Deep Learning and Machine Learning Techniques for Time Series Analysis: A Survey

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Abstract

This survey provides a comprehensive overview of the transformative impact of deep learning and machine learning techniques on time series analysis, highlighting their applications across diverse domains. By integrating advanced models such as Long Short-Term Memory (LSTM) networks, significant improvements have been achieved in predictive accuracy and model robustness, particularly in industrial aging processes and healthcare applications. The survey explores the role of models like the TMF method in detecting ECG patterns associated with Atrial Fibrillation, demonstrating high classification accuracy and interpretability. In environmental forecasting, the Unet-LSTM model effectively predicts global Sea Surface Temperature anomalies, capturing significant climate events with notable precision. The integration of change-point detection and remaining useful life estimation techniques enhances system health monitoring, providing a framework for assessing system longevity. Furthermore, the development of new datasets has improved the modeling and forecasting of N2O emissions in wastewater treatment, addressing environmental challenges. The survey underscores the critical role of deep learning in revolutionizing time series analysis, offering robust tools for capturing complex temporal patterns and enhancing predictive capabilities. Ongoing research promises to expand the applications of time series models, paving the way for innovative solutions to emerging challenges in various fields.

1 Introduction

1.1 Importance of Time Series Analysis

Time series analysis is crucial across various domains, significantly enhancing data-driven decision-making. In finance, it aids in economic forecasting and market volatility management, with techniques essential for detecting fraudulent activities, such as pump and dump schemes in cryptocurrency markets [1], and predicting currency pair volatility in Forex markets [2].

In environmental sciences, time series analysis facilitates the timely detection of pipe bursts in Water Distribution Networks (WDNs), minimizing water loss and environmental damage [3]. It also plays a pivotal role in forecasting urban air pollution levels, enabling proactive health measures [4], and analyzing sea surface temperature variability, which enhances understanding of global climate dynamics [5].

The energy sector leverages time series forecasting for power grid management and electrical load prediction, optimizing resource allocation [6]. In healthcare, it is vital for early detection of nonconvulsive seizures in EEG data, improving patient outcomes [7], and monitoring nitrous oxide production in wastewater treatment plants, which is essential for mitigating its global warming potential [8].

Anomaly detection in manufacturing, finance, and healthcare is another critical application of time series analysis, where identifying anomalous subsequences signals significant events [9]. For instance,

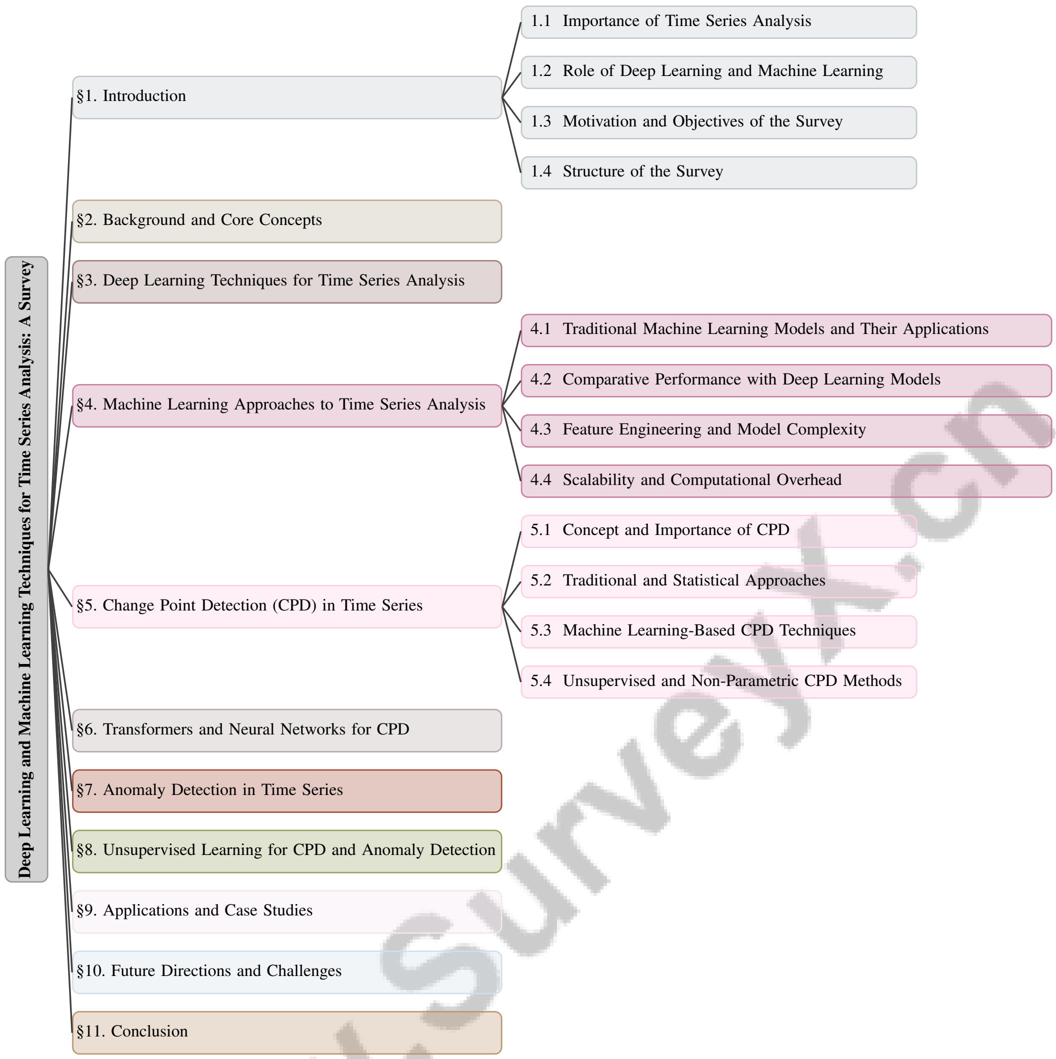


Figure 1: chapter structure

the timely detection of fuel leakages at service stations can prevent severe contamination and financial repercussions [10]. The prevalence of time series data in medicine, robotics, and video analytics underscores its significance in fostering innovation and enhancing operational efficiencies [11].

1.2 Role of Deep Learning and Machine Learning

Deep learning and machine learning have transformed time series analysis by addressing challenges related to temporal dependencies and non-linear interactions, thereby enhancing predictive accuracy across various domains. Techniques such as Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Transformers have significantly improved the predictive capabilities of time series models [6], effectively capturing complex patterns often overlooked by traditional methods.

LSTM networks excel at managing intricate temporal dependencies, making them invaluable for predicting complex phenomena [6]. CNNs enhance feature engineering by integrating deep neural networks with step-wise linear regressions and exponential smoothing, which improves the prediction of directional trend changes in financial time series [6]. The Temporal Fusion Transformer (TFT) exemplifies a novel approach that leverages detailed data to enhance forecasting accuracy, emphasizing the importance of domain-specific insights in model architectures [6].

Hybrid models, such as those combining LSTM with traditional statistical methods like ARIMA, showcase the advantages of integrating deep learning with established approaches, particularly in refining algorithmic investment strategies [6]. Machine learning frameworks are essential for enhancing signal extraction and trading allocation, as demonstrated in statistical arbitrage applications [7]. Furthermore, deep learning techniques provide scalable algorithms capable of modeling high-dimensional data, improving privacy risk assessments in time series contexts [12].

Transformer-based models are critical for understanding the impact of individual features on predictions, particularly in contexts such as COVID-19 infection predictions [11]. Additionally, deep learning techniques advance time series anomaly detection, offering innovative methods for identifying unexpected events. The introduction of model-agnostic approaches, like the MultiWave model, which utilizes both time and frequency domain information, highlights the robustness of these techniques in filtering non-informative frequency components [9].

The integration of deep learning and machine learning into time series analysis has driven significant innovations, improving predictive accuracy, enhancing model interpretability, and providing scalable solutions for complex data challenges. These advancements have transformed time series forecasting and opened new avenues for research and application across diverse fields [3].

1.3 Motivation and Objectives of the Survey

This survey is motivated by the need to address significant challenges and limitations in current methodologies for time series forecasting and anomaly detection, especially in sectors like finance, healthcare, and energy management where precise predictions and timely anomaly detection are critical. In finance, the complexity of high market volatility in cryptocurrency price prediction necessitates a deeper understanding of model suitability and performance [13]. Moreover, employing machine learning for statistical arbitrage can enhance predictive accuracy and market efficiency [14].

In healthcare, automating continuous EEG (cEEG) recordings analysis is vital for the swift identification of harmful EEG patterns, improving patient outcomes [7]. Similarly, accurate forecasting of power consumption and anomaly detection in load data are essential for optimizing resource allocation and ensuring grid stability in energy management [15]. The detection of gravitational wave signals prior to merger events further exemplifies the potential of advanced deep learning methods to enhance detection capabilities in astrophysics [16].

The primary objective of this survey is to provide a comprehensive overview of state-of-the-art deep learning methods for time series anomaly detection, reflecting the growing interest and applicability of these methods across various domains [17]. Additionally, the survey systematically evaluates and compares various anomaly detection algorithms for time series data, addressing the challenge of selecting the most suitable technique for specific tasks [9]. By examining evaluation metrics used in time series anomaly detection, the survey aims to tackle the lack of consensus on the best metrics for specific scenarios [18].

Moreover, this survey addresses the challenges of efficiently processing and analyzing time series data, which involves managing variable-length sequences and ensuring invariance to small time shifts [11]. By providing an overview of machine learning techniques to enhance forecasting accuracy in chaotic time series, it aims to contribute to advancements in time series analysis [6]. Ultimately, this survey seeks to highlight state-of-the-art techniques and identify areas for future research and development, thus enhancing time series analysis across diverse fields.

1.4 Structure of the Survey

This survey is structured to provide a comprehensive examination of deep learning and machine learning techniques for time series analysis. It begins with an introduction emphasizing the importance and applications of change point detection techniques across fields such as environmental monitoring, social network analysis, and dynamic systems. This foundational overview prepares readers for an in-depth examination of methodologies and findings presented in subsequent sections, including the integration of topological data analysis with existing nonparametric methods, the development of a size-agnostic framework for evolving networks, and the application of graph similarity learning for real-time change point detection in dynamic networks [19, 20, 21, 22]. The background section elucidates key definitions and interrelationships among essential concepts such as change point detection (CPD), anomaly detection, and unsupervised learning, underscoring their significance in time series analysis.

The survey categorizes current methods into four primary areas: forecasting-based, reconstruction-based, representation-based, and hybrid methods, facilitating a structured understanding of diverse approaches employed in the field [17]. The section on deep learning techniques explores various models such as recurrent neural networks (RNNs), long short-term memory networks (LSTMs), convolutional neural networks (CNNs), and transformers, discussing their architectures, strengths, and limitations in handling time-dependent data. This is followed by a comparison of traditional machine learning approaches against deep learning models, highlighting feature engineering and model complexity considerations [6].

Subsequently, we address change point detection (CPD) in time series, reviewing both traditional statistical methods and machine learning-based approaches, including unsupervised and non-parametric methods. The effectiveness of transformers and neural networks in capturing complex temporal dependencies in CPD is then analyzed. Anomaly detection in time series is investigated with a focus on unsupervised learning, addressing various challenges and highlighting state-of-the-art techniques, including a comparative analysis of six unsupervised methods evaluated against diverse anomaly types using the UCR anomaly archive. The discussion extends to frameworks utilizing adversarial and self-supervised learning, along with a comprehensive evaluation of performance metrics tailored for time-series data, model stability, and the incorporation of prior knowledge about anomalies, ultimately aiming to enhance the understanding of these methods' applicability in real-world scenarios across fields such as system monitoring, healthcare, and cybersecurity [23, 24].

The survey also highlights the use of unsupervised learning techniques in both CPD and anomaly detection, discussing graph-based and temporal dependency models while reviewing specific evaluation metrics and benchmarks. Real-world applications and case studies across finance, healthcare, and IoT demonstrate the practical impact of these technologies. In conclusion, we outline key future directions and challenges in time series analysis, emphasizing strategies to enhance model interpretability, overcome data limitations, and improve computational efficiency. We advocate for adopting advanced machine learning techniques, including deep learning and ensemble methods, to address complexities inherent in time series data, such as temporal dependencies and anomalies. Additionally, we propose developing modular model selection frameworks like ADecimo to facilitate identifying the most effective anomaly detection methods tailored to specific datasets, establishing a comprehensive roadmap for ongoing research and development efforts in this evolving field [25, 26, 27, 28, 29].The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Definitions and Fundamental Concepts

Time series analysis is a statistical approach to examining data points collected sequentially over time, crucial for identifying patterns and making predictions in fields such as finance, healthcare, and environmental studies. This analysis faces challenges like temporal dependencies and varying data lengths, essential for understanding its core concepts [11]. It is particularly beneficial for forecasting and anomaly detection, where the sequential data nature complicates analysis due to these dependencies.

Change Point Detection (CPD) is integral to time series analysis, focusing on identifying shifts in statistical properties. It is vital for detecting fuel variance shifts that suggest leakages, crucial for safety and efficiency in industrial operations [10]. This is particularly important in high-dimensional industrial processes, where timely detection is essential. In financial markets, CPD aids in predicting stock price movements, despite challenges from noise and volatility [12].

Deep learning models, including Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Transformers, have become essential for time series forecasting, surpassing traditional methods like ARIMA. These architectures excel in capturing complex temporal dependencies, proving invaluable in finance, economics, and online advertising. Studies show LSTM and CNNs significantly reduce forecasting errors, with LSTM reducing error rates by 84-87

Unsupervised learning techniques are crucial in time series analysis, especially for clustering and anomaly detection. A benchmark for anomaly detection in time series data emphasizes effective feature selection and model design [12]. Unsupervised Metric Learning (UML) enhances data point separability without labeled data, addressing challenges with non-linear separability, advantageous for datasets with non-linear relationships where traditional methods like ARIMA may fall short.

Hierarchical time series forecasting requires generating forecasts that align with hierarchical structures for accurate aggregations and insights across levels [30]. This approach is useful in environmental monitoring, where long-term datasets, such as pollution data, need hierarchical analysis to inform policy and management decisions.

Machine learning in time series analysis extends to uncertainty estimation in regression tasks, with spiking neural networks (SNNs) offering a novel approach distinct from traditional neural networks. In traffic data streams, identifying sustained anomalies amid periodic but noisy patterns poses unique challenges [31].

The foundational concepts outlined here facilitate the effective application of machine learning and deep learning techniques to analyze temporal data, enabling valuable insights and informed decision-making. By leveraging methodologies like stacked autoencoders, LSTMs, and attention-based architectures such as the Temporal Fusion Transformer, practitioners can address complexities in time-series data—such as temporal dependencies and noise—enhancing predictive accuracy across domains like finance and online advertising [29, 32, 33]. Integrating these advanced methodologies continues to enhance the accuracy and applicability of time series analysis across diverse fields.

2.2 Interrelationships Among Core Concepts

The interrelationships among deep learning, change point detection (CPD), and anomaly detection are crucial for advancing time series analysis. Deep learning models, such as artificial neural networks (ANNs), fuzzy neural networks, and optimization algorithms, have been pivotal in analyzing chaotic time series data, providing robust frameworks for capturing complex temporal patterns and dependencies [6]. These models enhance anomaly and change point detection by leveraging their capacity to learn from data with intricate temporal structures.

CPD techniques segment time series into regions of piecewise stationarity, allowing for precise modeling of phenomena like stellar activity [34]. This segmentation is vital for identifying structural changes, indicating significant shifts in underlying processes. Integrating CPD with machine learning, exemplified in real-time fuel leakage detection, illustrates how machine learning advancements improve detection capabilities by analyzing data streams in real-time [10].

Anomaly detection benefits from deep anomaly detection models that categorize techniques based on their approaches and architectures [17]. These models address traditional methods' limitations, which often discard data points based on significant deviations, thus improving anomaly detection systems' performance [35]. The interplay between anomaly detection and CPD is further illustrated by combining these techniques with bag-of-words clustering, enhancing anomalous pattern detection and analysis [7].

The use of dilated convolutions and self-attention mechanisms to capture temporal dependencies underscores the importance of integrating advanced deep learning architectures with time series analysis [31]. These mechanisms enable models to manage high dimensionality and non-linear relationships, common challenges in real-world applications [30]. Furthermore, the interrelationship between traditional machine learning methods and time series data's unique characteristics necessitates developing specialized tools to address temporal data complexities [11].

2.3 Significance in Time Series Analysis

The significance of core concepts such as deep learning, change point detection (CPD), and anomaly detection in time series analysis is evident in their transformative impact on data analysis and interpretation. The UCR Time Series Anomaly Archive provides a crucial resource for the anomaly detection community, facilitating more reliable evaluations of model performance [36]. This archive addresses continuous anomaly detection challenges, particularly difficult due to the scarcity of labeled anomalies and the need for ongoing detection rather than isolated point anomalies [37].

CPD is pivotal in identifying shifts in data patterns, essential for applications like predictive maintenance, where timely detection of changes can prevent costly failures [38]. The Tensor-Based

Multivariate Polynomial Optimization (TeMPO) framework emphasizes CPD's importance by enhancing nonlinear functions' analysis across applications [39]. This framework exemplifies integrating advanced mathematical models to refine change point detection and analysis.

Anomaly detection is critical in time series analysis, with methods like the Dynamic Distributed Processing Algorithm (DDPA) offering significant advantages in scalability and processing efficiency [40]. Robust anomaly detection techniques are crucial for applications in finance and healthcare, where detecting subtle deviations can indicate significant underlying issues. These methods' effectiveness is often evaluated using metrics that ensure reasoning models' correctness and robustness, enhancing insights' reliability derived from time series data [28].

In healthcare, the correlation between pupillometric responses and neural activity illustrates time series analysis's potential in diagnosing and understanding conditions like ADHD, where attention and neural responses are impaired [41]. This highlights the interdisciplinary applications of time series analysis, where physiological data can provide insights into cognitive and neurological health.

The availability of comprehensive datasets, including two years of time-aggregated raw data with high temporal resolution, is crucial for advancing time series data analysis and interpretation [8]. Such datasets enable applying sophisticated models that capture complex temporal patterns and dependencies, improving prediction accuracy.

Integrating advanced concepts like deep learning and model selection techniques into time series analysis significantly enhances analytical capabilities, allowing for more effective anomaly detection and improved forecasting. This development increases prediction precision and expands time series analysis's applicability across diverse fields, including healthcare, manufacturing, and environmental monitoring, accommodating various datasets' unique characteristics and addressing challenges posed by temporal dependencies and complex patterns [25, 23, 17, 42, 29]. Continuous development and refinement of these techniques are essential for addressing the dynamic and complex nature of time-dependent data, ultimately leading to more informed decision-making and innovative solutions across various domains.

3 Deep Learning Techniques for Time Series Analysis

Category	Feature	Method
Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs)	Temporal Dependency Capture Sequential Layer Training	DLSP[43], GCNN[44] LL[45]
Convolutional Neural Networks (CNNs) in Time Series	Transfer Learning Techniques Model Integration Strategies Real-Time Processing	TSU-Net[46] AMCNN-LSTM[47] SNC[48]
Transformer Models for Time Series	Temporal Dynamics	TFT-Morris[49], PCPAD[15], SCOTT[50], PBIM[51], TFT[32], TADDY[52]
Hybrid and Ensemble Models	Integrated Methodologies	IMR[35], sg-LASSO[53], UPF[54], ULSTM[5], NND[55], CPD-BoW[7], DCTW[30], MOCPD[10]

Table 1: This table provides a comprehensive overview of various deep learning methodologies for time series analysis, categorized into Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs), Convolutional Neural Networks (CNNs), Transformer Models, and Hybrid and Ensemble Models. Each category highlights specific features and methods, showcasing their contributions to capturing temporal and spatial dependencies and improving predictive accuracy.

Exploring deep learning techniques for time series analysis reveals diverse methodologies designed to address the complexities of sequential data. This section focuses on foundational frameworks, particularly Recurrent Neural Networks (RNNs) and their advanced variant, Long Short-Term Memory (LSTM) networks, which have proven effective in capturing temporal dependencies and enhancing predictive capabilities across various applications. Table 1 presents a detailed categorization of deep learning techniques employed in time series analysis, emphasizing their distinct features and methods across different neural network architectures. Additionally, Table 5 offers a comprehensive comparison of deep learning models applied in time series analysis, emphasizing their distinct characteristics and application areas. **??** illustrates a hierarchical classification of these deep learning techniques, categorizing them into RNNs and LSTMs, Convolutional Neural Networks (CNNs), Transformer Models, and Hybrid and Ensemble Models. Each category is depicted with specific methodologies and applications, showcasing their contributions to capturing both temporal and spatial dependencies, improving predictive accuracy, and addressing the limitations of traditional methods.

This visual representation reinforces the discussion by providing a clear framework for understanding the landscape of deep learning approaches in time series analysis.

3.1 Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs)

Method Name	Temporal Dependencies	Problem Solving	Application Areas
GCNN[44]	Temporal Dependencies	Vanishing Gradient Problem	Speech Recognition
DLSP[43]	Complex Temporal Dependencies	Vanishing Gradient Problem	Real-time Forecasting
LL[45]	Time Series Data	Imbalanced Datasets	Anomaly Detection

Table 2: Comparison of methods addressing temporal dependencies and problem-solving capabilities across various application areas, highlighting the use of GCNN, DLSP, and LL techniques. The table illustrates how these methods manage challenges such as the vanishing gradient problem and imbalanced datasets, applied in domains like speech recognition, real-time forecasting, and anomaly detection.

RNNs and LSTMs are pivotal in modeling sequential data, significantly advancing time series analysis by capturing temporal dependencies. RNNs maintain a hidden state that retains information from previous time steps, essential for learning both short and long-term dependencies. Gated RNNs, especially when combined with Convolutional Neural Networks (CNNs), excel in multi-step load forecasting, outperforming traditional methods [44].

LSTMs, a specialized form of RNNs, address the vanishing gradient problem by incorporating memory cells that retain information over extended periods, making them adept at handling long-range dependencies. Their superiority is demonstrated in industrial process degradation prediction [56] and cryptocurrency price forecasting, effectively managing complex temporal dependencies [13]. They are utilized in environmental monitoring for forecasting scour based on historical data [43] and in health informatics through layered learning methods for early anomaly detection in time series data [45]. Furthermore, LSTMs facilitate predictive tasks, including GAN-based models for forecasting growth frames, highlighting their capacity to manage intricate temporal dynamics [57].

RNNs and LSTMs significantly enhance time series analysis by effectively capturing complex temporal dependencies, thereby improving predictive accuracy in fields such as financial forecasting, anomaly detection, and speech recognition, addressing limitations of traditional methods like ARIMA [46, 58, 59, 29, 60]. Their ongoing development, particularly in conjunction with other machine learning techniques, promises further innovations in sequential data modeling. Table 2 provides an overview of different methods employed in the context of RNNs and LSTMs, showcasing their ability to handle temporal dependencies and solve specific problems across diverse application areas.

3.2 Convolutional Neural Networks (CNNs) in Time Series

CNNs have emerged as powerful tools for capturing spatial hierarchies within time series data, significantly enhancing analysis accuracy and efficiency. By treating time as an additional dimension, CNNs effectively model spatial dependencies, crucial for tasks like price forecasting [13]. Their architecture, comprising convolutional, pooling, and fully connected layers, facilitates hierarchical feature extraction, improving generalization across datasets.

The integration of CNNs with other architectures, such as LSTMs, has led to hybrid models like AMCNN-LSTM, utilizing attention mechanisms for improved feature extraction and memory retention, showcasing CNNs' potential to enhance time series model performance by capturing both spatial and temporal dependencies [47]. In real-time applications, CNNs are favored for their balance of speed and accuracy, making them suitable for scenarios requiring rapid processing [61]. Innovations like StreamiNNC optimize CNNs for online streaming inference by processing new information in overlapping windows, reducing computational overhead [48].

Pretrained weights in CNNs, as seen in certain anomaly detection frameworks, enable generalization to new anomalies across different time series, enhancing robustness and applicability [46]. Thus, CNNs are pivotal in time series analysis, capturing spatial hierarchies and automating feature extraction, streamlining the analysis process in applications like anomaly detection and forecasting. Recent advancements, especially when combined with transfer learning, demonstrate that CNNs outperform traditional methods, contributing to robust monitoring systems in complex environments such as industrial settings and the Internet of Things (IoT) [29, 17, 61, 46].

3.3 Transformer Models for Time Series

Method Name	Temporal Dependencies	Application Domains	Interpretability Challenges
TFT[32]	Temporal Patterns Capture	Online Advertising Revenues	Interpretability Enhances Insights
TFT-Morris[49]	Complex Interactions	Covid-19 Forecasting	Interpretability And Accuracy
SCOTT[50]	Complex Temporal Relationships	Time Series Classification	-
PCPAD[15]	Long-distance Dependencies	Power Grid Management	-
TADDY[52]	Spatial-temporal Information	Social Networks	-
PBIM[51]	Complex Temporal Relationships	Covid-19 Forecasting	Complexity OF Models

Table 3: Overview of transformer-based models applied to time series analysis, highlighting their capabilities in capturing temporal dependencies, application domains, and interpretability challenges. The table includes models such as TFT, TFT-Morris, SCOTT, PCPAD, TADDY, and PBIM, each demonstrating unique strengths and limitations in various domains like online advertising, COVID-19 forecasting, and power grid management.

Transformer models have revolutionized time series analysis by providing robust frameworks for capturing complex temporal dependencies, thereby enhancing predictive accuracy and interpretability. Table 3 presents a comprehensive comparison of transformer-based models used in time series analysis, focusing on their ability to capture temporal dependencies, the application domains they are employed in, and the interpretability challenges they face. The Temporal Fusion Transformer (TFT) exemplifies this innovation, employing attention mechanisms to identify temporal patterns and variable importance, improving forecast interpretability [32]. TFT has been effectively applied to predict county-level COVID-19 infections, showcasing its capability in managing time-dependent data [49].

Transformers also excel in cryptocurrency price prediction, adeptly modeling intricate temporal dependencies, vital in financial markets [13]. Their integration with architectures like Temporal Convolutional Networks in SCOTT enhances their ability to learn both global and local features from time series data [50]. The self-attention mechanisms of transformers facilitate efficient long-range dependency capture, exemplified in power consumption forecasting, leading to improved predictive performance [15]. Furthermore, transformers' innovative capacity to capture spatial and temporal information simultaneously, as demonstrated in TADDY, addresses traditional methods' limitations of processing these features separately [52].

Despite their advantages, transformers face interpretability challenges, particularly in forecasting applications such as COVID-19 predictions, where model complexity necessitates efforts to clarify decision-making processes [51]. Thus, transformer models play a crucial role in advancing time series analysis by providing sophisticated tools for modeling complex temporal dependencies, with applications across finance, online advertising, and industrial monitoring. These advancements enhance predictive accuracy and facilitate innovative approaches to anomaly detection and trend analysis, driving progress in time-series analysis [26, 62, 29, 32, 60].

3.4 Hybrid and Ensemble Models

Method Name	Integration Approach	Predictive Accuracy	Application Domains
sg-LASSO[53]	Structured Machine Learning	Improved Forecasting Performance	Economic Forecasting
UPF[54]	Combined Forecasting Methods	Enhanced Prediction Accuracy	Hospital Demand Prediction
ULSTM[5]	Convolutional Encoder-decoder	Improved Prediction Accuracy	Marine Heatwave Hotspots
NND[55]	Machine Learning Techniques	Superior Forecasting Accuracy	Hierarchical Time Series
IMR[35]	Iterative Approach	Better Accuracy	Anomaly Detection
CPD-BoW[7]	Changepoint Detection	Enhanced Forecasting Outcomes	Eeg Data Analysis
MOCPD[10]	Hybrid And Ensemble	Improved Detection Accuracy	Real-time Scenarios
DCTW[30]	Deep Learning Architectures	Superior Alignment Performance	Temporal Alignment Applications

Table 4: Table ef presents a comparative analysis of various hybrid and ensemble models utilized in time series analysis, highlighting their integration approaches, predictive accuracy, and application domains. The table underscores the diverse methodologies employed to enhance forecasting performance across different sectors, emphasizing the adaptability and effectiveness of these models.

Table 4 provides a detailed examination of hybrid and ensemble models in time series analysis, illustrating their integration strategies and predictive capabilities across a range of application domains. Hybrid and ensemble models are essential in time series analysis, enhancing performance and robustness by integrating diverse methodologies. These models leverage individual components' strengths, addressing standalone models' shortcomings to improve predictive accuracy. The sparse-group LASSO method exemplifies a hybrid approach, effectively combining traditional and nontraditional data to refine forecasting outcomes [53]. Similarly, Vollmer et al.'s unified predictive framework integrates various time series and machine learning models, enhancing prediction robustness and demonstrating hybrid models' efficacy [54].

The Unet-LSTM method illustrates hybrid models' effectiveness in learning complex data patterns, capturing seasonal cycles and interannual variability to enhance prediction accuracy [5]. Another innovative approach, the NND framework, integrates time series data with explanatory variables in a deep learning context, producing reconciled forecasts that highlight hybrid methodologies' importance [55].

In anomaly detection, the IMR method merges anomaly detection principles with data repairing, resulting in more accurate and efficient repairs compared to existing methods [35]. The CPD-BoW model further explores hybrid approaches by integrating change point detection with clustering techniques, enhancing performance in EEG data analysis [7]. These models illustrate how combining different analytical techniques can lead to substantial improvements in time series analysis.

The MOCPD method successfully fuses traditional statistical methods with machine learning principles to enhance fuel leakage detection, demonstrating hybrid models' practical benefits in real-world applications [10]. Additionally, the DCTW framework extends traditional alignment methods to include deep learning, enabling the discovery of non-linear transformations that significantly improve alignment performance [30].

Feature	Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs)	Convolutional Neural Networks (CNNs) in Time Series	Transformer Models for Time Series
Dependency Capture	Temporal Dependencies	Spatial Hierarchies	Long-range Dependencies
Application Domain	Financial Forecasting	Anomaly Detection	Cryptocurrency Prediction
Model Integration	With Cnns	With Lstms	With Tcns

Table 5: Table summarizing the comparison of deep learning models used in time series analysis, highlighting their unique features, application domains, and integration capabilities. The table provides insights into how Recurrent Neural Networks (RNNs) and Long Short-Term Memory Networks (LSTMs), Convolutional Neural Networks (CNNs), and Transformer Models address different dependencies and are utilized in various predictive tasks. This comparison underscores the strengths and application-specific advantages of each model type in capturing temporal, spatial, and long-range dependencies.

4 Machine Learning Approaches to Time Series Analysis

4.1 Traditional Machine Learning Models and Their Applications

Traditional machine learning models are essential in time series analysis, adept at capturing temporal patterns, particularly in financial applications. Autoregressive models and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) techniques are prominent for modeling volatility, often compared to deep learning methods like the 2-LSTM model for predictive performance [2]. These models excel in identifying linear relationships but benefit from integration with advanced methods to address non-linear dependencies.

In anomaly detection, traditional models have evolved to transition from contextual to point anomaly detection, exemplified by the Hybrid Pump and Dump Detection Method (HPDDM), which combines distance and density metrics [1]. Such methods are effective in identifying anomalies, particularly in financial datasets, as demonstrated by experiments on GPS data with labeled errors and synthetic sensor data [35]. A comprehensive evaluation of 71 algorithms across 976 time series datasets underscores the efficacy of traditional techniques in diverse scenarios [9], emphasizing the importance of selecting appropriate metrics for time series anomaly detection (TSAD) [18].

Tools like the Tslearn library facilitate preprocessing, feature extraction, clustering, classification, and regression of time series data, showcasing the versatility of traditional models [11]. The prevalence of Artificial Neural Network (ANN)-based methods in chaotic time series forecasting highlights the adaptability of traditional models when combined with modern approaches [6]. In industrial contexts, these models are employed to detect anomalies in multi-time series data from diverse sensors, addressing the need for timely and accurate detection [60]. The integration of the Levenberg-Marquardt (LM) optimizer further refines traditional methods to enhance anomaly detection capabilities [12].

Traditional machine learning models remain integral to time series analysis, providing a robust foundation for advancements in the field. Recent developments reveal the effectiveness of both linear methods, such as penalized regressions and ensemble models, and non-linear approaches, including deep learning techniques and tree-based methods. These models are particularly valuable in economics and finance, where they improve forecast reliability and accuracy through the utilization of large datasets and sophisticated algorithms [29, 53, 11, 27]. Their enduring relevance is evident, especially when complemented by modern techniques that address limitations in managing complex, non-linear data relationships.

4.2 Comparative Performance with Deep Learning Models

The comparative analysis of traditional machine learning models and deep learning approaches in time series analysis reveals distinct strengths and limitations. Traditional models, such as the Holt-Winters method, often outperform certain deep learning techniques in terms of RMSE and MAE, particularly in applications where interpretability and computational efficiency are prioritized [4]. These models are favored in contexts where transparency is essential.

Conversely, deep learning models excel at capturing complex temporal correlations and dependencies that traditional methods struggle to address. For example, LSTM networks achieve significant reductions in RMSE, averaging 84-87

In anomaly detection, research indicates that no single method consistently outperforms others, underscoring the need for a diverse approach that integrates multiple techniques to enhance detection capabilities [63]. Deep learning models, such as MedTsLLM, have shown superior performance in analyzing complex medical time series data, offering actionable insights for clinicians and marking a significant advancement in multimodal data integration [64].

Despite their advantages, traditional models retain relevance in scenarios prioritizing computational efficiency and simplicity. The IMR method, evaluated using RMS error, exemplifies the continued applicability of traditional approaches when comparing repaired results against ground truth [35]. Additionally, deep learning techniques face challenges related to adversarial vulnerabilities, with existing methods inadequately addressing the potential for adversarial examples in time series classification [65].

While deep learning models generally provide superior predictive accuracy and manage complex data structures, traditional models remain valuable in contexts where interpretability and efficiency are paramount. The development of hybrid approaches aims to bridge the gap between these methodologies, offering robust solutions for various time series analysis challenges [31].

4.3 Feature Engineering and Model Complexity

Feature engineering and model complexity are crucial for advancing time series analysis, particularly in improving predictive accuracy and robustness. Extracting meaningful features from raw time series data is essential for capturing temporal dependencies and stochasticity, thereby enhancing anomaly detection capabilities [62]. Techniques like trend and seasonality extraction significantly improve the performance of membership inference models, illustrating the importance of tailored feature engineering [66].

The complexity of models, such as Long Short-Term Memory (LSTM) networks and Echo State Networks, directly impacts their effectiveness. These advanced models outperform simpler alternatives in predicting degradation in industrial processes, highlighting the necessity of employing sophisticated models to handle intricate temporal correlations [56].

Innovative approaches, including pre-trained models for feature extraction, present significant advantages by minimizing the need for extensive labeled datasets while enhancing anomaly detection accuracy [67]. StreamiNNC exemplifies this by reducing computational requirements during streaming inference, allowing for the efficient utilization of pre-trained Convolutional Neural Networks (CNNs) with minimal modifications [48].

Federated learning frameworks, such as FSLSTM, utilize stacked LSTM architectures to analyze time series data from IoT sensors, demonstrating the importance of model complexity in distributed learning environments where data privacy and scalability are critical [68]. The MAD-GAN method illustrates the integration of complex models in unsupervised anomaly detection, employing a GAN framework with LSTM-RNNs to capture temporal correlations in multivariate time series data [69].

However, processing data from multiple sensors with varying natures and scales often requires extensive preprocessing and domain expertise, highlighting the challenges associated with feature engineering in time series analysis [60]. The significance of feature engineering is further underscored in probabilistic conformal prediction (PPC), which captures underlying data distributions and assesses conformity probabilities, thereby enhancing model reliability [70].

4.4 Scalability and Computational Overhead

Scalability and computational overhead are critical factors influencing the deployment of machine learning models in time series analysis, especially with large-scale or high-frequency data. Traditional approaches, such as ARIMA and GARCH, typically offer computational efficiency and scalability when dealing with well-defined linear relationships and smaller datasets [2]. However, these models can become computationally intensive when extended to complex, non-linear patterns or high-dimensional data, necessitating the integration of advanced techniques.

Deep learning models, including LSTMs and CNNs, enhance capabilities for modeling intricate temporal dependencies but often incur increased computational overhead due to their complex architectures [6]. For instance, training LSTM networks demands substantial computational resources, particularly with high-dimensional or lengthy sequence data, which can hinder scalability in resource-constrained environments [56]. Pre-trained models, as demonstrated in innovative anomaly detection frameworks, help alleviate some challenges by reducing the necessity for extensive training on large datasets [67].

Federated learning frameworks like FSLSTM address scalability issues by enabling distributed learning across multiple devices, reducing computational burdens on individual nodes and enhancing the model's capacity to handle large-scale time series data from IoT sensors [68]. This approach leverages distributed systems' computational power to manage the training process, ensuring scalability while maintaining data privacy.

StreamiNNC offers a novel solution for online streaming inference by processing only new information in overlapping windows, significantly reducing computational overhead and facilitating the efficient deployment of CNNs in real-time applications [48]. This method exemplifies how optimization techniques can enhance the scalability of deep learning models in dynamic environments requiring rapid processing.

Hybrid models that integrate LSTMs with traditional statistical methods further enhance scalability by leveraging the strengths of both components, optimizing computational efficiency without compromising predictive performance [6]. These models demonstrate the potential for scalable solutions that balance computational demands with the need for accurate and robust time series analysis.

5 Change Point Detection (CPD) in Time Series

The identification of change points in time series analysis is critical for detecting significant shifts in data behavior, influencing decision-making processes. This section delves into Change Point Detection (CPD), emphasizing its fundamental role across applications and the necessity for effective detection mechanisms in today's data-driven landscape. Understanding CPD's significance provides insight into its implications and the methodologies discussed in subsequent sections.

5.1 Concept and Importance of CPD

Change Point Detection (CPD) is a vital analytical method in time series analysis, focusing on identifying moments when a dataset's statistical properties significantly shift. These change points indicate structural changes or anomalies, marking transitions between different states of the data-generating process [71]. The primary aim of CPD is to detect abrupt changes in a time series's underlying state, which is crucial for timely interventions and informed decision-making, particularly in environments with continuous data streams and limited labeled data. This requires robust unsupervised methods capable of swiftly and accurately identifying unexpected changes [10].

CPD's significance spans various domains, including finance, healthcare, and industrial applications. In industrial contexts, CPD is essential for monitoring equipment health and predicting system failures, thus preventing costly downtimes and ensuring operational efficiency [10]. In healthcare, CPD aids in segmenting continuous EEG data into homogeneous intervals, facilitating effective analysis and early intervention [72]. Additionally, in dynamic networks, CPD is crucial for identifying anomalous activity periods, with the ability to detect anomalous graphs and vertices being vital for maintaining network integrity [19].

CPD is also pivotal in remote sensing, where it encounters challenges due to complex textures, seasonal variations, and climate changes. Detecting sequential anomalies in time series data, where abnormal sequences appear at unknown times, is another critical application of CPD, enabling timely hazard prevention [10]. The adaptability of CPD techniques to various networks and their real-time detection capabilities further emphasize their importance [19].

Challenges in CPD include the need to optimally segment data while balancing model complexity and goodness of fit. This requires a nuanced approach to accurately detect abrupt changes in time series data without prior knowledge of the number of change points, minimizing false positives [72]. The concept of CPD is integral to time series analysis, providing a robust framework for detecting significant changes in data patterns, leading to enhanced operational efficiency, security, and decision-making across multiple domains.

5.2 Traditional and Statistical Approaches

Traditional and statistical approaches to Change Point Detection (CPD) have been foundational in time series analysis, providing essential tools for identifying shifts in data patterns. Classical methods, such as Cumulative Sum (CUSUM) algorithms and Generalized Likelihood Ratio Tests (GLRT), are recognized for their effectiveness when prior information is available [71]. However, these methods often face limitations in environments lacking such knowledge, which can hinder their ability to accurately detect change points.

Many existing CPD methods overlook the dynamic nature of dependency structures, either ignoring them or assuming static correlations over time [73]. This oversight can result in inaccuracies, especially in complex real-world datasets where correlations may evolve. Furthermore, traditional methods often depend on extensive labeled data, which is time-consuming to obtain and may be based on assumptions that do not hold true in practice, affecting detection accuracy [74].

In high-dimensional contexts, methods like rank energy statistics are sensitive to small data perturbations, leading to high false alarm rates and reduced effectiveness [75]. Such sensitivity poses significant challenges in environments characterized by inherent data variability, necessitating more robust approaches that can accommodate fluctuations without compromising detection accuracy.

The computational demands of traditional CPD techniques also present challenges, as many require extensive computation or the storage of the entire observed time series, which is not feasible in streaming or real-time applications [76]. In contrast, methods like Greedy Online Change Point Detection (GOCPD) enhance computational efficiency in streaming data by evaluating the likelihood of data segments and optimizing the search for candidate change points using ternary search [77].

In rapidly changing environments, such as dynamic networks, traditional CPD methods struggle to capture evolving patterns, complicating effective anomaly identification [78]. This limitation highlights the need for advanced techniques that can adapt to data evolution, improving the robustness and reliability of change point detection in complex settings.

The traditional and statistical methods that have historically underpinned CPD face significant challenges in addressing dynamic, high-dimensional, and real-time data streams. These limitations arise from their reliance on strong assumptions and low expressive power, which can hinder performance in complex scenarios such as industrial quality control, finance, and healthcare. Recent advancements in representation learning and neural network-based approaches offer promising alternatives by capturing intricate data structures without restrictive assumptions. However, these emerging methods require robust theoretical foundations to ensure reliability and effectiveness. Continued innovation in CPD techniques, particularly those integrating traditional methodologies with modern machine learning frameworks, is essential for enhancing the detection of abrupt changes across diverse applications [23, 79, 80, 81, 82].

5.3 Machine Learning-Based CPD Techniques

Machine learning-based approaches have significantly advanced Change Point Detection (CPD) by providing robust frameworks that adapt to diverse and dynamic data environments. These techniques utilize sophisticated algorithms to improve the accuracy and efficiency of detecting change points in time series data. For instance, Wang et al. proposed a neural online density-ratio estimator for non-parametric change point detection, showcasing the adaptability of machine learning techniques to evolving data streams [71].

The Time-Invariant Representation Change Point Detection (TIRE) method, an autoencoder-based approach, learns a partially time-invariant representation of time series data, effectively capturing underlying temporal dynamics while minimizing distortions [83]. This method exemplifies how machine learning can deliver stable and accurate change point detection by focusing on invariant features.

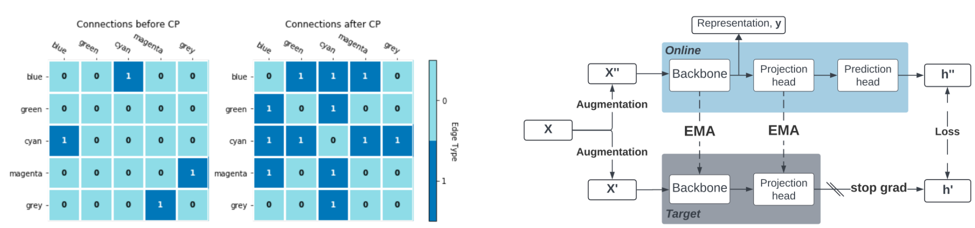
Contrastive learning techniques, such as those utilized in the method, create embedded representations that maximize shared information between contiguous time intervals while minimizing it across separated intervals, enhancing change point detection [72]. This underscores the significance of learning informative representations that capture underlying temporal dynamics, crucial for accurate change point detection.

In dynamic network environments, employing a siamese graph neural network to learn a graph similarity function illustrates the effectiveness of machine learning in efficiently detecting changes [19]. This method demonstrates the potential of advanced neural network architectures in addressing the complexities of dynamic data environments.

The integration of Gaussian process derivatives into the Active Learning framework, as seen in the DACD method, offers a more flexible and accurate detection of abrupt changes compared to existing methods [84]. This innovation emphasizes active learning's role in enhancing CPD capabilities by focusing on the most informative data points, thereby improving detection accuracy.

Additionally, the application of NLP-based methods for CPD, leveraging textual data derived from audio rather than relying solely on vocal characteristics, showcases the versatility of machine learning approaches in exploring new domains and data types [85]. This highlights the potential of integrating diverse data sources to enhance CPD performance.

Machine learning-based CPD techniques represent significant advancements in detecting change points, offering robust frameworks that adapt to complex temporal dynamics and enhance detection accuracy across various scenarios. The ongoing development of CPD methodologies, particularly through integrating deep learning and non-parametric approaches, holds great promise for effectively addressing the challenges posed by dynamic data environments. These innovations aim to improve the accuracy and reliability of CPD solutions across applications such as medical monitoring, finance, and video surveillance, enabling efficient detection of abrupt shifts in data distributions while accommodating outlier sensitivity and scalability [80, 81, 86, 82].



(a) Comparison of Connections Before and After CP[73]

(b) Online and Target Models for Representation Learning[82]

Figure 2: Examples of Machine Learning-Based CPD Techniques

AI-generated, for reference only.

As illustrated in Figure 2, Change Point Detection (CPD) in time series is a critical task aimed at identifying points where the statistical properties of a sequence of observations change. Machine learning-based CPD techniques have emerged as powerful tools in this domain, providing sophisticated methods for detecting these changes with high accuracy. The accompanying figure presents two examples of such techniques. The first image, "Comparison of Connections Before and After CP," visually compares matrix representations of connections before and after a CP operation. This matrix is color-coded into five categories, each with distinct rows and columns representing various connections and edge types, highlighting the structural changes induced by CP. The second image, "Online and Target Models for Representation Learning," depicts a flowchart that outlines the process of representation learning through online and target models, detailing the transformation of input data through neural networks and subsequent projection into lower-dimensional spaces, facilitating efficient change detection. Together, these visual examples underscore the complexity and effectiveness of machine learning-based CPD techniques in analyzing time series data.

5.4 Unsupervised and Non-Parametric CPD Methods

Unsupervised and non-parametric methods for change point detection (CPD) have gained prominence due to their ability to identify shifts in data distributions without requiring labeled data, which is particularly advantageous in real-world scenarios where labeling is costly or impractical. These methods focus on intrinsic changes in statistical properties, employing advanced techniques to enhance detection accuracy and robustness. The iCPD method exemplifies this approach, optimizing computational resources by swiftly detecting prior-data conflicts and determining when detailed change-point analyses are necessary [87].

The TIRE method, which integrates time-domain and frequency-domain information, enhances change point identification in time series data [83]. By combining these domains, TIRE effectively captures underlying temporal dynamics, providing a comprehensive framework for CPD. Similarly, the DACD method employs an active learning framework to efficiently identify change-point locations without relying on parametric assumptions, thus offering flexibility and adaptability to various data environments [84].

In dynamic network environments, the s-GNN method utilizes a graph similarity function learned from pairs of graph snapshots to detect change points [19]. This approach is particularly effective in dynamic graphs, where the absence of raw attribute information and the coupling of spatial and temporal information pose significant challenges [52]. The NOUGAT method further exemplifies the potential of unsupervised techniques by modifying the cost function to ensure unbiased density ratio estimation, utilizing a stochastic gradient descent approach to enhance CPD accuracy [71].

Contrastive learning frameworks, such as that employed in Deldari et al.'s method, leverage dependencies within time series data to improve change point detection [72]. This approach emphasizes the importance of learning informative representations that capture underlying temporal dynamics, which is crucial for accurate change point identification. Future research in unsupervised and non-parametric CPD methods could explore extending these techniques to multi-channel settings with multivariate generative models, further enhancing their applicability. The development of unsupervised and non-parametric CPD methods promises to improve the robustness and applicability of change point detection across various domains, addressing the challenges of unlabeled data environments.

6 Transformers and Neural Networks for CPD

6.1 Neural Network Architectures for CPD

Neural network architectures have revolutionized Change Point Detection (CPD) by offering sophisticated frameworks that capture complex temporal dependencies in time series data. These architectures leverage deep learning techniques to enhance both the precision and efficiency of change detection. For instance, the AMTNet model, which integrates multiscale feature extraction and attention mechanisms within a transformer structure, excels in capturing intricate data patterns, surpassing traditional methods [88]. The CROPS algorithm further demonstrates innovation by computing optimal segmentations through a penalized cost function, offering a robust framework for accurate time series segmentation [89]. Similarly, the NODE method frames the estimation of the

AI-generated, for reference only.

density ratio between data distributions as a binary classification problem, enhancing sensitivity to distributional changes [80].

The TSCPD method extends CPD applications beyond numerical data by identifying change points in speaker identity through textual analysis derived from audio [85]. Additionally, Bouchikhi et al.'s kernel-based approach ensures precise change-point detection by maintaining the estimated density ratio at 1 under the null hypothesis [71]. These neural network architectures enhance CPD in streaming time series data through online density-ratio estimation and deep representation learning, effectively modeling complex temporal dependencies and identifying changes across multiple time scales with high accuracy. By incorporating continual learning and spectral normalization, these frameworks adeptly capture intricate data patterns without imposing restrictive assumptions, making them particularly effective in real-world applications such as healthcare, finance, and climate monitoring [90, 80, 82]. Ongoing developments in these architectures promise further improvements in CPD effectiveness and reliability across various domains.

6.2 Graph-Based Approaches

Graph-based models have emerged as powerful tools for enhancing CPD capabilities, especially in dynamic environments where data relationships are complex and continuously evolving. These models leverage the inherent structure of graphs to capture dependencies and interactions within data, providing a robust framework for detecting change points. Graph Neural Networks (GNNs), for instance, utilize graph similarity functions to efficiently detect changes in dynamic networks, integrating spatial and temporal information for improved CPD accuracy [19]. The s-GNN method addresses the challenges of detecting change points in dynamic graphs by learning a graph similarity function from graph snapshots, allowing for precise change identification [19]. This adaptability underscores the potential of graph-based approaches in complex data environments.

Integrating graph-based models with neural network architectures enhances their effectiveness in addressing challenges such as anomaly detection in dynamic graphs. Techniques like attention mechanisms and temporal encoding facilitate better capture of structural and temporal dynamics in evolving datasets [91, 19, 92, 22, 52]. For example, siamese networks, often used with GNNs, enhance change point detection by focusing on the similarity between graph structures over time. Graph-based approaches extend CPD applications beyond traditional numerical data, exploring domains such as social and communication networks, where data is naturally represented as graphs. The capability of these models to process high-dimensional data and capture intricate interdependencies is crucial for enhancing CPD methodologies across applications like signal processing, machine learning, and video surveillance. Innovative frameworks such as Tensor-Based Multivariate Optimization (TeMPO) and representation learning techniques address the limitations of traditional CPD methods, demonstrating superior performance in real-world scenarios through improved accuracy and efficiency in anomaly detection and classification [39, 70, 80, 81, 82].

Graph-based models thus offer significant advancements in CPD by providing flexible and robust frameworks that leverage the structural properties of graphs. The integration of neural networks into CPD methodologies enhances the precision and relevance of applications, addressing the complexities of evolving data landscapes through non-parametric approaches that do not rely on predefined distribution assumptions. Recent methods utilizing online density-ratio estimation and continual learning frameworks effectively identify abrupt changes in streaming time series data, improving detection accuracy across diverse real-world scenarios, including medical monitoring and video surveillance [90, 39, 80, 81, 32].

6.3 Evaluation and Benchmarking

Evaluation and benchmarking of CPD techniques are essential for assessing their effectiveness and robustness across diverse datasets and applications. These processes use various metrics and methodologies to ensure that CPD models accurately identify shifts in data distributions. A key metric in evaluating CPD performance is the Receiver Operating Characteristic (ROC) curve, which illustrates the trade-offs between true positive rates and false positive rates across different threshold settings [80]. The ROC curve, combined with the mean of test statistics from multiple Monte Carlo runs, provides a comprehensive framework for assessing the reliability and precision of CPD models under various conditions.

Benchmark	Size	Domain	Task Format	Metric
IAP[56]	36,058	Chemical Engineering	Time Series Prediction	Mean Squared Error
ADecimo[25]	1,980	Time Series Analysis	Anomaly Detection	AUC-PR, VUS-PR
TSB-AD[93]	1,070	Anomaly Detection	Anomaly Detection	VUS-PR
PGP[57]	3,162	Plant Phenotyping	Segmentation	SSIM, mIoU
UCR[36]	1,000	Medicine	Anomaly Detection	F1-score
ARB[28]	10,000	Automated Reasoning	Logical Proof Generation	Accuracy, F1-score
CPD[21]	600,000	Social Network Analysis	Change Point Detection	Precision, Recall
MTAD-Bench[63]	2,400,000	Anomaly Detection	Anomaly Detection	F1, AP

Table 6: The table presents a comprehensive selection of benchmarks used in the evaluation and benchmarking of Change Point Detection (CPD) techniques. It highlights the diversity of datasets across various domains, including chemical engineering, time series analysis, and medicine, along with the task formats and metrics employed to assess model performance. This information is crucial for understanding the effectiveness and applicability of CPD models in different contexts.

Benchmark	Size	Domain	Task Format	Metric
IAP[56]	36,058	Chemical Engineering	Time Series Prediction	Mean Squared Error
ADecimo[25]	1,980	Time Series Analysis	Anomaly Detection	AUC-PR, VUS-PR
TSB-AD[93]	1,070	Anomaly Detection	Anomaly Detection	VUS-PR
PGP[57]	3,162	Plant Phenotyping	Segmentation	SSIM, mIoU
UCR[36]	1,000	Medicine	Anomaly Detection	F1-score
ARB[28]	10,000	Automated Reasoning	Logical Proof Generation	Accuracy, F1-score
CPD[21]	600,000	Social Network Analysis	Change Point Detection	Precision, Recall
MTAD-Bench[63]	2,400,000	Anomaly Detection	Anomaly Detection	F1, AP

Table 7: The table presents a comprehensive selection of benchmarks used in the evaluation and benchmarking of Change Point Detection (CPD) techniques. It highlights the diversity of datasets across various domains, including chemical engineering, time series analysis, and medicine, along with the task formats and metrics employed to assess model performance. This information is crucial for understanding the effectiveness and applicability of CPD models in different contexts.

In addition to ROC curves, metrics such as precision, recall, and F1-score are commonly utilized to evaluate CPD techniques, offering a balanced view of performance by considering both accuracy and completeness of detected change points [85]. These metrics are particularly valuable in comparing CPD models against traditional approaches, as demonstrated in studies where methods derived from textual data outperformed voice-based diarization models in capturing change points with higher precision and recall.

Proposed CPD frameworks have shown high recall and precision across various datasets, underscoring their robustness and applicability in real-world scenarios [22]. Comprehensive evaluations that incorporate diverse datasets validate that CPD models maintain effectiveness across different types of data and application contexts.

The evaluation and benchmarking of CPD techniques are crucial for the advancement of the field, providing essential insights into model performance across applications such as industrial quality control, healthcare, and finance. These evaluations highlight the strengths and limitations of various methods—including traditional unsupervised techniques and emerging representation learning approaches—guiding the development of more accurate and reliable detection methods. By addressing critical issues like dataset integrity and evaluation measure reliability, researchers can systematically compare a wide range of algorithms, identifying the most effective strategies for detecting anomalies in time series data and enhancing the robustness and applicability of CPD solutions in real-world scenarios [23, 82, 93]. Through a comprehensive range of metrics and benchmarks, researchers can ensure that CPD models are well-equipped to handle the complexities of time series data, ultimately enhancing their applicability across various domains. Table 7 provides a detailed overview of the benchmarks employed in the evaluation and benchmarking of CPD techniques, illustrating the diversity of datasets and metrics used to assess model performance across different domains.

7 Anomaly Detection in Time Series

7.1 Challenges in Anomaly Detection

Anomaly detection in time series data presents significant challenges due to temporal dependencies and dynamic characteristics. The rarity of anomalies amidst large volumes of normal data complicates detection criteria, limiting the effectiveness of supervised methods [42]. The efficacy of anomaly detection algorithms is contingent upon dataset characteristics, anomaly types, and parameter settings, necessitating careful algorithm selection and tuning [9]. Many methods struggle with non-linear interactions and temporal dependencies, especially in the presence of long-range dependencies and quasi-periodic components [94].

Dynamic environments add complexity with multivariate data streams, where non-linear relationships can obscure detection [69]. Current methods often fail to adapt to evolving graph structures, missing subtle anomalies [92]. Moreover, limitations in point adjustment protocols may overestimate model performance, reducing real-world applicability [24]. The opacity of deep learning models complicates interpretability, a critical factor in applications requiring trust [95]. Privacy concerns further challenge the development of adaptable models, necessitating privacy-preserving techniques due to data sharing restrictions from edge devices [47].

Addressing these challenges requires innovative methodologies that enhance model adaptability, interpretability, and robustness, while considering privacy and scalability. Advancements should integrate comprehensive encoding strategies for unattributed nodes, leverage temporal and spatial patterns, and utilize stochastic models to capture complex dependencies, ensuring practical applicability in sectors such as social networks, cybersecurity, and online advertising [62, 52, 32, 93]. Developing advanced unsupervised methods that autonomously learn complex dependencies is crucial for advancing anomaly detection in time series analysis.

7.2 Deep Learning Models for Anomaly Detection

Deep learning models have significantly advanced anomaly detection in time series by capturing complex temporal dependencies. The Anomaly Transformer, using an association discrepancy criterion, achieves state-of-the-art results across benchmarks, exemplifying the ability of transformer architectures to capture intricate temporal patterns [42]. The ALGAN model, incorporating an Adjusted-LSTM within a GAN framework, improves detection accuracy in both univariate and multivariate time series, highlighting the effectiveness of generative models [94].

The TADDY framework leverages a transformer model to learn coupled spatial-temporal information for anomaly detection in dynamic graphs, demonstrating the versatility of transformers in complex datasets [52]. Federated learning frameworks, like those proposed by Liu et al., enable collaborative training of deep anomaly detection models while maintaining data locality, addressing privacy concerns and enhancing robustness [47]. The LM optimizer showcases superior performance in time series anomaly detection, underscoring the importance of optimization techniques [12].

Unsupervised methods, such as the adaptive fusion of graph invariants, enhance detection in graph time series, emphasizing the role of graph-based techniques [96]. Comparative studies suggest classical machine learning methods may outperform deep learning in certain contexts, indicating the need for tailored approaches based on anomaly type [23, 17]. The continuous development and integration of these models promise to enhance anomaly detection solutions' applicability and efficiency.

7.3 Frameworks and Models for Anomaly Detection

The landscape of anomaly detection in time series is characterized by diverse frameworks and models addressing challenges related to temporal dependencies and data complexity. The Anomaly Transformer, employing a two-branch Anomaly-Attention mechanism, achieves state-of-the-art results across benchmarks, illustrating the potential of transformer architectures [42]. GANs, utilized in frameworks like ALGAN, employ an Adjusted-LSTM to model normal behavior and detect anomalies, highlighting the effectiveness of generative models [94].

Methods using non-conformity measures, such as KNN-ICAD and LOF-ICAD, emphasize historical data's role in enhancing detection accuracy [97]. Counterfactual explanations improve model interpretability by generating variations deemed normal [95]. Patch-based models like PatchAD emphasize scalability and efficiency through lightweight multiscale architectures, integrating graph learning techniques with neural networks to reduce false alarms [98, 99, 92, 100].

Hierarchical frameworks, such as the THOC network, utilize multi-scale feature integration to capture anomalies across temporal scales, enhancing sensitivity and accuracy [62, 23, 42, 9]. The evolution of frameworks and models is driven by advancements in neural network architectures, unsupervised learning techniques, and rigorous benchmarking. Emerging hybrid models, combining attention mechanisms with autoencoders, enhance online anomaly detection by capturing both local and long-term patterns. Surrogate metrics for model selection in the absence of labeled datasets enable practitioners to identify suitable methods [101, 23, 102]. These innovations promise to enhance the robustness and applicability of anomaly detection solutions in time series analysis.

7.4 Techniques Leveraging Adversarial and Self-Supervised Learning

Adversarial and self-supervised learning techniques have advanced anomaly detection in time series by enhancing model robustness and reducing reliance on labeled datasets. Adversarial learning models like TAnoGAN learn general data distributions through adversarial training, effectively identifying anomalies [103]. TadGAN, with its cycle-consistent GAN architecture, improves anomaly scoring by focusing on pattern reconstruction [104]. Self-supervised learning, exemplified by the Quantile-based LSTM, identifies anomalies without extensive labeling, highlighting its robustness [105].

Hybrid approaches, such as Hofkes' method, combine smoothing with anomaly detection, achieving low false rates and offering insights into underlying processes [106]. Incorporating uncertainty into predictions, as seen in HypAD, enhances accuracy and reduces false alarms [107]. The application of adversarial and self-supervised learning provides sophisticated tools for capturing complex data patterns. Advancements like OmniAnomaly and Distribution-Augmented Contrastive Reconstruction (DACR) improve reliability and versatility across fields, including system monitoring and cybersecurity, by leveraging advanced approaches such as stochastic recurrent neural networks and contrastive learning [62, 108, 23].

8 Unsupervised Learning for CPD and Anomaly Detection

In the field of unsupervised learning, the identification and analysis of change points and anomalies in time series data are essential tasks that require advanced methodologies due to their significant implications across various domains such as system monitoring, healthcare, and cybersecurity. These tasks involve detecting abrupt changes in data that may indicate critical transitions in system behavior or performance. The complexity of time series data, coupled with the scarcity of labeled anomaly data, necessitates the development of sophisticated approaches that can effectively select the most suitable models for specific applications. Recent studies have demonstrated that while numerous methods exist, no single approach universally excels across all datasets; therefore, a comprehensive evaluation of these techniques, including their performance metrics and adaptability to different types of anomalies, is crucial for practical implementation. [101, 23, 24, 109]. As we delve deeper into the various approaches employed in this domain, it becomes evident that graph-based and temporal dependency models stand out for their ability to effectively capture the intricate relationships and dependencies within multivariate time series data. This leads us to explore the specific frameworks that have been developed, notably those that utilize graph structures and temporal dynamics to enhance the detection of anomalies and change points.

8.1 Graph-Based and Temporal Dependency Models

8.2 Graph-Based and Temporal Dependency Models

Graph-based and temporal dependency models have emerged as pivotal frameworks in unsupervised learning for change point detection (CPD) and anomaly detection, offering sophisticated methods to capture complex relationships inherent in time series data. These models leverage the structural properties of graphs to represent and analyze the interconnected nature of multivariate time series data, facilitating the identification of anomalies and change points with greater accuracy. The use of stochastic modeling is particularly crucial in capturing the complexities of multivariate time series data, enabling models to distinguish between normal and anomalous patterns more effectively [69].

The integration of graph representations significantly advances the modeling of intricate dependencies, enhancing detection capabilities in unsupervised settings. For instance, GAN-AD employs a GAN architecture to model the distribution of multivariate time series data, effectively capturing complex temporal and spatial relationships, resulting in high accuracy in anomaly detection with minimal false alarms [110]. This approach underscores the potential of generative models to detect anomalies based on reconstruction and discrimination losses, providing robust frameworks for detecting anomalies without requiring labeled training data [111].

Hybrid models, such as those employing autoencoders with attention mechanisms, illustrate the potential of combining graph-based and temporal models for unsupervised anomaly detection. These advanced models integrate autoencoders and attention mechanisms to enhance anomaly detection in time series data. The autoencoders effectively capture local structural patterns through compressed embeddings, while the attention mechanisms facilitate the learning of long-term dependencies by analyzing relationships across the entire series. This hybrid approach not only improves the accuracy of anomaly detection but also allows for efficient parallel processing, making it suitable for diverse applications in fields such as healthcare, cybersecurity, and industrial monitoring. By leveraging these complementary techniques, the models provide a robust framework for identifying anomalies in complex temporal datasets, addressing the challenges posed by the rarity and subtlety of abnormal events. [23, 17, 42, 112, 102]. The integration of these components underscores the importance of leveraging both spatial and temporal information to enhance detection capabilities.

Furthermore, the use of generative models highlights the effectiveness of incorporating smoothness priors to capture normal patterns in the presence of anomalies, significantly outperforming traditional models. This approach exemplifies the potential of integrating generative and recurrent networks to enhance the model's ability to capture and utilize temporal information, addressing limitations in previous methods [69].

The categorization of techniques into point outliers, subsequence outliers, and outlier time series, with distinctions between univariate and multivariate methods, provides a structured framework for understanding the diverse approaches employed in anomaly detection. This organization facilitates the development of targeted models that address specific types of anomalies, thereby improving detection accuracy across different scenarios. Future research should focus on expanding the number of datasets and including more contextual anomalies to better evaluate the effectiveness of various detection methods [63].

Graph-based and temporal dependency models serve as advanced frameworks for unsupervised learning in change point detection (CPD) and anomaly detection, effectively addressing key challenges such as the representation of unattributed nodes and the extraction of discriminative knowledge from coupled spatial-temporal data. These models leverage sophisticated techniques, such as dynamic graph transformers and attention mechanisms, to capture intricate relationships within evolving graph structures. As demonstrated by recent studies, including the TADDY and AddGraph frameworks, these approaches significantly enhance detection accuracy across various applications, including social networks, e-commerce, and cybersecurity, outperforming traditional methods in real-world scenarios. [91, 52]. The continued development and integration of these models promise to enhance their applicability across diverse domains, addressing the challenges inherent in time series data analysis.

8.3 Evaluation Metrics and Benchmarks

Evaluation metrics and benchmarks are critical for assessing the performance and robustness of unsupervised learning approaches in change point detection (CPD) and anomaly detection. These metrics provide a standardized framework to compare different models and determine their effectiveness in capturing complex temporal patterns and anomalies in time series data. The use of precision, recall, and F1-score metrics is prevalent in evaluating unsupervised learning models, offering insights into their ability to accurately identify true positives while minimizing false positives and negatives [85]. These metrics are crucial for understanding the trade-offs between sensitivity and specificity in detection tasks.

The Receiver Operating Characteristic (ROC) curve and the area under the ROC curve (AUC) are also commonly used to evaluate the performance of unsupervised models, providing a graphical representation of the trade-offs between true positive rates and false positive rates across different threshold settings [80]. These metrics are particularly useful for comparing the performance of various models under different operating conditions, ensuring that the chosen model offers the best balance between detection accuracy and false alarm rates.

Benchmark datasets play a vital role in evaluating unsupervised learning approaches, providing a consistent basis for comparing model performance across different scenarios. The use of diverse datasets, such as those capturing different types of anomalies or change points, ensures that models are tested under a wide range of conditions, enhancing their generalizability and robustness. The inclusion of real-world datasets, alongside synthetic datasets, is essential for validating the applicability of models in practical settings [22].

Moreover, the development of comprehensive benchmarks that incorporate a variety of dataset characteristics, such as temporal dependencies, noise levels, and anomaly types, is crucial for advancing the field. These benchmarks facilitate the systematic evaluation of models, allowing researchers to identify strengths and weaknesses in their approaches and guide future improvements. The ongoing enhancement and diversification of benchmark datasets are crucial for effectively tackling the dynamic challenges in time series analysis. This is essential to ensure that models can accurately capture intricate patterns and identify anomalies, given the current issues with existing datasets that often contain flaws and biases. Recent research highlights the need for high-quality, heterogeneous datasets and reliable evaluation measures to provide a more accurate assessment of anomaly detection algorithms. By addressing these shortcomings, the development of comprehensive benchmarking resources, such as the UCR Time Series Anomaly Archive and the TSB-AD, can facilitate meaningful comparisons among different methodologies and foster genuine advancements in the field. [25, 23, 36, 93]

The advancement of unsupervised learning techniques in change point detection (CPD) and anomaly detection relies heavily on the implementation of rigorous evaluation metrics and comprehensive benchmarks. These tools are crucial for accurately assessing model performance across various applications, such as system monitoring, healthcare, and cybersecurity. By providing a systematic approach to evaluate different anomaly detection methods—ranging from classical to deep learning techniques—researchers can identify the most effective models for specific types of anomalies. Furthermore, the integration of surrogate metrics and careful selection of evaluation criteria enables the development of more accurate and reliable detection methods, ultimately enhancing the ability to navigate the complexities of data streams and improve real-world applications. [101, 23, 18, 113, 82]

9 Applications and Case Studies

Recent advancements in time series analysis have underscored its adaptability across various fields, effectively tackling complex challenges. This section delves into case studies illustrating the transformative impact of time series methodologies, particularly in finance and economic forecasting.

9.1 Finance and Economic Forecasting

Time series analysis is pivotal in finance and economic forecasting, offering tools for predicting market trends, managing risks, and optimizing investment strategies. Advanced anomaly detection methods, such as OmniAnomaly, effectively identify irregular patterns in financial datasets, achieving an F1-Score of 0.86 [62]. Such models enhance the reliability of financial analyses. Change point detection (CPD) methods, like the asymptotic distribution-free approach, are crucial for identifying shifts in economic indicators, supporting timely interventions and market stability [114]. Deep learning techniques, such as the attention-autoencoder hybrid model, enable real-time monitoring of financial systems, exemplifying how neural network architectures can improve economic trend analysis [102]. Furthermore, innovative anomaly detection methods support real-time energy management solutions, illustrating the broader applicability of time series analysis in resource optimization [67]. The evolution of time series analysis in finance is driven by innovations in anomaly detection and CPD, alongside machine learning advancements like the Temporal Fusion Transformer and robust regression techniques. These innovations facilitate more accurate forecasting solutions tailored to diverse economic contexts, enhancing decision-making for analysts and businesses [62, 53, 32, 27].

9.2 Healthcare and Biomedical Applications

Time series analysis is increasingly vital in healthcare and biomedical fields, enhancing insights into patient data and diagnostic capabilities. CPD methods are essential for segmenting continuous EEG data into homogeneous intervals, aiding in the analysis and early intervention for neurological conditions [72]. Anomaly detection techniques monitor physiological signals, such as heart rate variability, aiding in the diagnosis of conditions like ADHD by identifying deviations from normal patterns [41]. Deep learning models, particularly LSTM networks, predict critical health episodes by modeling pre-conditional events, improving early anomaly detection in time series data [45]. The integration of machine learning techniques extends to multi-channel EEG data analysis, where models like CPD-BoW enhance detection capabilities through CPD and clustering techniques [7]. Hierarchical time series forecasting methods allow for accurate aggregations across different data levels, facilitating comprehensive analyses of physiological signals and environmental factors affecting health outcomes [30]. Innovations like MedTsLLM, leveraging large language models for analyzing complex physiological signals, significantly enhance diagnostic capabilities, improving patient monitoring and clinical decision-making [7, 64].

9.3 Industrial and Energy Management

Time series analysis is foundational in industrial and energy management, offering methodologies for optimizing operations and enhancing efficiency. In industrial contexts, time series techniques monitor machinery health and predict equipment failures, preventing costly downtimes. Anomaly detection models analyze multi-time series data from heterogeneous sensors, utilizing temporal dependencies to identify patterns indicating potential malfunctions, facilitating proactive maintenance [60]. In the energy sector, time series analysis forecasts power consumption and manages energy resources. Advanced models, including LSTM networks, predict electrical load patterns, enabling effective resource allocation and grid stability [6]. The integration of deep learning with traditional statistical methods, such as ARIMA, showcases the benefits of hybrid models in refining energy forecasting and management strategies. Moreover, innovative anomaly detection methods optimize operational efficiency and resource utilization in real-time energy management solutions [67].

9.4 IoT and Sensor Networks

Time series analysis is increasingly vital in IoT and sensor networks, providing methodologies for processing vast data generated by these systems. The proliferation of IoT devices has led to an exponential increase in time-dependent data, presenting analytical challenges due to temporal dependencies and complex data point relationships. This necessitates sophisticated techniques, including graph-based models and federated learning frameworks, to extract actionable insights and improve decision-making across domains like industrial applications, system monitoring, and cybersecurity [115, 23, 47, 100]. In sensor networks, time series analysis applies to environmental monitoring, smart cities, and industrial automation. Models analyzing sensor data, such as air quality and weather patterns, provide accurate forecasts, supporting proactive management strategies [11]. In smart cities, time series analysis optimizes traffic flow and energy consumption, predicting peak usage periods for efficient resource allocation [60]. In industrial automation, time series analysis monitors equipment performance and predicts maintenance needs, enhancing operational efficiency [60]. Federated learning frameworks enhance the robustness and scalability of time series models in IoT environments [68].

9.5 Other Domains and Emerging Applications

Time series analysis extends into video analytics, robotics, and social media, where the temporal nature of data is crucial for extracting insights. In video anomaly detection, frameworks like STM-AE demonstrate efficacy, achieving high AUCs on datasets like UCSD Ped2 and CUHK Avenue [116]. In robotics, time series analysis is essential for motion prediction and control, where understanding sequential sensor data is vital for responsive systems [35, 25, 17, 62, 29]. Social media platforms utilize time series analysis for trend detection and sentiment analysis, employing techniques like non-parametric change-point detection to monitor public opinion shifts [117, 11, 71, 118]. In telecommunications, time series analysis aids in network traffic forecasting and anomaly detection, optimizing resources and enhancing service quality [37, 32, 23, 62]. The expanding scope of time series analysis underscores its adaptability, offering robust solutions for diverse challenges. As temporal data complexity rises, sophisticated methodologies leveraging deep learning hold potential to enhance anomaly detection and foster innovation across domains, including speech recognition and predictive analytics [117, 29].

10 Future Directions and Challenges

The future of time series analysis is shaped by the increasing complexity of datasets with temporal dependencies, which introduce behavioral variations at similar time points. While deep learning techniques have advanced feature extraction and improved forecasting accuracy, the balance between traditional and deep learning methods remains critical. Traditional approaches may surpass complex models in certain anomaly detection scenarios [117, 29, 23]. As the field progresses, enhancing model interpretability and robustness is essential for effective applications across diverse domains.

10.1 Enhancing Model Interpretability and Robustness

With growing data complexity, improving interpretability and robustness in time series models is paramount. Future research should develop advanced evaluation metrics to address current gaps and integrate domain knowledge with hyperparameter optimization [18, 27]. Hybrid approaches that combine machine learning techniques can boost forecasting accuracy in chaotic systems by leveraging existing algorithms' strengths [6, 9]. Optimizing sub-sequence lengths and model stability is crucial for expanding applications like predictive maintenance [69].

Understanding decision-making in complex neural architectures requires interpretability improvements, such as perturbation-based methods for analyzing transformer predictions [95]. Integrating exogenous variables could enhance forecasting models [4], while techniques like TiSAT improve detection precision [119]. Applying benchmarks in contexts like wastewater treatment could address interpretability challenges [8]. Innovations by Deldari et al. demonstrate improvements over traditional methods, achieving higher F1-scores [72].

A multifaceted strategy incorporating domain knowledge, hybrid methodologies, and computational resource optimization is vital for enhancing model interpretability and robustness. This approach addresses dynamic data challenges and leverages advanced techniques like transformer models for anomaly detection, ultimately improving performance across real-world applications [62, 52, 120].

10.2 Addressing Data Limitations and Diversity

Addressing data limitations and ensuring diversity in datasets are key challenges in advancing time series analysis. Simplified models may be more practical under constrained resources, as noted by Kendrick et al. [21]. Comprehensive evaluation frameworks are essential for overcoming data limitations and enhancing anomaly detection robustness [24]. Ensuring dataset diversity captures a wide range of temporal patterns and anomalies, crucial for model generalization.

Effective anomaly detection in multivariate time series requires integrating diverse data sources and accounting for environmental factors [62, 18]. Incorporating exogenous variables can enhance predictive accuracy. Unsupervised learning techniques, including graph-based models, offer promising avenues for addressing data limitations by capturing complex relationships without extensive labeled data.

10.3 Improving Anomaly and Change Point Detection

Enhancing anomaly and change point detection requires advancements in model architectures and optimization techniques. Optimizing window lengths remains challenging, particularly with GANs [94]. Adaptive algorithms for dynamic window size adjustment are essential for model stability. Augmentation and negative mining techniques can bolster robustness in detecting change points [72]. Precise detection of low leak rates is critical in applications like fuel leakage detection [10].

Advanced clustering algorithms and deep learning techniques can automate detection models in dynamic environments, such as financial markets [62, 23, 42]. Graph-based anomaly detection incorporating temporal structures can enhance false positive rate control in complex networks [19, 121]. A multifaceted strategy combining state-of-the-art model architectures with sophisticated optimization techniques is crucial for improving anomaly and change point detection across various applications [42, 109, 121, 9, 62].

10.4 Optimizing Computational Efficiency and Scalability

Optimizing computational efficiency and scalability is vital for deploying time series analysis in real-time applications and large-scale environments. StreamiNNC reduces computational overhead in CNNs, enhancing efficiency without compromising capabilities [48]. Cadence excels in detecting change points with computational efficiency, suitable for IoT applications [115]. TeMPO optimizes parameter reduction, improving model performance in time series analysis [39].

Real-time applications, such as gravitational wave detection, require efficient deep learning models for timely analysis [16]. Future research will focus on enhancing the computational efficiency of NODE and exploring applications across domains [80]. Addressing computational challenges involves developing optimization techniques that maintain accuracy and robustness.

A multifaceted strategy encompassing architectural innovations and parameter reduction techniques is essential for enhancing computational efficiency and scalability. Leveraging advanced optimization algorithms can significantly improve anomaly detection capabilities in complex datasets, ensuring effective analysis in real-world applications [25, 29, 12, 93].

10.5 Expanding Applications and Real-World Integration

Expanding time series analysis into new applications and integrating it into real-world scenarios is driven by model advancements and evaluation methods. Future research could explore complex reasoning tasks and adaptive evaluation methods to enhance applicability across domains [28]. Sentiment analysis and robustness against market shocks are potential expansion areas in financial markets [13].

Applying time series analysis to forecasting problems like consumer behavior or epidemic dynamics offers promising research avenues [26]. Graph structure learning with deep learning techniques presents another direction for expanding applications, particularly in G-TSAD [118]. Hierarchical time series analysis provides insights, with future research focusing on optimizing models for real-time deployment.

Exploring LSTM networks' application to other data types and training parameters could expand time series analysis reach [58]. Ongoing expansion into new applications is driven by model development and evaluation advancements, enhancing anomaly detection methods across diverse applications such as healthcare and cybersecurity [23, 17, 42, 117, 29].

11 Conclusion

This survey has explored the profound impact of deep learning and machine learning methodologies on time series analysis, underscoring their vital contributions across diverse sectors. Techniques such as Long Short-Term Memory (LSTM) networks have significantly improved the forecasting of industrial aging processes, offering valuable insights for optimizing maintenance schedules. Similarly, the TMF method has demonstrated remarkable accuracy and interpretability in identifying ECG patterns associated with Atrial Fibrillation, showcasing the transformative potential of machine learning in healthcare applications.

In the realm of environmental forecasting, models like Unet-LSTM have excelled in predicting global Sea Surface Temperature (SST) anomalies, effectively capturing major climatic events such as the 2010-11 La Niña and the 2015-16 El Niño, with impressive precision. This highlights the critical role of deep learning in enhancing climate prediction models and advancing our understanding of global environmental dynamics.

Additionally, the integration of change-point detection with remaining useful life estimation has propelled advancements in system health monitoring, providing a holistic framework for assessing the durability and reliability of essential systems. The development of novel datasets has further facilitated the modeling and forecasting of N_2O emissions in wastewater treatment, offering valuable resources for tackling environmental challenges.

The survey emphasizes the central role of deep learning and machine learning in revolutionizing time series analysis, equipping researchers with robust tools to capture intricate temporal patterns and enhance predictive precision across various domains. Ongoing research and innovation in this field are poised to broaden the scope and application of time series models, driving the creation of innovative solutions to emerging challenges across multiple industries.

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