
Deep Learning for Time Series Anomaly Detection and Outlier Detection: A Survey

www.surveyx.cn

Abstract

Deep learning has revolutionized time series analysis, providing advanced tools for anomaly and outlier detection across diverse applications. This survey underscores the transformative impact of deep learning techniques, such as LSTM-GRU models, which have demonstrated superior predictive accuracy in domains like stock selection and healthcare. In healthcare, models like TempPNet enhance chronic disease management, while the TE-SSL framework advances predictions in neurodegenerative disorders, highlighting deep learning's potential in medical diagnostics. The survey also explores advancements in anomaly detection, where models like LLMAD offer competitive performance and interpretability, marking significant progress in time series anomaly detection. In finance, deep learning models outperform traditional methods, improving prediction accuracy and market insights. Additionally, self-attention models like SAKT and RKT surpass traditional RNN-based models, particularly in educational technology, by incorporating contextual data to enhance performance. Despite these advancements, challenges remain in scalability, interpretability, and adaptability to real-time processing. Addressing these challenges requires innovative solutions, including hybrid and unsupervised approaches, to enhance model robustness and efficacy. As research continues to evolve, the potential for deep learning to revolutionize time series anomaly and outlier detection remains substantial, offering improved accuracy, interpretability, and adaptability in handling complex temporal data.

1 Introduction

1.1 Significance of Deep Learning in Time Series Analysis

Deep learning represents a significant advancement in time series data analysis, excelling in pattern recognition and anomaly detection across various domains. This approach effectively overcomes limitations inherent in traditional methods, such as Fourier transforms, particularly in classifying time series from complex dynamical systems [1]. Its robustness is especially notable in financial markets, where deep learning outperforms conventional machine learning techniques in predicting market trends and volatility.

The transformative impact of deep learning extends to fields like educational technology and brain activity analysis. In educational contexts, deep learning enhances Knowledge Tracing (KT), facilitating precise tracking of student learning progress through large-scale performance datasets [2]. Additionally, deep neural networks analyze complex data such as fMRI recordings, yielding insights into neural processes [3].

Despite these advancements, the field faces challenges, including the rapid evolution of methodologies and the selection of suitable loss functions and performance metrics. To address these issues, incorporating probabilistic approaches into deep learning models has been suggested, integrating model and data uncertainty to improve prediction robustness [4].

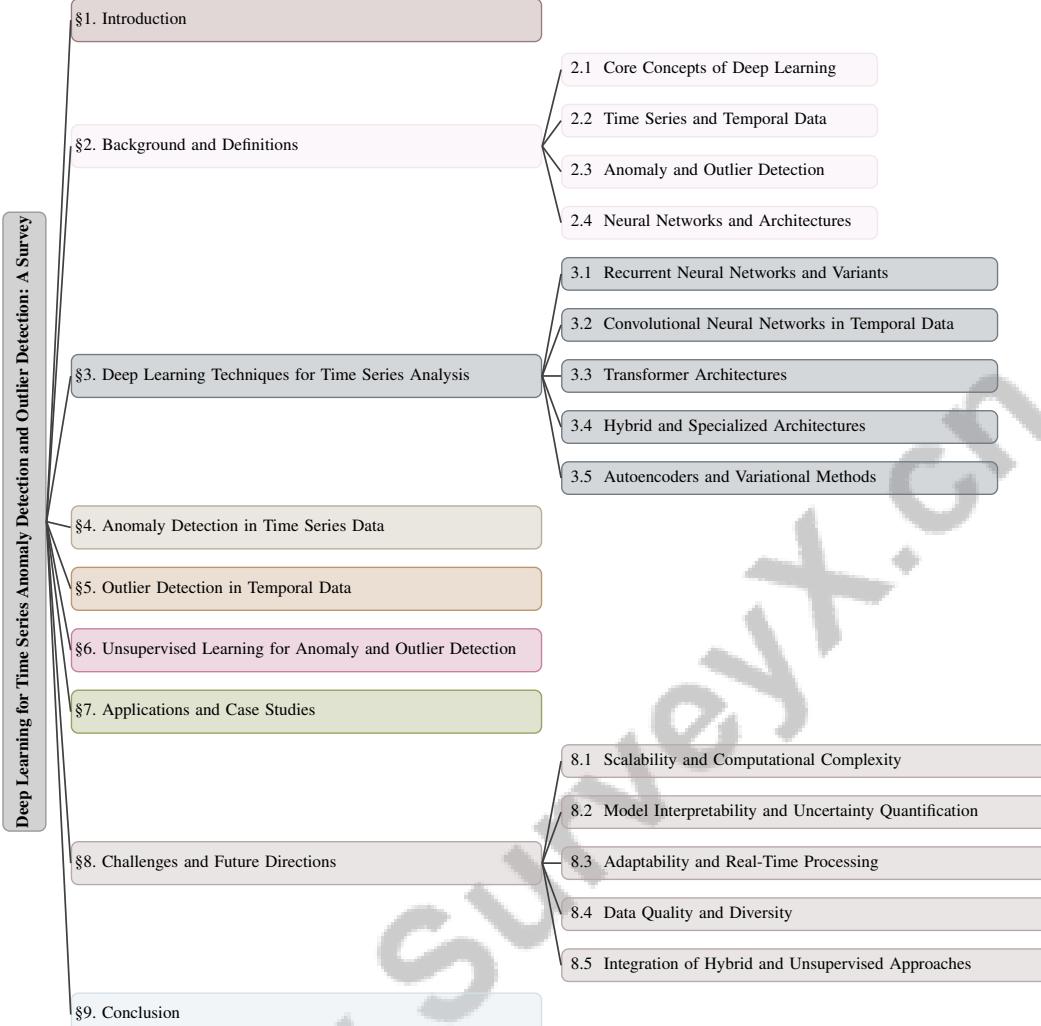


Figure 1: chapter structure

In traffic management, deep learning enables the analysis of extensive datasets, such as millions of traffic accident records, leading to enhanced edge-level regression and classification tasks [5]. These developments underscore the vital role of deep learning in time series analysis, emphasizing its potential for significant insights and innovations across various applications. Addressing existing knowledge gaps and challenges remains crucial for further enhancing the efficacy of deep learning in this domain [6].

1.2 Role of Neural Networks and Unsupervised Learning

Neural networks are fundamental to temporal data analysis, with architectures like Recurrent Neural Networks (RNNs) effectively capturing complex temporal dependencies. RNNs excel in modeling sequential data, as seen in audio processing, while Convolutional Neural Networks (CNNs) are proficient in spatial pattern recognition [7]. This adaptability highlights the versatility of neural networks across diverse data modalities.

The integration of specialized techniques, such as Temporal Frame Interpolation (TFI) with a Multi-Level Dice loss function, demonstrates the potential of neural networks to enhance performance in tasks requiring precise temporal alignment [8]. Furthermore, architectures like the LSTM-GRU gated network exemplify their capability in processing complex temporal financial data, effectively modeling intricate time-dependent patterns [9].

Combining neural networks with unsupervised learning methodologies broadens their applicability in temporal data analysis, enabling the extraction of meaningful patterns without labeled data. Unsupervised deep learning frameworks leverage deep neural networks (DNNs) to approximate optimal policies, showcasing their potential to derive insights from complex datasets autonomously [10]. Techniques such as those proposed by Huang et al. eliminate the need for manual supervision by progressively discovering sample-anchored neighborhoods, aiding in learning class decision boundaries [11].

Innovative approaches like the Choquet Integral Multi-layer Perception (ChIMP) enhance information fusion by representing the fuzzy Choquet integral as a neural network [12]. Additionally, modularizing neural networks into smaller components for independent updates, as seen in associated learning methods, underscores their adaptability and robustness in temporal data processing [13].

The development of compact and robust neural networks, such as deep diagonal-circulant networks using structured matrices, illustrates their role in reducing computational complexity while maintaining accuracy [14]. The significance of activation functions in enhancing neural network capabilities further contributes to their effectiveness in temporal data analysis [15]. Collectively, these advancements highlight the crucial role of neural networks and unsupervised learning techniques in advancing time series analysis, facilitating the extraction of valuable insights across various domains.

1.3 Motivation for the Survey

This survey is motivated by the complex challenges and increasing interest in applying deep learning techniques for time series anomaly and outlier detection. A critical issue is the reliance on large volumes of labeled data, which are often scarce, necessitating exploration of unsupervised and semi-supervised approaches to improve performance in dynamic environments. The limitations of current methodologies, particularly in predicting discrete-time bifurcations, underscore the need for advanced techniques capable of discerning critical transitions in various systems [16].

In renewable energy, the volatile nature of wind energy and data noise highlight the necessity for precise forecasting models, further emphasizing the importance of this survey in addressing these challenges [17]. Traditional machine learning models also struggle with intricate biomedical datasets, such as respiratory sounds, which require innovations in performance consistency and dataset comparability [18].

The integration of zero-bias deep neural networks with Quickest Event Detection algorithms aims to enhance detection speed and reliability, reflecting a growing focus on improving real-time learning capabilities in deep neural networks [4]. This aligns with the broader trend of leveraging deep learning's advantages over conventional methods, particularly in modeling complex, high-dimensional functions [19].

Moreover, the challenges posed by current deep learning architectures' inability to learn causal structures, exacerbated by the scarcity of datasets containing known causal relationships and complexities in defining real-world interventions, further drive this survey's relevance [3]. The demand for novel machine learning techniques that effectively utilize multimodal diagnostic data in autonomous materials synthesis also highlights the necessity of this survey [13].

Finally, the potential of deep sequential latent variable models utilizing Gaussian processes for dimensionality reduction and data imputation, which offer enhanced interpretability and performance, underscores the need for advanced methodologies in this field [20]. Collectively, these motivations emphasize the urgency and significance of this survey in illuminating the challenges and opportunities within the rapidly evolving landscape of deep learning applications for time series anomaly and outlier detection. The benchmark for financial forecasting further illustrates the growing interest and challenges in financial time series prediction, necessitating ongoing research and model evaluation [21]. Researchers continue to encounter difficulties in understanding the intricate architectures of deep learning models and the extensive data requirements for effective training, justifying the need for this comprehensive survey [6].

1.4 Structure of the Survey

The survey is organized into nine sections, each addressing critical aspects of deep learning applications in time series anomaly and outlier detection. The introductory section establishes the

significance of deep learning in time series analysis, highlighting its transformative impact across domains such as financial markets, educational technology, and brain activity analysis. Following this, the role of neural networks and unsupervised learning is examined, emphasizing the adaptability of advanced architectures in processing temporal data.

The motivation section explores the challenges and growing interest in applying deep learning techniques for anomaly and outlier detection, stressing the need for unsupervised and semi-supervised approaches due to the scarcity of labeled data. The subsequent section provides background and definitions, offering an overview of core concepts, terminologies, and methodologies relevant to the topic.

The survey then investigates deep learning techniques for time series analysis, detailing various architectures such as RNNs, CNNs, and Transformers, and their applications in modeling sequential data. This is followed by sections on anomaly detection methodologies, challenges, and innovative solutions, as well as techniques for outlier detection in temporal datasets.

The role of unsupervised learning in anomaly and outlier detection is further explored, highlighting the principles and methodologies employed in these applications. The survey also includes a section on applications and case studies, presenting real-world examples of successful implementations across domains like finance, healthcare, cybersecurity, traffic management, and manufacturing.

Finally, the survey comprehensively addresses current challenges and future directions in the deep learning field, emphasizing critical issues such as scalability, model interpretability, adaptability to diverse data types, data quality assurance, and the integration of hybrid and unsupervised learning approaches. It underscores the need for a deeper understanding of these areas to overcome existing model limitations, often viewed as black boxes, and encourages the research community to address these gaps to foster innovation and application across various domains, including structured data modeling and resource-constrained environments [22, 23, 24]. The conclusion summarizes key findings and reinforces the importance of deep learning in advancing time series anomaly and outlier detection. The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Core Concepts of Deep Learning

Deep learning has revolutionized time series analysis by automating complex feature representation learning from raw data, reducing the need for manual feature engineering [25]. This is essential for addressing temporal dependencies in time series data, complicating classification and prediction tasks [26]. For instance, OntoEnricher uses supervised sequential deep learning to enhance security ontologies by extracting concepts from unstructured text, showcasing deep learning's versatility in sequential data [25].

Long Short-Term Memory (LSTM) networks are crucial for capturing long-range dependencies in sequential data, excelling in financial forecasting by modeling high-dimensional time series [27]. The TSMixer architecture exemplifies advancements by using stacked MLPs for capturing temporal and cross-variate dependencies [27]. Multiscale LSTM models, incorporating multiple currency pairs, enhance prediction accuracy in financial markets [28].

Despite their advantages, deep learning models face challenges like local optima and reduced generalization due to a focus on overall performance metrics [26]. Associated Learning (AL) addresses these by decomposing networks into components with independent objectives, enhancing robustness and adaptability [13]. Selecting appropriate loss functions and performance metrics is critical for effective model training and evaluation [29].

The intersection of deep learning and business analytics has led to innovative architectures integrating embedding layers for categorical variables with deep neural networks, enhancing predictive modeling [17]. Activation functions, viewed as magnifying functions, improve model expressiveness and performance by representing each neuron's output as a Super Plane in an infinite-dimensional space [15].

Challenges like clustering accuracy in deep representations, especially with auto-encoders, remain significant research areas, vital for enhancing unsupervised anomaly detection [30]. The focus on

deep learning in AI research has led to an 'epistemic monoculture,' highlighting the need for diverse research approaches [19].

These core concepts empower models to effectively analyze temporal datasets, advancing the field by tackling challenges like computational complexity and model interpretability [20]. The exploration of probabilistic neural networks and models, including Bayesian neural networks and variational autoencoders, enriches the landscape by integrating uncertainty, enhancing prediction robustness [4].

2.2 Time Series and Temporal Data

Time series and temporal data are characterized by their sequential nature, with observations at successive intervals presenting unique challenges in domains like finance, energy, and environmental monitoring. Sophisticated modeling techniques are required to capture complex temporal patterns. For instance, datasets reflecting KOSPI 200 index change ratios facilitate binary classification for trend prediction, illustrating intricate temporal dependencies [21].

In energy systems, accurate time series analysis depends on factors like input normalization and precise historical data availability, essential for reliable predictions. Shared trends and seasonal patterns complicate correlated multivariate time series modeling, requiring advanced techniques [31].

Temporal data also involve spatial dependencies, as seen in traffic flow prediction, where interactions between locations and factors like road conditions affect traffic patterns [32]. Environmental monitoring faces challenges like irregular spatial distributions and computational demands of modeling complex systems like Gaussian processes [33].

Extracting longer concepts from unstructured text is another challenge, as seen in methodologies enhancing information security ontologies [25]. The lack of generalized criteria for determining a system's learning capability complicates time series analysis, necessitating continuous advancements in analytical techniques [34].

Analyzing time series and temporal data is complex due to dependencies and patterns leading to varying behaviors among similar data points. Advanced analytical techniques, like deep learning models, automate feature extraction and capture underlying temporal dynamics. Recent advancements in deep learning enhance predictive performance by developing sophisticated representations adapting to temporal datasets' unique characteristics. Tools like TimeTuner visualize relationships among features and predictions, facilitating informed feature engineering, crucial for improving prediction accuracy and reliability [35, 36, 37].

2.3 Anomaly and Outlier Detection

Anomaly and outlier detection are pivotal in time series analysis for identifying deviations from expected patterns that indicate significant events, errors, or threats across domains. These techniques are vital in system monitoring, financial forecasting, and cybersecurity, where atypical patterns signal malfunctions, market disruptions, or security breaches [18]. In Forex markets, predicting intraday volatility is challenging, where observable ranges act as volatility proxies, and accurate anomaly detection can preemptively address potential fluctuations [28].

In economic contexts, anomaly detection is crucial for forecasting rare events like recessions, highlighting precise anomaly identification's importance in mitigating potential economic disasters [16]. In healthcare, anomaly detection identifies subtle brain abnormalities in diseases like Alzheimer's, underscoring the need for models performing well across all training cases without compromising individual errors [38, 26].

The main challenge in anomaly detection is the focus on deep learning methodologies, prioritizing predictive accuracy at the expense of interpretability and ethical considerations [19]. This focus hinders exploring alternative methods offering more interpretable solutions. The complexity of high-dimensional spaces modeled by neural networks and the critical role of activation functions add difficulty [15].

Unsupervised anomaly detection methods, utilizing L2 normalization during auto-encoder training, outperform traditional reconstruction error-based methods [30]. Evaluating models with metrics like Mean Absolute Error (MAE) and Area Under the Receiver Operating Characteristic Curve (AUROC) is crucial for assessing accuracy and reliability [5]. However, the abundance of loss functions and

evaluation metrics challenges practitioners in selecting the most suitable ones for specific applications [29].

Detecting anomalies and outliers in time series data ensures system integrity, improves predictive accuracy, and reduces risks by identifying atypical patterns deviating from standard trends. Recent advancements, like Large Language Models (LLMs) for anomaly detection, enhance accuracy and interpretability, enabling informed decision-making. Self-supervised learning techniques and novel algorithms improve anomaly detection systems, addressing challenges like imbalanced datasets. These innovations contribute to a robust framework for anomaly detection, applicable in critical sectors like cybersecurity, finance, and healthcare [39, 40, 36, 41, 42]. As deep learning evolves, its integration into anomaly detection frameworks promises to address challenges and unlock new opportunities in time series analysis.

2.4 Neural Networks and Architectures

Neural networks are fundamental to time series analysis, offering architectures that effectively model complex temporal dependencies. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), are extensively used for capturing spatial and sequential patterns [13]. CNNs, traditionally linked with image processing, use one-dimensional convolutions for temporal data, facilitating local feature extraction across time steps. This adaptation benefits applications like video anomaly detection and financial time series classification, where Large Kernel Convolutional Neural Network (LKCNN) techniques learn chaotic features from simpler dynamics [1].

RNNs and variants are designed for sequential data, maintaining hidden states encapsulating information from previous steps, making them suitable for tasks like natural language processing and speech recognition, where input order is crucial. Advanced RNN architectures, such as bidirectional LSTM cells, show significant improvements in transcription tasks, showcasing their efficacy in complex temporal modeling [2].

The continuous evolution of neural network architectures aims to enhance training efficiency and model generalization. Automated architectural evolution methods have become essential as neural network complexity surpasses manual optimization capabilities, leading to frameworks automating model selection and optimizing inference by aligning client data representations with pre-trained expert models [13].

Exploring neural networks within causal Bayesian Networks and Functional Causal Models emphasizes independent mechanisms in defining causal structures, enhancing interpretability and robustness [3]. Theoretical exploration indicates neural networks map low-dimensional spaces into an infinite-dimensional Super Space (SS) through activation functions, enhancing model expressiveness and performance [15].

The diverse array of neural network architectures and ongoing development highlight their pivotal role in advancing time series analysis, enabling meaningful insights extraction from temporal datasets, fostering innovation across domains and applications [20]. The integration of neural networks into time series analysis continues to evolve, providing sophisticated tools for addressing intricate dependencies and patterns inherent in temporal data.

3 Deep Learning Techniques for Time Series Analysis

In advancing methodologies for time series analysis, deep learning techniques have proven particularly effective in managing sequential data. This section explores architectures developed to address the unique challenges posed by time-dependent datasets, beginning with Recurrent Neural Networks (RNNs) and their variants, which excel in capturing temporal dependencies crucial for accurate predictions across various applications. Table 4 provides a detailed classification of deep learning techniques employed in time series analysis, showcasing their respective features and methods across different architectural categories. Figure 2 illustrates the hierarchical structure of these deep learning techniques, categorizing key architectures such as Recurrent Neural Networks, Convolutional Neural Networks, Transformer Architectures, Hybrid and Specialized Architectures, and Autoencoders with Variational Methods. Each category is further broken down into specific models, applications, and innovations, highlighting their roles and advancements in addressing the challenges of temporal data

Category	Feature	Method
Recurrent Neural Networks and Variants	Training Efficiency Robustness and Noise Handling	AL[13] Rest[43]
Convolutional Neural Networks in Temporal Data	Temporal Data Analysis	CNN-LSTM-AR[44], IDLD[46] CNN-COPD[45],
Transformer Architectures	Temporal Analysis	TST[47]
Hybrid and Specialized Architectures	Efficient Representations Evolutionary Design	GpGp[33], DCNN[14] EGP-RN[48]
Autoencoders and Variational Methods	Temporal and Multimodal Analysis Probabilistic and Adversarial Methods Adaptive Learning Strategies Performance Evaluation	TempPNet[49], DMAE[50] AT[51], VAE[52] TE-SSL[53], iDBN[54] GLS[26]

Table 1: This table presents a comprehensive summary of various deep learning methods applied to time series analysis, categorized into Recurrent Neural Networks and Variants, Convolutional Neural Networks in Temporal Data, Transformer Architectures, Hybrid and Specialized Architectures, and Autoencoders and Variational Methods. Each category highlights specific features and methods, demonstrating advancements in training efficiency, robustness, temporal data analysis, and evolutionary design to address the challenges of temporal data processing.

Category	Feature	Method
Recurrent Neural Networks and Variants	Training Efficiency Robustness and Noise Handling	AL[13] Rest[43]
Convolutional Neural Networks in Temporal Data	Temporal Data Analysis	CNN-LSTM-AR[44], IDLD[46] CNN-COPD[45],
Transformer Architectures	Temporal Analysis	TST[47]
Hybrid and Specialized Architectures	Efficient Representations Evolutionary Design	GpGp[33], DCNN[14] EGP-RN[48]
Autoencoders and Variational Methods	Temporal and Multimodal Analysis Probabilistic and Adversarial Methods Adaptive Learning Strategies Performance Evaluation	TempPNet[49], DMAE[50] AT[51], VAE[52] TE-SSL[53], iDBN[54] GLS[26]

Table 2: This table presents a comprehensive summary of various deep learning methods applied to time series analysis, categorized into Recurrent Neural Networks and Variants, Convolutional Neural Networks in Temporal Data, Transformer Architectures, Hybrid and Specialized Architectures, and Autoencoders and Variational Methods. Each category highlights specific features and methods, demonstrating advancements in training efficiency, robustness, temporal data analysis, and evolutionary design to address the challenges of temporal data processing.

processing. This visual representation not only enhances the understanding of the interconnectedness of these architectures but also emphasizes the evolution of deep learning strategies in the context of time series analysis.

3.1 Recurrent Neural Networks and Variants

Recurrent Neural Networks (RNNs) and their variants, including Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), are vital for modeling sequential data due to their proficiency in capturing temporal dependencies, making them effective in time series analysis [55]. These architectures excel in domains where input order and temporal context are critical, such as financial forecasting and biomedical signal processing [56]. For instance, LSTMs have been utilized to model intraday and interday dependencies in Forex trading, offering a comprehensive volatility forecasting approach through multiple LSTM models [28].

As illustrated in Figure 3, which depicts the hierarchical categorization of RNNs and their variants, these models are not only pivotal in sequential data modeling but also demonstrate integration with hybrid and innovative methods to address various challenges through advanced solutions. RNNs' adaptability is further highlighted by their integration with other architectures. The CNN-LSTM model exemplifies this hybrid approach, effectively learning trends and seasonal components from multivariate time series, as seen in wind speed forecasting [44]. Such models leverage CNNs' feature extraction strengths and LSTMs' sequence modeling capabilities, enhancing prediction accuracy in complex datasets.

Innovative methodologies have further improved RNN performance. The Evolutionary Genetic Programming for Recurrent Nodes (EGP-RN) method evolves recurrent node architectures through a tree-based representation, enabling complex network structures that enhance performance [48]. Addi-

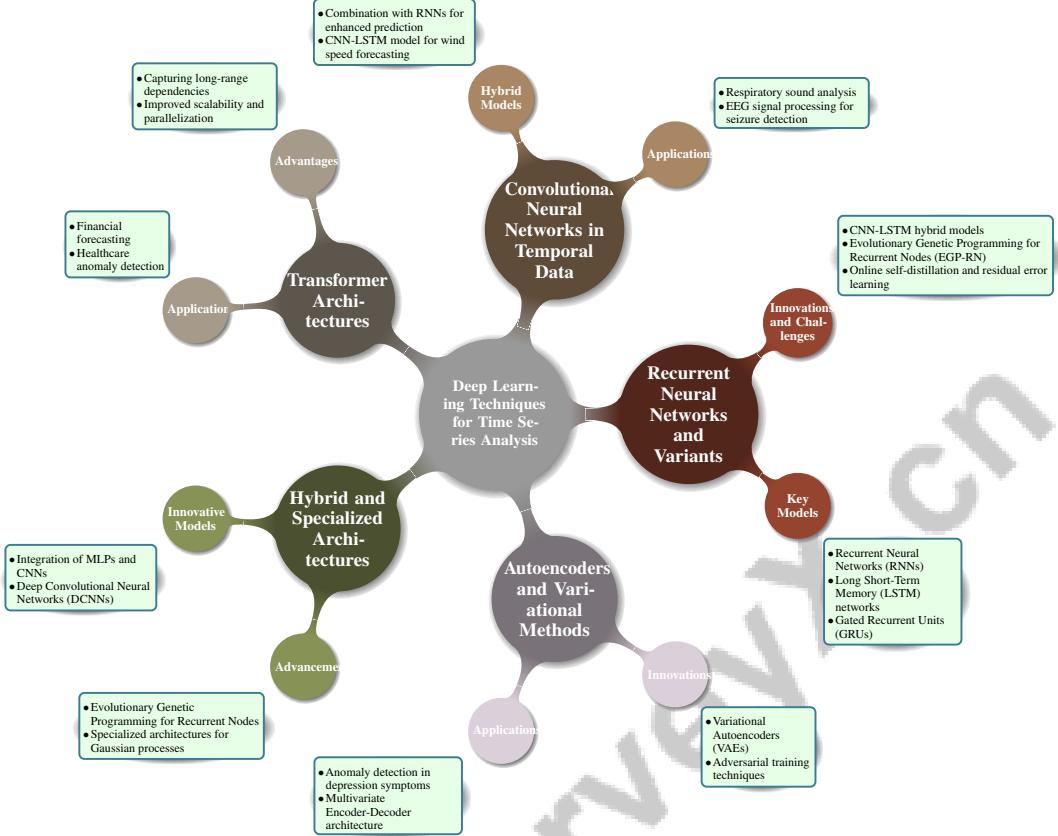


Figure 2: This figure illustrates the hierarchical structure of deep learning techniques for time series analysis, categorizing key architectures such as Recurrent Neural Networks, Convolutional Neural Networks, Transformer Architectures, Hybrid and Specialized Architectures, and Autoencoders with Variational Methods. Each category is further broken down into specific models, applications, and innovations, highlighting their roles and advancements in addressing the challenges of temporal data processing.

tionally, associated learning allows independent parameter updates across components, significantly improving RNN training throughput [13].

Despite their capabilities, RNNs face challenges like the vanishing gradient problem and overfitting, prompting advanced training methodologies. Online self-distillation and residual error learning address these challenges by categorizing research based on forecasting tasks [31]. Moreover, adversarial training and spectral regularization enhance RNN noise robustness, employing sparsity regularization for model compression [43].

The evolution of RNNs and their variants underscores their critical role in sequential data analysis. By integrating cutting-edge techniques and addressing temporal data processing challenges, these architectures drive progress across diverse fields, enhancing prediction accuracy and insight reliability in applications like financial forecasting, cybersecurity threat detection, and medical image analysis [20, 25, 57, 6, 41].

3.2 Convolutional Neural Networks in Temporal Data

Convolutional Neural Networks (CNNs) have been adeptly adapted for temporal data analysis, leveraging their ability to capture spatial hierarchies and local dependencies crucial for understanding complex temporal patterns. This adaptation is exemplified in tasks like respiratory sound analysis, where CNNs enhance detection accuracy over traditional methods [45]. CNNs' effectiveness in temporal data is further demonstrated in image classification tasks related to temporal sequences, showcasing their versatility [58].

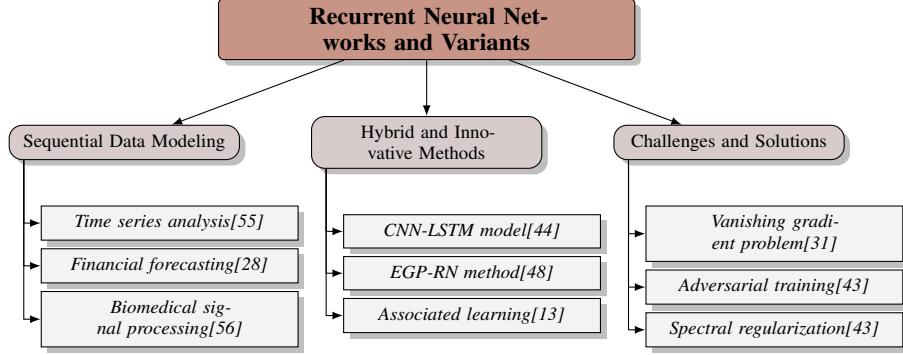


Figure 3: This figure illustrates the hierarchical categorization of Recurrent Neural Networks (RNNs) and their variants, focusing on their applications in sequential data modeling, integration with hybrid and innovative methods, and addressing challenges through advanced solutions.

Method Name	Structural Features	Task Type	Integration Potential
CNN-COPD[45]	Spatial Hierarchies	Sound Analysis	Combining Cnnns
IDLD[46]	Multiple Convolutional Layers	Eeg Signal Interpretation	Combining Domain Knowledge
CNN-LSTM-AR[44]	Spatial Hierarchies	Wind Speed Forecasting	Hybrid Cnn-LSTM

Table 3: Overview of various convolutional neural network (CNN) methodologies applied in temporal data analysis, highlighting their structural features, task types, and integration potential. The table summarizes the adaptability and hybridization of CNNs across different applications, demonstrating their efficacy in enhancing predictive performance in temporal datasets.

In biomedical signal processing, CNNs interpret EEG signals for seizure detection. Long kernel sizes in convolutional layers capture low-frequency components essential for accurate detection, highlighting CNNs' adaptability in processing temporal sequences with varying frequencies [46]. This capability underscores CNNs' potential to model temporal dependencies by extracting meaningful features from sequential data, enhancing predictive performance across applications.

Integrating CNNs with other architectures further amplifies their effectiveness. Combining CNNs with RNNs, hybrid models leverage CNNs' feature extraction and RNNs' sequence modeling strengths, offering a comprehensive approach to complex temporal datasets. This hybridization benefits applications like wind speed forecasting, where the CNN-LSTM model effectively learns trends and seasonal components from multivariate time series [44].

The adaptation of CNNs for temporal data analysis demonstrates their flexibility and robustness in capturing complex temporal patterns, essential for addressing temporal dependencies in time series data. Table 3 provides a comprehensive summary of CNN methodologies adapted for temporal data analysis, illustrating their structural features, task applications, and potential for integration with other architectures. This capability makes CNNs invaluable for advancing time series analysis, facilitating the extraction of intricate features and relationships within multivariate time series, enhancing forecasting accuracy across applications like financial market predictions and resource consumption forecasting [35, 59]. Their continued evolution and integration with other architectures promise to unlock new opportunities for innovation and improved accuracy in temporal data processing across diverse domains.

3.3 Transformer Architectures

The application of Transformer architectures in time series analysis marks a significant advancement, offering a robust framework for capturing complex temporal dependencies without traditional sequential models' limitations. The Time-Series Transformer method exemplifies this innovation, leveraging self-attention to model long-range dependencies in temporal data [47]. This approach addresses recurrent models' challenges, such as the vanishing gradient problem, by allowing parallelization and improved scalability.

Transformers excel in tasks involving multivariate data integration, capturing complex cross-variate interactions and significantly enhancing predictive accuracy. This capability benefits scenarios requiring tailored machine learning models for diverse data sources, such as the ExpertMatcher framework, which automates model selection for clients with limited resources [60, 23]. This is crucial in domains like finance and healthcare, where understanding variable interplay over time is essential for accurate forecasting and anomaly detection. Transformers' flexibility enables adaptation to various data modalities, expanding their applicability in diverse time series applications.

Attention mechanisms in Transformer models enhance temporal sequence feature identification, improving model interpretability and offering insights into data dynamics. This advancement aids in understanding specific predictions' reasons and fosters nuanced comprehension of complex cognitive tasks across applications like financial time series analysis and natural language processing [21, 6, 24]. This is beneficial in complex systems where understanding individual components' contributions is vital for decision-making.

Deploying Transformer architectures in time series analysis represents a paradigm shift, offering a powerful tool for modeling intricate temporal patterns and advancing deep learning models' capabilities. As research delves into developing and enhancing deep learning models, their capacity to transform time series analysis across domains, including finance, anomaly detection, and feature engineering, becomes evident, demonstrating significant improvements in predictive accuracy and interpretability compared to traditional methods [37, 35, 36, 57, 41].

As shown in Figure 4, Transformer architectures have emerged as a pivotal innovation in "Deep Learning Techniques for Time Series Analysis," significantly enhancing sequential data processing. This figure illustrates the hierarchical structure of Transformer Architectures in Time Series Analysis, highlighting key innovations, applications, and future challenges. The innovations include the Time-Series Transformer and multivariate data integration, while applications focus on predictive accuracy and anomaly detection. Future directions address challenges in model interpretability and data modality adaptation. The first part of the figure presents a flowchart with nodes labeled v1, v2, v3, and v4, culminating in an output node. This diagram exemplifies the structured flow of information, akin to Transformer models' sequential processing, where each node represents a stage in data transformation, leading to a refined output. The second part of the figure traces Artificial Intelligence and Machine Learning's evolution from the 1950s to the present, highlighting key advancements paving the way for sophisticated models like Transformers. Together, these images underscore Transformer architectures' transformative impact in AI and ML, particularly in time series analysis, where capturing temporal dependencies is crucial [61, 6].

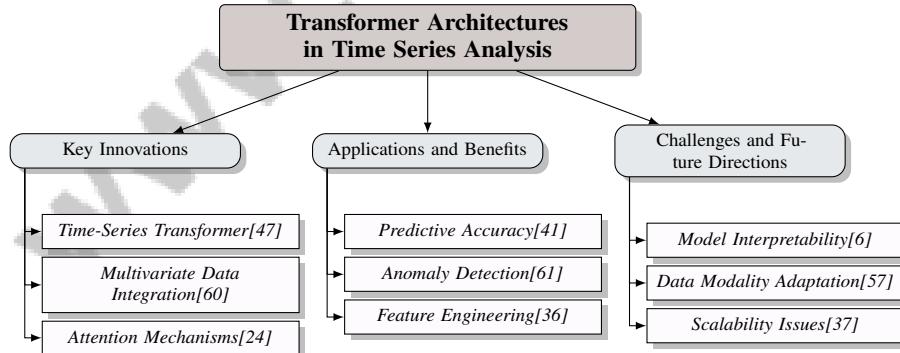


Figure 4: This figure illustrates the hierarchical structure of Transformer Architectures in Time Series Analysis, highlighting key innovations, applications, and future challenges. The innovations include the Time-Series Transformer and multivariate data integration, while applications focus on predictive accuracy and anomaly detection. Future directions address challenges in model interpretability and data modality adaptation.

3.4 Hybrid and Specialized Architectures

Innovative hybrid and specialized architectures have emerged as pivotal advancements in enhancing time series analysis, offering improved efficiency and accuracy in modeling complex temporal data.

Integrating multilayer perceptrons (MLPs) and convolutional neural networks (CNNs) exemplifies architectures that leverage both models' strengths to capture intricate temporal patterns [62]. These architectures are particularly effective in applications requiring spatial and temporal feature synthesis, providing a comprehensive framework for analyzing time series data.

One notable innovation is deep convolutional neural networks (DCNNs), where weight matrices are structured as products of diagonal and circulant matrices, enabling a more compact representation [14]. This approach reduces computational complexity while maintaining robust predictive capabilities, making it suitable for large-scale temporal datasets. DCNNs' compactness facilitates deployment in resource-constrained environments, expanding applicability across domains.

Exploring novel node architectures through genetic programming has led to significant advancements in recurrent neural networks (RNNs). The Evolutionary Genetic Programming for Recurrent Nodes (EGP-RN) method allows for discovering innovative node architectures that outperform traditional LSTM designs, enhancing design space exploration and improving model performance [48]. This evolutionary approach underscores hybrid architectures' potential to adapt and optimize structures for specific time series applications.

Additionally, improving Gaussian processes' efficiency while maintaining accurate predictions and uncertainty estimates has inspired developing specialized architectures for large spatial datasets [33]. These specialized models address scaling challenges in Gaussian processes, providing a framework for integrating uncertainty quantification into time series analysis.

These hybrid and specialized architectures represent a significant leap forward in time series analysis. By leveraging diverse neural network architectures' unique strengths and integrating cutting-edge design principles, these advanced models enhance predictive accuracy and scalability. This progress facilitates resolving complex cognitive tasks often surpassing human capabilities and opens new avenues for transformative applications across fields like finance, healthcare, and cybersecurity. As deep learning evolves, it empowers researchers and practitioners to harness vast data for improved statistical pattern recognition and decision-making [20, 6].

3.5 Autoencoders and Variational Methods

Autoencoders and variational methods are crucial in time series anomaly detection, offering sophisticated frameworks for learning compact and meaningful data representations essential for identifying deviations from expected patterns. Autoencoders' versatility is demonstrated through models like TempPNet, which employs a temporal prototype layer to analyze walking test sequences, effectively detecting anomalies in depression symptoms [49]. This highlights autoencoders' ability to distill essential features from complex datasets, facilitating irregularity identification.

The multivariate Encoder-Decoder architecture further exemplifies autoencoders' potential in improving prediction accuracy and anomaly detection by leveraging separate encoder modules for different data modalities. This approach allows flexible exploration of multivariate patterns relevant to deep learning techniques in time series analysis [50]. Such architectures underscore autoencoders' capacity to focus on relevant features across diverse data streams.

Variational methods, particularly Variational Autoencoders (VAEs), enhance traditional autoencoders by incorporating probabilistic elements, enabling data uncertainty modeling and new data sample generation. This probabilistic framework is crucial for robust anomaly detection, providing a comprehensive understanding of data distributions. VAEs' use in capturing nuanced decision-making processes, like imitating Air Traffic Control Officer (ATCO) reactions based on historical trajectory data, illustrates their capability in modeling complex temporal dynamics [52].

Integrating adversarial training techniques with autoencoders further enhances deep learning-based systems' resilience against adversarial attacks, improving anomaly detection frameworks' robustness [51]. This approach emphasizes incorporating diverse training samples to bolster model performance under challenging conditions.

Innovative methods like iDBN, an iterative learning algorithm for training deep belief networks, allow simultaneous weight adjustment across layers based on sensory inputs. This advancement enhances deep learning models' capabilities in anomaly detection [54]. Autoencoders' adaptability in refining feature extraction processes is crucial for enhancing anomaly detection.

Applying Gradient Lexicase Selection in training deep neural networks, focusing on individual training case performance, further supports these models' generalization capabilities [26]. Additionally, the Time and Event-aware Self Supervised Learning (TE-SSL) framework is proposed as a novel approach for improving predictive capabilities in Alzheimer's disease progression analysis, showcasing self-supervised learning's potential in augmenting anomaly detection [53].

Overall, autoencoders and variational methods in time series anomaly detection represent a significant advancement. These advanced models, particularly Large Language Models (LLMs), provide robust methodologies for detecting anomalies and uncovering hidden patterns across domains like cybersecurity, finance, and healthcare, significantly improving anomaly detection's accuracy and interpretability in time series analysis. Techniques like in-context anomaly detection and the Anomaly Detection Chain-of-Thought (AnoCoT) approach enhance detection performance and offer detailed explanations for findings, facilitating better decision-making processes [39, 63, 64, 41, 42]. As research continues to innovate and refine these methodologies, their potential to transform temporal data analysis remains substantial.

Feature	Recurrent Neural Networks and Variants	Convolutional Neural Networks in Temporal Data	Transformer Architectures
Primary Application	Sequential Data Modeling	Temporal Pattern Analysis	Long-range Dependencies
Unique Feature	Temporal Dependencies Capture	Spatial Hierarchies Capture	Self-attention Mechanism
Challenges Addressed	Vanishing Gradient Problem	Complex Temporal Patterns	Scalability And Parallelization

Table 4: This table provides a comparative analysis of three prominent deep learning architectures—Recurrent Neural Networks (RNNs) and their variants, Convolutional Neural Networks (CNNs) in temporal data, and Transformer architectures. It highlights their primary applications, unique features, and the specific challenges each method addresses in the context of time series analysis. This comparison underscores the distinct capabilities and limitations of each architecture, aiding in the selection of appropriate models for specific temporal data tasks.

4 Anomaly Detection in Time Series Data

4.1 Methodologies for Anomaly Detection

The field of anomaly detection in time series data has been significantly advanced through the integration of deep learning techniques, which have improved the precision and efficiency of detecting deviations. Graph neural networks (GNNs) exemplify this progress by utilizing road network structures to predict traffic accidents, thereby capturing complex spatial and temporal dependencies essential for anomaly detection [5]. Similarly, the p-Pairs-learning 2-LSTM method enhances predictive performance in financial markets by effectively modeling intricate temporal patterns [28]. LSTMs are particularly adept at capturing complex temporal dependencies, making them indispensable for financial time series anomaly detection.

Attention mechanisms further augment deep learning models by improving trend prediction accuracy, particularly in financial contexts, where emphasizing relevant temporal features is crucial for effective anomaly detection [21]. This allows models to dynamically prioritize time steps, enhancing anomaly identification. The Large Kernel Convolutional Neural Network (LKCNN) has also proven effective in classifying chaotic versus non-chaotic time series, providing a robust framework for anomaly detection in complex datasets [1].

The evolution of anomaly detection methodologies is driven by the necessity for robust models that address the complexities inherent in temporal datasets. The integration of hybrid models, attention mechanisms, and graph-based approaches marks significant progress, enabling effective identification of irregular patterns across diverse fields, including finance, medical imaging, and predictive analytics. These innovations not only enhance detection performance but also overcome challenges posed by traditional methods, facilitating a systematic understanding and application of anomaly detection strategies [20, 39].

As depicted in Figure 5, various methodologies have been developed to enhance the accuracy of predictive models by identifying deviations from expected patterns in time series data. The first example illustrates a self-predictive method for contrastive learning that maintains consistent data representations despite transformations, involving geometric transformations and synthetic anomaly creation. The second example features an anomaly detection framework leveraging contextual

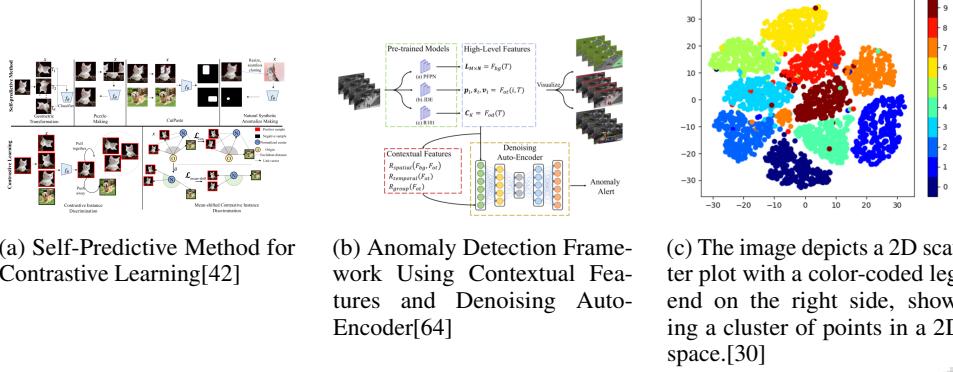


Figure 5: Examples of Methodologies for Anomaly Detection

features and denoising auto-encoders, utilizing pre-trained models to extract high-level features for visualization and anomaly alert generation. Lastly, a 2D scatter plot visually represents data clusters with a color-coded legend, demonstrating anomaly detection through unsupervised learning techniques. Collectively, these examples underscore the innovative strategies advancing anomaly detection in time series data [42, 64, 30].

4.2 Challenges in Anomaly Detection

Anomaly detection in time series data is fraught with challenges that impede accurate deviation identification, primarily due to the complexities and limitations of current methodologies. The ‘black-box’ nature of deep learning models complicates interpretability and generalization across datasets, hindering the understanding of decision-making processes, especially in critical fields like financial decision support and software performance configuration [65, 57].

The scarcity of labeled data for training anomaly detection models presents another significant challenge, particularly in unsupervised learning scenarios where labeled anomalous data is limited. This scarcity necessitates the development of methods capable of functioning with minimal supervision [10]. Furthermore, the complexity of functional optimization problems, including instantaneous constraints, complicates the creation of robust anomaly detection frameworks.

Domain shifts due to variations in system configurations further challenge model transferability across contexts. Current methods often inadequately address these shifts, leading to diminished detection accuracy in new or evolving environments [66]. This issue is exacerbated by data bias and drift, which can significantly affect model performance over time [67].

Traditional early warning signals have proven inadequate for identifying critical transitions, particularly in predicting discrete-time bifurcations, highlighting the need for advanced techniques capable of capturing subtle changes preceding significant events [68]. Additionally, the trade-off between robustness and accuracy is evident in methodologies that excel in real-world scenarios but may lack precision in controlled environments [43].

These challenges underscore the urgent need for ongoing research and innovation in anomaly detection methodologies, particularly as new techniques—such as those leveraging self-supervised learning and large language models—emerge to better address dataset complexities, enhance interpretability, and improve accuracy in identifying atypical patterns across various industries, including finance and healthcare [39, 57, 42, 41]. Overcoming these obstacles will facilitate more accurate and reliable anomaly detection across diverse applications.

4.3 Solutions and Innovations

Innovative solutions in anomaly detection for time series data have been pivotal in addressing traditional methodologies’ challenges. One advancement is the development of compact and robust neural network architectures, such as deep convolutional neural networks with structured weight matrices. This approach significantly reduces parameters while maintaining high accuracy and enhances

robustness against adversarial examples, making it suitable for environments where computational efficiency and security are critical [14].

Future research directions include the co-evolution of network architectures alongside recurrent nodes, as suggested by methodologies like Evolutionary Genetic Programming for Recurrent Nodes (EGP-RN). This approach proposes integrating ensemble techniques to further enhance performance, offering a promising avenue for improving the adaptability and accuracy of anomaly detection models in dynamic environments [48].

In business analytics, deep learning models have demonstrated superior prediction accuracy over traditional machine learning methods, capturing intricate patterns in complex datasets and providing a robust framework for anomaly detection across various applications. This comparative analysis emphasizes deep learning's potential to revolutionize predictive modeling in business, yielding enhanced insights and decision-making capabilities [17].

The innovative solutions highlighted in recent research underscore significant advancements in anomaly detection achieved through advanced neural network architectures and methodologies, particularly deep learning approaches. These developments have notably improved detection performance across complex datasets, including large image and text collections, and have led to a surge in new methods, such as generative models and one-class classification techniques. By systematically unifying these approaches and addressing the challenges posed by black-box models, researchers are paving the way for further breakthroughs in the field, ultimately transforming our understanding and application of anomaly detection [39, 24].

As illustrated in Figure 6, the key advancements and applications of these innovative solutions in anomaly detection are prominently highlighted, showcasing neural network improvements, business analytics applications, and ongoing research challenges. Leveraging compact models, co-evolutionary techniques, and the superior predictive capabilities of deep learning will address critical challenges in anomaly detection, paving the way for more accurate and reliable systems across diverse applications.

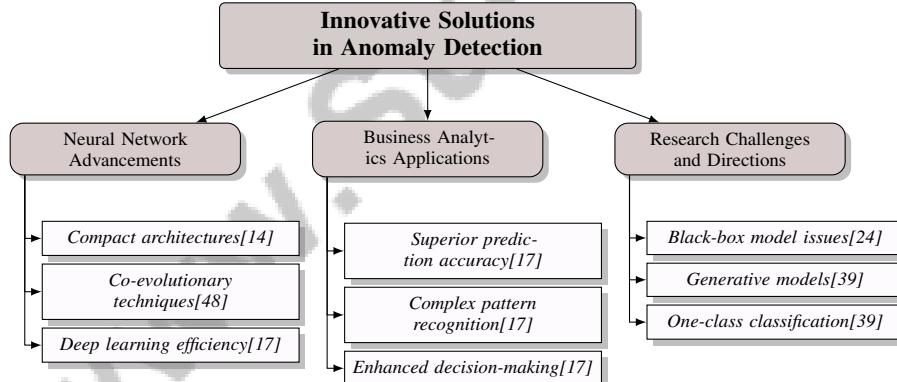


Figure 6: This figure illustrates the key advancements and applications of innovative solutions in anomaly detection, highlighting neural network improvements, business analytics applications, and ongoing research challenges.

5 Outlier Detection in Temporal Data

Identifying outliers in temporal data is essential for extracting valuable insights and making informed decisions. This section explores various methodologies aimed at improving outlier detection, focusing on the innovative application of deep learning models. By leveraging advanced architectures and techniques, researchers can identify significant deviations within temporal datasets. The following subsection highlights the contributions of deep learning models to outlier detection, emphasizing their unique advantages and applications across diverse fields.

5.1 Leveraging Deep Learning Models for Temporal Outlier Detection

Deep learning models have become vital tools for detecting significant deviations in temporal data, adept at capturing complex patterns and dependencies crucial for accurate outlier identification. Architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) networks, enhance outlier detection by effectively modeling spatial and temporal features [13]. In financial markets, deep learning models excel in volatility forecasting by capturing intricate dependencies, with multiple LSTM models effectively identifying outliers in financial time series [28]. CNNs applied to respiratory sound analysis also significantly improve detection accuracy, showcasing deep learning's versatility in handling temporal data [45].

Hybrid models like CNN-LSTM architectures further enhance outlier detection by combining CNNs' feature extraction strengths with LSTMs' sequence modeling capabilities, proving effective in wind speed forecasting by learning trends and seasonal components from multivariate time series [44]. Incorporating attention mechanisms into deep learning models refines the focus on relevant temporal features, improving detection accuracy, particularly in financial time series where dynamic weighting of time steps enhances deviation detection [21].

The application of deep learning models for temporal outlier detection marks a significant advancement in the field. By integrating sophisticated architectures and techniques, these models uncover hidden patterns and anomalies across various domains, improving the accuracy and reliability of outlier detection. As research progresses, the potential of deep learning methodologies to enhance temporal data analysis becomes increasingly evident, especially in applications such as financial forecasting, operational optimization, and security analytics, where traditional methods struggle with complex, non-linear relationships [35, 17, 25, 57, 19].

5.2 Applications and Implications of Outlier Detection

Outlier detection in temporal data holds significant promise across various domains, providing critical insights that drive decision-making and enhance operational efficiency. In finance, it is crucial for identifying unusual market behaviors that may signal significant economic events, enabling stakeholders to make informed decisions to mitigate risks and capitalize on opportunities [28]. In healthcare, outlier detection is vital for monitoring patient health and identifying deviations from normal physiological patterns that may indicate conditions requiring intervention. CNNs analyzing respiratory sounds improve anomaly detection linked to chronic obstructive pulmonary disease, enhancing diagnostic accuracy [45]. Deep learning models applied to EEG signal analysis facilitate early detection of neurological disorders, providing valuable insights for timely intervention [46].

Environmental monitoring benefits from outlier detection, where identifying anomalies in climate data aids in understanding changes and impacts. Deep learning techniques enable detection of unusual patterns in temperature, precipitation, and other variables, facilitating proactive measures against climate challenges [44]. In cybersecurity, outlier detection uncovers potential threats and vulnerabilities within networks, especially as attack surfaces proliferate. Advanced techniques like deep learning and self-supervised learning enhance anomaly detection, leading to more accurate identification of deviations from normal behavior, vital for effective security analytics and improving threat intelligence [39, 25, 42]. Analyzing network traffic patterns through deep learning reveals anomalies indicative of security breaches, strengthening defenses.

In manufacturing and process control, outlier detection is critical for maintaining product quality and efficiency. By identifying deviations in production processes using techniques like one-class anomaly detection and Bayesian recurrent neural networks, companies can implement timely corrective actions to mitigate defects and optimize resources, resulting in cost savings and improved reliability [40, 69].

The breadth of applications for outlier detection is extensive, with the potential to revolutionize sectors through advanced techniques like deep learning and generative models. Recent advancements have significantly improved performance on complex datasets, prompting renewed focus on innovative methods. These developments enhance prediction capabilities in business analytics and operations research, yielding operational benefits over traditional approaches. The field offers numerous opportunities for tailored solutions that generate substantial value across industries [17, 39]. As deep learning models evolve, their capacity to accurately detect outliers in temporal data will empower organizations to make data-driven decisions and tackle complex challenges.

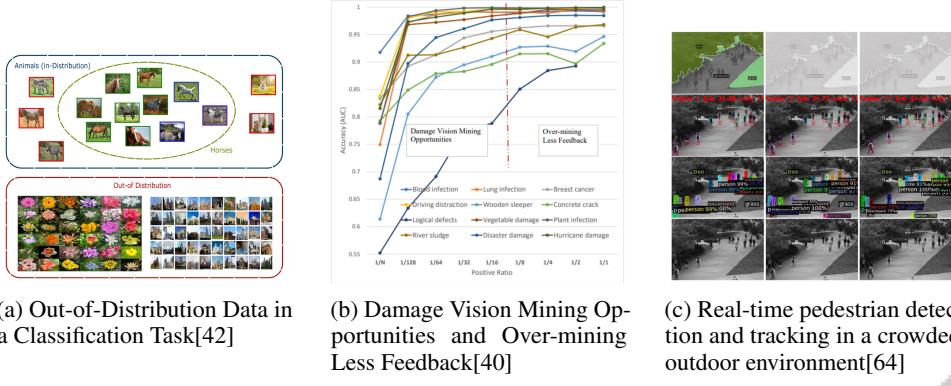


Figure 7: Examples of Applications and Implications of Outlier Detection

As illustrated in Figure 7, outlier detection in temporal data is a critical research area with significant applications across various domains. The first application, "Out-of-Distribution Data in a Classification Task," involves distinguishing between in-distribution images of animals and horses and out-of-distribution images such as flowers and buildings, highlighting the challenge of classifying data that deviates from the expected norm. The second example, "Damage Vision Mining Opportunities and Over-mining Less Feedback," uses a line graph to depict how the accuracy of detecting various damage types, like infections and structural defects, varies with different positive ratios, emphasizing the importance of precise outlier detection in medical and structural assessments. Lastly, "Real-time pedestrian detection and tracking in a crowded outdoor environment" exemplifies outlier detection's role in enhancing the accuracy and efficiency of real-time surveillance systems, where accurately identifying and tracking individuals in dynamic environments is crucial. Together, these examples underscore the diverse applications of outlier detection, highlighting its vital role in improving classification tasks, optimizing damage detection, and enhancing real-time tracking systems [42, 40, 64].

6 Unsupervised Learning for Anomaly and Outlier Detection

6.1 Principles of Unsupervised Learning in Anomaly Detection

Unsupervised learning is crucial for anomaly detection due to its ability to discern patterns and deviations without labeled data, addressing the challenge of limited labeled datasets in anomaly detection tasks [70, 24]. This approach facilitates models that learn invariant representations, aiding in recognizing unusual patterns that deviate from norms. The complexity of datasets and the diverse nature of anomalies necessitate advanced unsupervised learning techniques, which autonomously discover data structures, detecting anomalies not immediately apparent through traditional methods. This adaptability is beneficial in dynamic environments where normal behavior evolves, requiring models to continuously update their anomaly understanding.

A core principle is developing robust data representations crucial for identifying deviations from normal conditions. Techniques like unsupervised transfer learning and deep autoencoders enhance detection accuracy by leveraging complementary data from different units, enabling models to recognize previously unseen anomalies [66, 39, 30]. By capturing essential features and variations, unsupervised learning models improve detection capabilities across applications.

The principles of unsupervised learning in anomaly detection emphasize flexible, adaptive models uncovering hidden patterns and deviations. As research progresses, unsupervised learning techniques, particularly through frameworks like unsupervised transfer learning and self-supervised learning, are poised to significantly enhance anomaly detection in sectors such as cybersecurity, finance, and healthcare. These advancements address training challenges on limited data by transferring complementary operating conditions, leading to more accurate identification of abnormal patterns in diverse environments [66, 39, 30, 42].

6.2 Techniques and Methodologies

Unsupervised anomaly detection techniques are vital for identifying data deviations without labeled instances, often scarce in real-world scenarios. Deep learning advancements and clustering approaches leverage unsupervised transfer learning, enhancing detection by utilizing complementary data from various operational conditions, particularly beneficial in industrial applications where comprehensive healthy operating condition datasets are time-consuming to obtain. Techniques like adversarial deep learning and L2 normalization in autoencoder representations bolster anomaly detection robustness, facilitating effective data clustering and improving anomaly identification accuracy within complex datasets [66, 39, 30].

Autoencoders, prominent in unsupervised anomaly detection, are neural networks that learn efficient data representations by encoding inputs into a lower-dimensional space and reconstructing them. The reconstruction error indicates anomaly likelihood, with high errors suggesting the model's failure to capture input features, indicating potential anomalies [30]. Variational Autoencoders (VAEs) extend this by incorporating probabilistic elements, modeling data uncertainty, and providing a more robust anomaly detection framework [52].

Clustering-based methods partition data into groups based on similarity, identifying anomalies as points not conforming to clusters or distant from cluster centroids. These methods are effective when normal data exhibits distinct clustering patterns, making deviations more apparent [30]. Graph-based approaches represent data as graphs, detecting anomalies based on deviations in graph structure, useful in applications where data point relationships are crucial, such as social network analysis and traffic monitoring [5].

Integrating deep learning with traditional statistical methods leads to hybrid models that enhance anomaly detection capabilities, combining deep learning's feature extraction strengths with traditional methods' statistical rigor, providing a comprehensive approach to anomaly identification [17].

The evolution of unsupervised anomaly detection techniques reflects the need for robust models addressing diverse dataset complexities. By employing advanced methodologies and integrating sophisticated neural network architectures, these approaches significantly enhance anomaly detection across domains, including finance, medical imaging, and predictive analytics. This integration improves accuracy and reliability, facilitating automatic recognition of complex patterns in large datasets, addressing challenges that traditional machine learning methods struggled with. Developing diverse techniques, such as generative models and one-class classification, underscores the necessity for a unified framework connecting deep and shallow anomaly detection strategies, paving the way for future research and application advancements [20, 39].

7 Applications and Case Studies

The integration of deep learning across various domains underscores its transformative potential. This section explores its applications in finance, healthcare, cybersecurity, traffic management, and manufacturing.

7.1 Finance and Trading Strategies

Deep learning enhances financial markets and trading strategies by offering advanced predictive models for market trends, volatility, and anomalies, crucial for decision-making and risk management. Architectures like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) adeptly capture complex temporal dependencies in financial time series data, improving prediction accuracy and event identification [6]. In trading, these models analyze extensive historical data to identify profitable opportunities with greater precision than traditional methods, overcoming challenges in feature extraction and non-linear dynamics. Research demonstrates a 5.66% increase in predictive accuracy over benchmark models following financial disclosures [20, 71, 57]. Neural networks optimize trading strategies by leveraging high-dimensional datasets, enhancing trade timing and execution, while detecting anomalies to mitigate risks.

In portfolio management, deep learning models assess asset correlations and optimize allocations, surpassing traditional methods in predictive performance and decision-making support by accurately predicting market movements and volatility [20, 28, 72, 57]. Their adaptability to changing market

conditions underscores their significance in dynamic trading environments. As methodologies evolve, deep learning's potential to transform financial decision-making remains substantial, particularly in forecasting stock movements and analyzing complex financial data [20, 71, 17, 57, 24].

7.2 Healthcare and Bioelectrical Signal Processing

Deep learning's integration into healthcare, especially for bioelectrical signal analysis and medical imaging, has markedly improved diagnostic accuracy and patient monitoring. Advanced algorithms learning hierarchical feature representations from data have surpassed traditional methods, enabling precise identification and classification of complex patterns in medical images, addressing variability in pathology and clinician fatigue [20, 6, 73]. CNNs and RNNs analyze bioelectrical signals like EEGs and ECGs, facilitating early detection of neurological and cardiovascular disorders.

In EEG analysis, deep learning enhances seizure pattern identification, providing clinicians with critical insights for timely intervention. Long kernel sizes in CNN architectures capture low-frequency components crucial for accurate anomaly detection, showcasing deep learning's adaptability in processing temporal sequences [46]. In respiratory sound analysis, CNNs improve COPD-related anomaly detection, enhancing diagnostic accuracy and patient outcomes [45]. Deep learning's transformative potential in healthcare diagnostics and patient care is significant, enabling more accurate interpretations of medical images and bioelectrical signals [73, 74, 20, 6, 24].

7.3 Cybersecurity and Anomaly Detection

Deep learning has become integral to cybersecurity, offering advanced techniques for detecting anomalies indicative of potential threats. Its ability to analyze vast network traffic data and identify patterns associated with malicious activities has significantly improved cybersecurity frameworks. CNNs and RNNs, along with their variants, model temporal and spatial characteristics of network data, enabling real-time anomaly detection [5].

Combining deep learning with graph-based approaches enhances anomaly detection by representing network data as graphs, capturing complex relationships between data points, and facilitating deviation identification from normal behavior [5]. Attention mechanisms in deep learning models improve focus on critical network data features, enhancing detection precision by dynamically weighting data point importance [21]. The application of deep learning in cybersecurity represents a significant advancement, offering powerful tools for threat identification and network security enhancement. Advanced architectures like Bidirectional LSTMs and generative models have shown improved accuracy in identifying security threats and vulnerabilities [20, 39, 25, 24].

7.4 Traffic Management and Prediction

Deep learning has transformed traffic management and prediction by analyzing complex patterns and improving forecasting accuracy. Techniques such as CNNs and RNNs model intricate spatial and temporal dependencies in traffic data, facilitating robust predictive frameworks [5]. Deep learning models process extensive datasets, including millions of traffic accident records, enabling accurate edge-level regression and classification tasks, crucial for optimizing traffic flow and reducing congestion [5]. Graph neural networks (GNNs) represent traffic data as graphs, capturing complex location interactions, and facilitating anomaly identification and traffic flow prediction [5]. Attention mechanisms further refine model focus on critical traffic data features, improving prediction precision by dynamically weighing time step importance [21].

The integration of deep learning in traffic management marks a substantial advancement, equipping researchers with sophisticated analytical tools to decipher intricate patterns. The DeepTFP algorithm employs three deep residual neural networks to model temporal and spatial dependencies effectively, significantly enhancing forecasting accuracy compared to traditional methods like LSTM networks. These advancements facilitate better transportation planning and congestion mitigation, supporting intelligent transportation systems [75, 32].

7.5 Manufacturing and Process Control

Deep learning's integration into manufacturing and process control has revolutionized the industry by enhancing precision and efficiency. CNNs and RNNs analyze complex datasets generated by manu-

factoring processes, identifying patterns and anomalies impacting product quality and operational efficiency [13]. In manufacturing, deep learning facilitates production line monitoring and control by analyzing sensor data to detect deviations from normal conditions, crucial for maintaining product quality and minimizing waste [17]. Deep learning extends to predictive maintenance, forecasting equipment failures and scheduling maintenance activities by analyzing historical data and identifying degradation patterns, minimizing downtime and extending machinery lifespan [17]. Attention mechanisms in deep learning models improve focus on critical process data features, enhancing anomaly detection and process optimization precision [21].

The implementation of deep learning in manufacturing signifies a transformative leap, providing sophisticated algorithms that enhance accuracy and operational efficiency. By leveraging hierarchical layers of latent features, deep learning facilitates high-dimensional data analysis, enabling data-driven decisions that optimize processes and improve outcomes across applications from quality control to predictive maintenance [71, 6].

8 Challenges and Future Directions

8.1 Scalability and Computational Complexity

Scalability and computational complexity present significant challenges in deploying deep learning models for time series analysis. These models often require extensive computational resources, especially with large datasets, as seen in Evolutionary Genetic Programming for Recurrent Nodes (EGP-RN), which demands significant resources for training [48]. The necessity for large datasets exacerbates issues of generalization and interpretability, particularly in dynamic environments [76, 56]. Enhancements in models like TSMixer should focus on improving interpretability and scalability to handle larger datasets effectively [27]. Associated learning methods may offer solutions by enabling parallel updates, thus enhancing performance in anomaly detection [13].

Current models face challenges with computational efficiency and managing uncertainty, crucial for robust predictions [4]. Aligning neural network representations with brain activity further complicates scalability [3]. Additionally, issues of explainability and ethics are critical for broader model applications [19]. Methods like ADAU, requiring comparable sample sizes between domains, face limitations with varying dataset sizes [66]. The quality of input data also affects feature learning, with noisy data adversely impacting performance [18].

Addressing these challenges requires developing efficient architectures, optimizing training methodologies, and exploring novel techniques to enhance scalability while managing computational complexity. Continued research is essential to broaden deep learning applications across diverse domains, overcoming current barriers [29].

8.2 Model Interpretability and Uncertainty Quantification

Model interpretability and uncertainty quantification are crucial for deploying deep learning models in fields requiring transparency and reliability. The complexity and black-box nature of these models obscure decision-making processes, posing challenges in applications like financial forecasting and anomaly detection [20]. Enhancing interpretability involves developing architectures that yield more separable clusters in Euclidean space, improving clustering accuracy and insights into model behavior [30].

Uncertainty quantification is vital in dynamic environments with limited labeled data, where robust techniques ensure reliable predictions despite data sparsity [5]. The classification of time series with unseen behaviors during training highlights the need to address uncertainty in predictions [1]. The generalizability of deep learning models is often limited by the need for large datasets and resource-intensive training, impacting their applicability across tasks [6]. In financial markets, benchmarks may not account for all market conditions, affecting model generalizability [21].

To address these challenges, a multifaceted approach is needed, including developing transparent models, integrating robust uncertainty quantification methods, and refining interpretability techniques. As research progresses, these models have the potential to achieve high accuracy and interpretability across fields like image and speech recognition, natural language processing, and financial analytics, despite ongoing challenges related to their black-box nature [76, 71, 57, 6, 24].

8.3 Adaptability and Real-Time Processing

The adaptability of deep learning models to real-time processing is crucial in time series analysis for applications requiring immediate decision-making. Future research aims to enhance the robustness of analog methods against noise and explore hybrid analog-digital systems for improved real-time processing [77]. Models like Rest maintain performance in noisy environments while being efficient for real-time applications on mobile devices, emphasizing the need for robust, computationally efficient models [43].

Deep SLDA highlights real-time processing capabilities, suitable for immediate learning and inference applications [78]. Associated learning allows for independent updates, enhancing efficiency crucial for time series analysis [13]. Future work should focus on refining model selection techniques to improve responsiveness and accuracy in real-time scenarios [71].

Optimizing LSTM architecture for lower computational overhead is critical, especially in resource-constrained environments where adaptability and efficiency are paramount [79]. Integrating lexicase selection in neural architecture search optimizes architectures and parameters, potentially enhancing adaptability to real-time demands [26]. Future research should prioritize optimizing hyperparameters using Bayesian Optimization and applying frameworks to real datasets to validate effectiveness in real-time scenarios [80]. These efforts underscore the need to enhance the adaptability of deep learning models to real-time processing needs, ensuring applicability across time-sensitive applications.

8.4 Data Quality and Diversity

Data quality and diversity are crucial for the performance of deep learning models in time series analysis. High-quality data supports robust representation learning, balancing complexity and training efficiency, essential for managing large datasets [81]. Conversely, noisy or poorly captured data can negatively impact model performance, as seen in adversarial training where adaptation to adversarial examples may reduce accuracy on unperturbed data [51]. This underscores the necessity of maintaining high data quality for reliable predictions.

Diversity within datasets is equally important, enabling models to generalize across various scenarios. A lack of diverse datasets can limit the applicability of deep learning methods, as seen in agricultural applications focused mainly on image analysis due to insufficient publicly available datasets [82]. The complexity of underlying physics or forces in certain applications can further limit deep learning applicability when data diversity is inadequate [83]. Probabilistic models face unresolved questions regarding optimal design and scalability to larger datasets, illustrating the impact of data quality and diversity on efficacy [4].

Addressing these challenges requires improving data collection methodologies and ensuring the availability of diverse, high-quality datasets to support robust deep learning model development and deployment across various domains.

8.5 Integration of Hybrid and Unsupervised Approaches

Integrating hybrid and unsupervised approaches in anomaly and outlier detection enhances detection capabilities and robustness across applications. Future research should explore using Generative Adversarial Networks (GANs) to generate synthetic data, providing a comprehensive understanding of data distributions and improving anomaly detection in time series analysis [16]. Balancing predictive accuracy with other epistemic values and adopting interdisciplinary approaches could further advance the field [19].

Enhancing hybrid models' robustness against adversarial attacks and improving interpretability are critical research areas. These efforts can develop models that are more accurate, transparent, and reliable in real-world applications [20]. Refining feature selection and currency pairs to enhance performance in financial markets and exploring additional features for volatility prediction could significantly improve hybrid approaches [28].

The integration of hybrid and unsupervised approaches is further supported by the need to enhance computational methods for inference in probabilistic models and explore architectures that better capture uncertainty. Applying these models in diverse real-world scenarios can yield valuable insights and improve detection capabilities [4]. Emerging trends suggest a focus on developing efficient

training techniques, enhancing interpretability, and investigating unsupervised and semi-supervised learning approaches, leading to significant advancements [6].

Future research should concentrate on creating adaptive loss functions and metrics that adjust dynamically based on data and task characteristics, improving hybrid and unsupervised approaches [29]. Enhancing robustness against similar-looking classes and investigating other normalization techniques may further improve performance in clustering and unsupervised anomaly detection [30].

The integration of hybrid and unsupervised approaches in anomaly and outlier detection signifies substantial advancement, combining deep learning techniques—such as self-supervised learning and generative models—with classical methods, enhancing performance on complex datasets and enabling robust detection in dynamic conditions. This evolution broadens applicable scenarios across domains like cybersecurity and healthcare, addressing challenges through innovative frameworks that leverage complementary data and improve training efficiency [66, 39, 42]. By leveraging innovative techniques and addressing challenges, these integrated approaches promise improved detection capabilities and resilience across applications, paving the way for more accurate and reliable systems in time series analysis.

9 Conclusion

The survey underscores the pivotal role of deep learning in enhancing time series anomaly and outlier detection, reflecting its transformative influence across diverse applications. The deployment of sophisticated neural network architectures, such as LSTM-GRU, has significantly bolstered predictive accuracy and decision-making in domains like financial stock analysis. In healthcare, models such as TempPNet demonstrate exceptional predictive capabilities and interpretability, highlighting the potential of deep learning to revolutionize chronic disease management and patient care. Similarly, frameworks like TE-SSL have propelled advancements in understanding neurodegenerative diseases, particularly Alzheimer's, showcasing the innovative potential of deep learning in medical diagnostics.

In the realm of anomaly detection, models like LLMAD have achieved competitive performance and enhanced interpretability, marking significant progress. Within financial markets, deep learning models consistently surpass traditional techniques, improving prediction accuracy and offering profound insights into market dynamics. Furthermore, the analysis of self-attention models, including SAKT and RKT, reveals their superiority over conventional RNN-based models, with RKT's use of contextual data significantly enhancing performance in educational technology.

These developments highlight deep learning's essential role in advancing time series anomaly and outlier detection. As research continues to evolve and refine these methodologies, the potential for deep learning to revolutionize various fields remains substantial, providing enhanced accuracy, interpretability, and adaptability in managing complex temporal data.

References

- [1] Nicolas Boullé, Vassilios Dallas, Yuji Nakatsukasa, and D. Samaddar. Classification of chaotic time series with deep learning, 2019.
- [2] Shalini Pandey, George Karypis, and Jaideep Srivastava. An empirical comparison of deep learning models for knowledge tracing on large-scale dataset, 2021.
- [3] Subba Reddy Oota, Zijiao Chen, Manish Gupta, Raju S. Bapi, Gael Jobard, Frederic Alexandre, and Xavier Hinaut. Deep neural networks and brain alignment: Brain encoding and decoding (survey), 2024.
- [4] Daniel T. Chang. Probabilistic deep learning with probabilistic neural networks and deep probabilistic models, 2021.
- [5] Abhinav Nippani, Dongyue Li, Haotian Ju, Haris N. Koutsopoulos, and Hongyang R. Zhang. Graph neural networks for road safety modeling: Datasets and evaluations for accident analysis, 2024.
- [6] Mohammad Mustafa Taye. Understanding of machine learning with deep learning: architectures, workflow, applications and future directions. *Computers*, 12(5):91, 2023.
- [7] Hendrik Purwins, Bo Li, Tuomas Virtanen, Jan Schlüter, Shuo-Yiin Chang, and Tara Sainath. Deep learning for audio signal processing. *IEEE Journal of Selected Topics in Signal Processing*, 13(2):206–219, 2019.
- [8] Lu Han, Xu-Yang Chen, Han-Jia Ye, and De-Chuan Zhan. Learning robust precipitation forecaster by temporal frame interpolation, 2023.
- [9] Qishuo Cheng. Intelligent optimization of mine environmental damage assessment and repair strategies based on deep learning, 2024.
- [10] Chengjian Sun, Changyang She, and Chenyang Yang. Unsupervised deep learning for optimizing wireless systems with instantaneous and statistic constraints, 2020.
- [11] Jiabo Huang, Qi Dong, Shaogang Gong, and Xiatian Zhu. Unsupervised deep learning by neighbourhood discovery, 2019.
- [12] Muhammad Aminul Islam, Derek T. Anderson, Anthony J. Pinar, Timothy C. Havens, Grant Scott, and James M. Keller. Enabling explainable fusion in deep learning with fuzzy integral neural networks, 2019.
- [13] Yu-Wei Kao and Hung-Hsuan Chen. Associated learning: Decomposing end-to-end backpropagation based on auto-encoders and target propagation, 2021.
- [14] Alexandre Araujo. Building compact and robust deep neural networks with toeplitz matrices, 2021.
- [15] John Chiang. Activation functions not to active: A plausible theory on interpreting neural networks, 2023.
- [16] Sam Dannels. Creating disasters: Recession forecasting with gan-generated synthetic time series data, 2023.
- [17] Mathias Kraus, Stefan Feuerriegel, and Asil Oztekin. Deep learning in business analytics and operations research: Models, applications and managerial implications, 2019.
- [18] Dan Xu, Elisa Ricci, Yan Yan, Jingkuan Song, and Nicu Sebe. Learning deep representations of appearance and motion for anomalous event detection, 2015.
- [19] Bernard J. Koch and David Peterson. From protoscience to epistemic monoculture: How benchmarking set the stage for the deep learning revolution, 2024.
- [20] Saptarshi Sengupta, Sanchita Basak, Pallabi Saikia, Sayak Paul, Vasilios Tsalavoutis, Frederick Atiah, Vadlamani Ravi, and Alan Peters. A review of deep learning with special emphasis on architectures, applications and recent trends, 2019.

-
- [21] Sangyeon Kim and Myungjoo Kang. Financial series prediction using attention lstm, 2019.
 - [22] Heejoon Koo and To Eun Kim. A comprehensive survey on generative diffusion models for structured data, 2023.
 - [23] Vivek Sharma, Praneeth Vepakomma, Tristan Swedish, Ken Chang, Jayashree Kalpathy-Cramer, and Ramesh Raskar. Expertmatcher: Automating ml model selection for users in resource constrained countries, 2019.
 - [24] Samira Pouyanfar, Saad Sadiq, Yilin Yan, Haiman Tian, Yudong Tao, Maria Presa Reyes, Mei-Ling Shyu, Shu-Ching Chen, and Sundaraja S Iyengar. A survey on deep learning: Algorithms, techniques, and applications. *ACM computing surveys (CSUR)*, 51(5):1–36, 2018.
 - [25] Lalit Mohan Sanagavarapu, Vivek Iyer, and Raghu Reddy. A deep learning approach for ontology enrichment from unstructured text, 2021.
 - [26] Li Ding and Lee Spector. Optimizing neural networks with gradient lexicase selection, 2023.
 - [27] Si-An Chen, Chun-Liang Li, Nate Yoder, Sercan O. Arik, and Tomas Pfister. Tsmixer: An all-mlp architecture for time series forecasting, 2023.
 - [28] Shujian Liao, Jian Chen, and Hao Ni. Forex trading volatility prediction using neural network models, 2021.
 - [29] Juan Terven, Diana M. Cordova-Esparza, Alfonso Ramirez-Pedraza, Edgar A. Chavez-Urbiola, and Julio A. Romero-Gonzalez. Loss functions and metrics in deep learning, 2024.
 - [30] Caglar Aytekin, Xingyang Ni, Francesco Cricri, and Emre Aksu. Clustering and unsupervised anomaly detection with l2 normalized deep auto-encoder representations, 2018.
 - [31] Maria Tzelepi, Charalampos Symeonidis, Paraskevi Nousi, Efstratios Kakavetsis, Theodoros Manousis, Pavlos Tosidis, Nikos Nikolaidis, and Anastasios Tefas. Deep learning for energy time-series analysis and forecasting, 2023.
 - [32] Yuanfang Chen, Falin Chen, Yizhi Ren, Ting Wu, and Ye Yao. Deeptfp: Mobile time series data analytics based traffic flow prediction, 2017.
 - [33] Arnab Hazra, Pratik Nag, Rishikesh Yadav, and Ying Sun. Exploring the efficacy of statistical and deep learning methods for large spatial datasets: A case study, 2023.
 - [34] Hao Wu. What is learning? a primary discussion about information and representation, 2015.
 - [35] John Cristian Borges Gamboa. Deep learning for time-series analysis. *arXiv preprint arXiv:1701.01887*, 2017.
 - [36] Aurélien Renault, Alexis Bondu, Vincent Lemaire, and Dominique Gay. Automatic feature engineering for time series classification: Evaluation and discussion, 2023.
 - [37] Jianing Hao, Qing Shi, Yilin Ye, and Wei Zeng. Timetuner: Diagnosing time representations for time-series forecasting with counterfactual explanations, 2023.
 - [38] Maëlys Solal, Ravi Hassanaly, and Ninon Burgos. Leveraging healthy population variability in deep learning unsupervised anomaly detection in brain fdg pet, 2023.
 - [39] Lukas Ruff, Jacob R. Kauffmann, Robert A. Vandermeulen, Grégoire Montavon, Wojciech Samek, Marius Kloft, Thomas G. Dietterich, and Klaus-Robert Müller. A unifying review of deep and shallow anomaly detection, 2021.
 - [40] Takato Yasuno. Few-shot 1/a anomalies feedback : Damage vision mining opportunity and embedding feature imbalance, 2023.
 - [41] Jun Liu, Chaoyun Zhang, Jiaxu Qian, Minghua Ma, Si Qin, Chetan Bansal, Qingwei Lin, Saravan Rajmohan, and Dongmei Zhang. Large language models can deliver accurate and interpretable time series anomaly detection, 2024.

-
- [42] Hadi Hojjati, Thi Kieu Khanh Ho, and Narges Armanfard. Self-supervised anomaly detection in computer vision and beyond: A survey and outlook, 2024.
 - [43] Rahul Duggal, Scott Freitas, Cao Xiao, Duen Horng Chau, and Jimeng Sun. Rest: Robust and efficient neural networks for sleep monitoring in the wild, 2020.
 - [44] Mulomba Mukendi Christian, Yun Seon Kim, Hyebong Choi, Jaeyoung Lee, and SongHee You. Enhancing wind speed and wind power forecasting using shape-wise feature engineering: A novel approach for improved accuracy and robustness, 2024.
 - [45] Shahran Rahman Alve, Muhammad Zawad Mahmud, Samiha Islam, and Mohammad Monirujjaman Khan. Chronic obstructive pulmonary disease prediction using deep convolutional network, 2024.
 - [46] Valentin Gabeff, Tomas Teijeiro, Marina Zapater, Leila Cammoun, Sylvain Rheims, Philippe Ryvlin, and David Atienza. Interpreting deep learning models for epileptic seizure detection on eeg signals, 2020.
 - [47] Soham Gadgil, Joshua Galanter, and Mohammadreza Negahdar. Transformer-based time-series biomarker discovery for copd diagnosis, 2024.
 - [48] Aditya Rawal and Risto Miikkulainen. From nodes to networks: Evolving recurrent neural networks, 2018.
 - [49] Jiaheng Xie, Xiaohang Zhao, Xiang Liu, and Xiao Fang. Care for the mind amid chronic diseases: An interpretable ai approach using iot, 2022.
 - [50] Gabriela Gómez Jiménez and Demian Wassermann. Deep multivariate autoencoder for capturing complexity in brain structure and behaviour relationships, 2024.
 - [51] Islam Debicha, Thibault Debatty, Jean-Michel Dricot, and Wim Mees. Adversarial training for deep learning-based intrusion detection systems, 2021.
 - [52] Alevizos Bastas and George A. Vouros. Data-driven prediction of air traffic controllers reactions to resolving conflicts, 2022.
 - [53] Jacob Thrasher, Alina Devkota, Ahmed Tafti, Binod Bhattacharai, and Prashnna Gyawali. Te-ssl: Time and event-aware self supervised learning for alzheimer's disease progression analysis, 2024.
 - [54] Matteo Zambra, Alberto Testolin, and Marco Zorzi. A developmental approach for training deep belief networks, 2022.
 - [55] Armstrong Aboah and Elizabeth Arthur. Comparative analysis of machine learning models for predicting travel time, 2021.
 - [56] Seonwoo Min, Byunghan Lee, and Sungroh Yoon. Deep learning in bioinformatics. *Briefings in bioinformatics*, 18(5):851–869, 2017.
 - [57] Stefan Feuerriegel and Ralph Fehrer. Improving decision analytics with deep learning: The case of financial disclosures, 2018.
 - [58] Yu. Gordienko, Yu. Kochura, O. Alienin, O. Rokovy, S. Stirenko, Peng Gang, Jiang Hui, and Wei Zeng. Dimensionality reduction in deep learning for chest x-ray analysis of lung cancer, 2018.
 - [59] Changwei Hu, Yifan Hu, and Sungyong Seo. A deep structural model for analyzing correlated multivariate time series, 2020.
 - [60] G. Jogesh Babu, David Banks, Hyunsoon Cho, David Han, Hailin Sang, and Shouyi Wang. A statistician teaches deep learning, 2021.
 - [61] Julie Keisler, Sandra Claudel, Gilles Cabriel, and Margaux Brégère. Automated deep learning for load forecasting, 2024.

-
- [62] Keiichi Tamai, Tsuyoshi Okubo, Truong Vinh Truong Duy, Naotake Natori, and Synge Todo. Universal scaling laws of absorbing phase transitions in artificial deep neural networks, 2024.
 - [63] Yong Shean Chong and Yong Haur Tay. Modeling representation of videos for anomaly detection using deep learning: A review, 2015.
 - [64] Chongke Wu, Sicong Shao, Cihan Tunc, and Salim Hariri. Video anomaly detection using pre-trained deep convolutional neural nets and context mining, 2020.
 - [65] Jingzhi Gong. Pushing the boundary: Specialising deep configuration performance learning, 2025.
 - [66] Gabriel Michau and Olga Fink. Unsupervised transfer learning for anomaly detection: Application to complementary operating condition transfer, 2020.
 - [67] Christian Janiesch, Patrick Zschech, and Kai Heinrich. Machine learning and deep learning. *Electronic Markets*, 31(3):685–695, 2021.
 - [68] Thomas M. Bury, Daniel Dylewsky, Chris T. Bauch, Madhur Anand, Leon Glass, Alvin Shriner, and Gil Bub. Predicting discrete-time bifurcations with deep learning, 2024.
 - [69] Weike Sun, Antonio R. C. Paiva, Peng Xu, Anantha Sundaram, and Richard D. Braatz. Fault detection and identification using bayesian recurrent neural networks, 2020.
 - [70] Fabio Anselmi, Joel Z. Leibo, Lorenzo Rosasco, Jim Mutch, Andrea Tacchetti, and Tomaso Poggio. Unsupervised learning of invariant representations in hierarchical architectures, 2014.
 - [71] Nicholas G. Polson and Vadim O. Sokolov. Deep learning, 2018.
 - [72] Muyang Ge, Shen Zhou, Shijun Luo, and Boping Tian. 3d tensor-based deep learning models for predicting option price, 2021.
 - [73] Dinggang Shen, Guorong Wu, and Heung-II Suk. Deep learning in medical image analysis. *Annual review of biomedical engineering*, 19(1):221–248, 2017.
 - [74] Linpeng Jin. Go beyond multiple instance neural networks: Deep-learning models based on local pattern aggregation, 2022.
 - [75] Yaguang Li and Cyrus Shahabi. A brief overview of machine learning methods for short-term traffic forecasting and future directions. *Sigspatial Special*, 10(1):3–9, 2018.
 - [76] Gary Marcus. Deep learning: A critical appraisal. *arXiv preprint arXiv:1801.00631*, 2018.
 - [77] Aditya Datar and Pramit Saha. The promise of analog deep learning: Recent advances, challenges and opportunities, 2024.
 - [78] Tyler L. Hayes and Christopher Kanan. Lifelong machine learning with deep streaming linear discriminant analysis, 2020.
 - [79] Aidin Ferdowsi and Walid Saad. Deep learning for signal authentication and security in massive internet of things systems, 2019.
 - [80] Ivan Kiskin, Udeepa Meepegama, and Steven Roberts. Super-resolution of time-series labels for bootstrapped event detection, 2019.
 - [81] Charu C Aggarwal et al. *Neural networks and deep learning*, volume 10. Springer, 2018.
 - [82] Andreas Kamilaris and Francesc X Prenafeta-Boldú. Deep learning in agriculture: A survey. *Computers and electronics in agriculture*, 147:70–90, 2018.
 - [83] Junqing Qiu, Guoren Zhong, Yihua Lu, Kun Xin, Huihuan Qian, and Xi Zhu. The newton scheme for deep learning, 2018.

Disclaimer:

SurveyX is an AI-powered system designed to automate the generation of surveys. While it aims to produce high-quality, coherent, and comprehensive surveys with accurate citations, the final output is derived from the AI's synthesis of pre-processed materials, which may contain limitations or inaccuracies. As such, the generated content should not be used for academic publication or formal submissions and must be independently reviewed and verified. The developers of SurveyX do not assume responsibility for any errors or consequences arising from the use of the generated surveys.

www.SurveyX.Cn