemporal choice, 2024.

[64] Allison Koenecke and Amita Gajewar. Curriculum learning in deep neural networks for financial forecasting, 2019.

Disclaimer:

SurveyX is an AI-powered system designed to automate the generation of surveys. While it aims to produce high-quality, coherent, and comprehensive surveys with accurate citations, the final output is derived from the AI's synthesis of pre-processed materials, which may contain limitations or inaccuracies. As such, the generated content should not be used for academic publication or formal submissions and must be independently reviewed and verified. The developers of SurveyX do not assume responsibility for any errors or consequences arising from the use of the generated surveys.
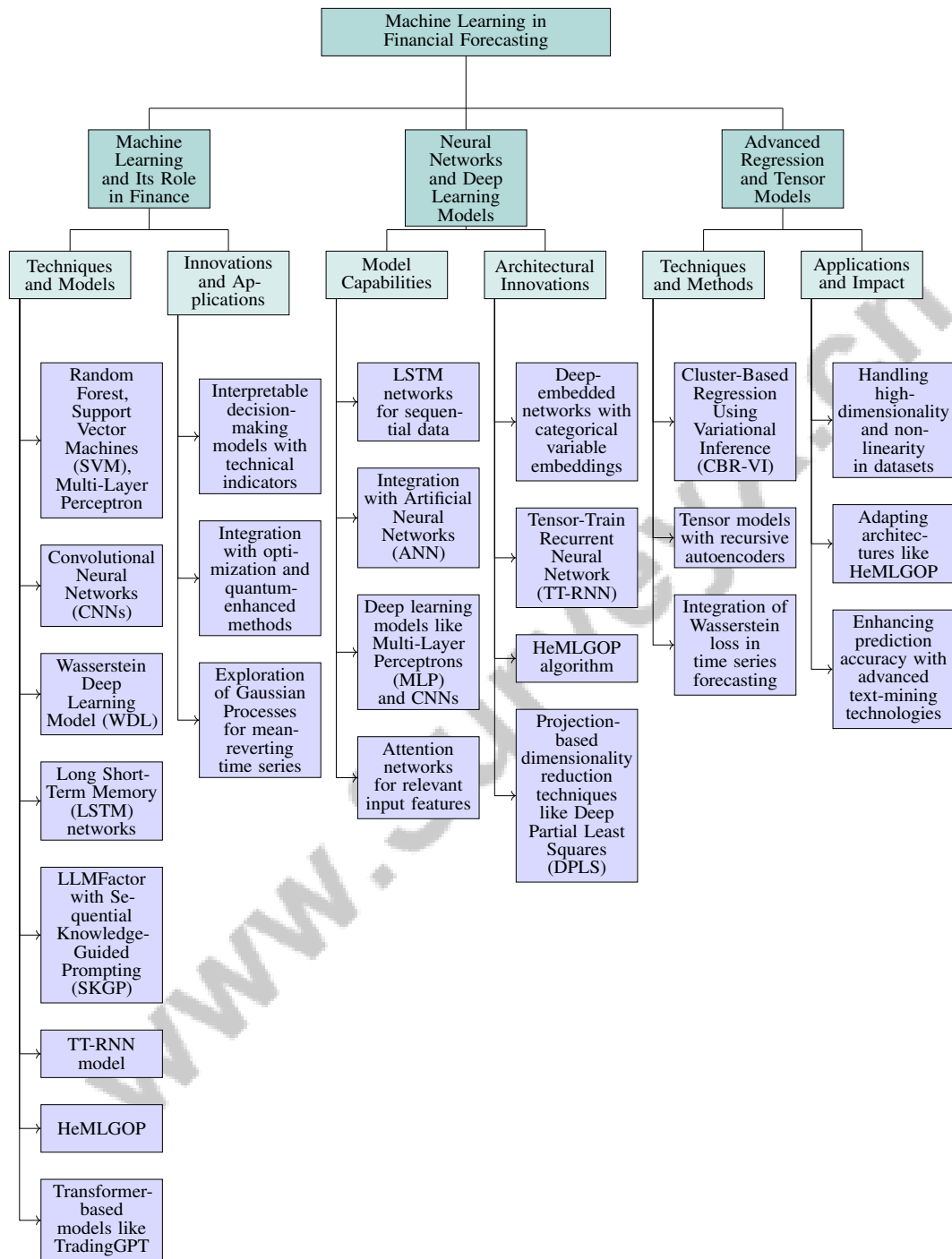
Figure 2: This figure illustrates the hierarchical structure of machine learning applications in financial forecasting, highlighting key techniques, models, and innovations across three main categories: Machine Learning and Its Role in Finance, Neural Networks and Deep Learning Models, and Advanced Regression and Tensor Models. Each category is further detailed with specific methods and their applications, showcasing the diverse and dynamic nature of financial market predictions.
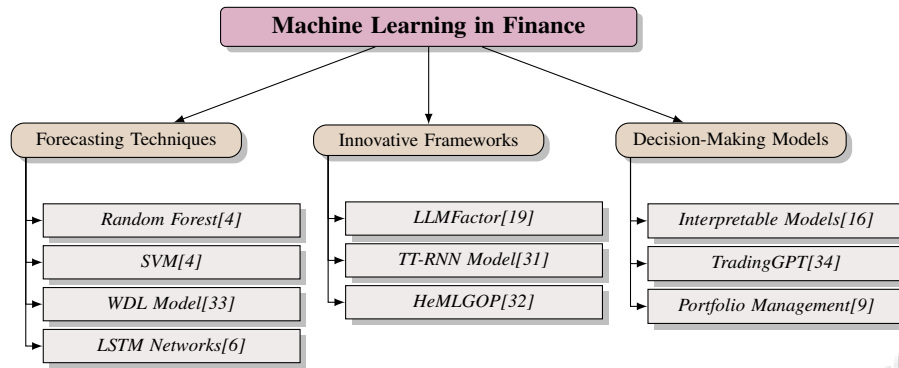
Figure 3: This figure illustrates the categorization of machine learning techniques and frameworks in financial forecasting. It highlights the primary forecasting techniques, innovative frameworks, and decision-making models that enhance financial prediction and decision-making processes.
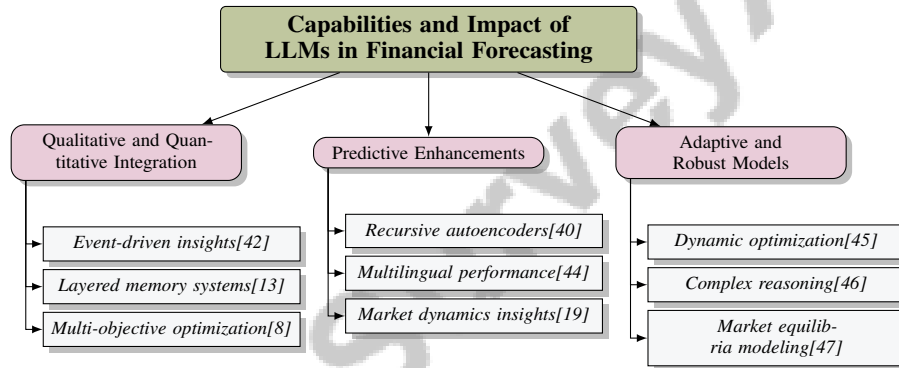

Figure 4: This figure illustrates the hierarchical categorization of the capabilities and impacts of Large Language Models (LLMs) in financial forecasting. It highlights three main areas: integration of qualitative and quantitative insights, enhancements in predictive accuracy, and the development of adaptive and robust models. Each category is supported by specific methodologies and innovations from recent research, showcasing LLMs' diverse applications in financial contexts.
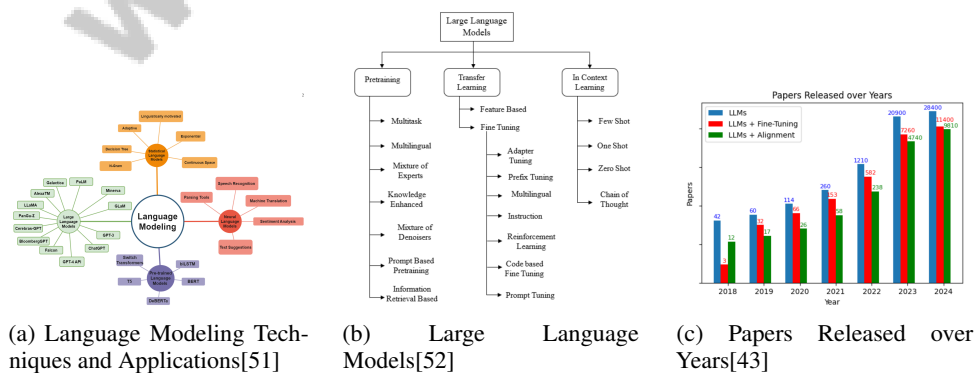

(a) Language Modeling Techniques and Applications[51]

(b) Large Language Models[52]

(c) Papers Released over Years[43]

Figure 5: Examples of Applications of LLMs in Sentiment Analysis and Market Trend Prediction

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1. Few-shot learning with GPT-4
2. Pretrained Falcon-40b-4bit
3. Fine-tuned Falcon-40b-4bit
4. Pretrained Llama-2-13b
5. Fine-tuned Llama-2-13b
6. Pretrained Llama-2-70b-4bit

(a) Deep Learning Models in Natural Language Processing[52]

(b) Few-shot learning with GPT-4[57]
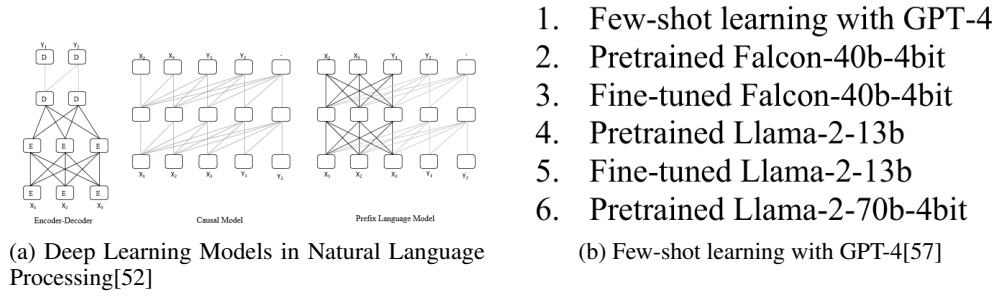
Figure 6: Examples of Innovative Methods and Frameworks Utilizing LLMs

(a) Transformer Recurrent Decoder Architecture[48]

(b) Schematic of Sections[51]

(c) Prompts and Techniques for Hallucination Mitigation in Large Language Models[55]
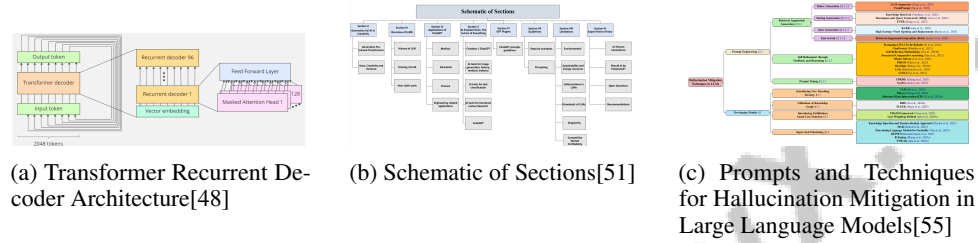
Figure 7: Examples of Applications and Case Studies

(a) Comparison of Simple and CoT-Based Error Detection in GPT-4 and Claude 2.1[58]

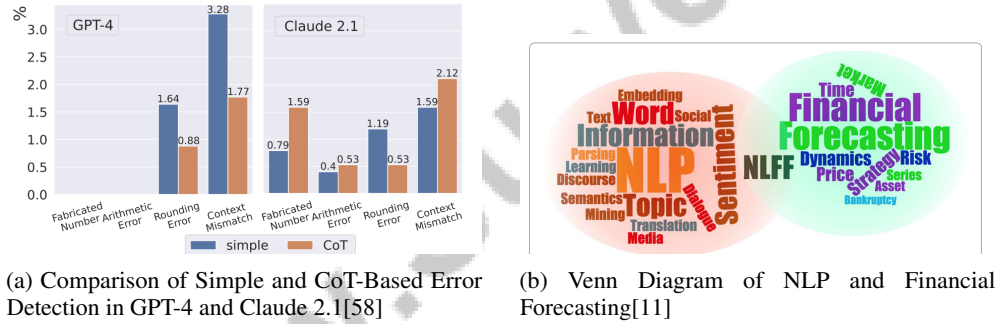(b) Venn Diagram of NLP and Financial Forecasting[11]
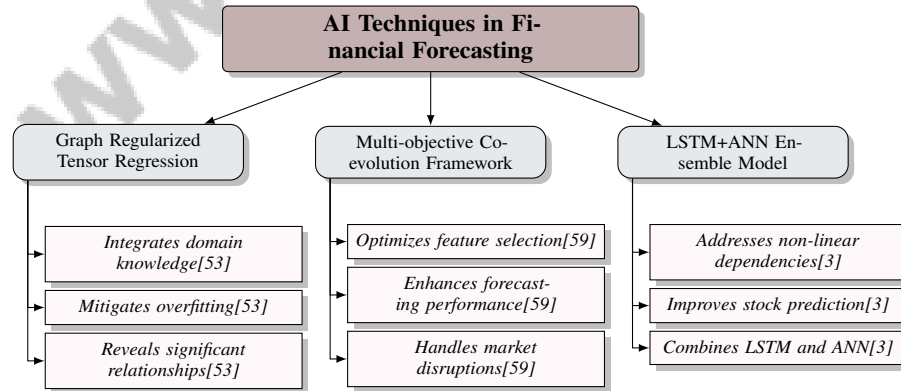
Figure 8: Examples of Innovative Hybrid Methodologies

Figure 9: This figure illustrates key AI techniques in financial forecasting, highlighting the use of Graph Regularized Tensor Regression for integrating domain knowledge, the Multi-objective Co-evolution Framework for optimizing feature selection and handling market disruptions, and the LSTM+ANN Ensemble Model for addressing non-linear dependencies and improving stock prediction accuracy.