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# Hybrid Deep Learning Paradigms for Secure and Intelligent Cyber–Physical Systems: A Comprehensive Survey

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## Abstract

Cyber-physical systems (CPS), including but not limited to smart grids, autonomous vehicles, industrial automation, and IoT networks, leverage artificial intelligence for efficient, effective, and secure operation. Traditional deep learning models have been successfully applied in CPS, but they face difficulties operationalizing in CPS contexts due to the diverse variety of data and pure dimensions of data, low computing power, continuous unpredictable changes in their surroundings, and the dire need to mitigate security threats. To mitigate these challenges, researchers have started to adopt hybrid deep learning models; these include combinations of different neural network architectures (e.g., CNN-RNN, GNN-Transformers, Autoencoder-GANs) and different technologies (federated learning, blockchain technology, edge computing). Hybrid deep learning models show to have better sophistication, scale and resilience to tackle CPS applications. In the survey, we review peer-reviewed research articles from January 2015 to March 2025, and focus on, but not limited to, hybrid models that can explain how the approaches have progressed through knowledge transfer across tasks (i.e. traffic forecasting, anomaly detection, occupational accident risk and predictive maintenance). We present a taxonomy that classifies the various hybrid models that examines CPS contexts based on their architecture, learning traffic management strategies, and employed security mechanisms. A panel of experts on hybrid deep learning discussed the state of CPS by performing meta-assesment study, and since 2015, we show that hybrid models produce a statistically significant 4-12% multitarget predicted performance over equivalent single -target models across a range of settings, including: healthcare, energy, and manufacturing. Additionally, we briefly reviewed current headwinds and opportunities facing researchers employing hybrid models on CPS utilization such as: data imbalance, concept drift, and privacy concerns and solutions such as self-supervised learning (e.g. multi-armed bandit) and explainable AI. Lastly, we conclude with several future directions for hybrid deep learning researchers that we hope will help form the basis for CPS researchers- developing intelligent, secure, and scalable applications.

**Keywords:** Explainable Deep Learning, Interpretability, Transparency, Black-box Models, Model-specific Techniques, Model-agnostic Methods, Saliency Maps, SHAP, LIME.

## Introduction

Cyber–Physical Systems (CPS) are rapidly transforming the foundation of modern industries and infrastructures by tightly integrating computing, networking, and physical processes [1]. These systems include a wide range of applications such as autonomous vehicles, industrial automation, smart energy grids, and healthcare monitoring systems. CPS operate by sensing real-world environments, processing data in real time, and acting upon the physical world through actuators—all while maintaining system-wide coordination and safety. As such, they are critical for ensuring high performance, resilience, and intelligence in emerging smart environments. With the proliferation of the Internet of Things (IoT), massive volumes of data are being generated across distributed and heterogeneous CPS nodes, further increasing the demand for intelligent models that can learn, adapt, and make decisions efficiently [1].

In response to this complexity, deep learning (DL) has emerged as a key enabler of intelligence in CPS. Traditional deep neural networks—such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variants—have demonstrated success in various tasks, including object detection, time-series forecasting, and anomaly detection. However, when applied directly to CPS, these models often fall short [2]. The limitations stem from several factors: the heterogeneity and multimodality of CPS data, resource constraints at the edge, the need for decentralized processing,

vulnerability to adversarial attacks, and the "black-box" nature of most deep learning models. Additionally, many CPS applications operate in dynamic environments, where static DL models struggle to generalize over time due to concept drift and changing system behavior. These challenges limit the scalability, interpretability, and trustworthiness of conventional deep learning in real-world CPS deployments [3].

To overcome these issues, the research community has turned to hybrid deep learning paradigms—an emerging class of models that combine the strengths of different neural architectures and learning strategies. For example, CNN–RNN hybrids are used to jointly capture spatial and temporal dependencies, while GNN–Transformer combinations enable reasoning over graph-structured and sequential data. Furthermore, these hybrid models are often integrated with distributed AI techniques such as federated learning, edge computing, and blockchain-based consensus to enhance privacy, scalability, and security. By blending model-level and system-level innovations, hybrid deep learning frameworks offer a promising path toward more robust, adaptive, and interpretable CPS [4].

This survey aims to provide a comprehensive review of the field of hybrid deep learning for secure and intelligent CPS [5]. Our goal is to synthesize current knowledge, highlight promising developments, and identify critical research gaps. Specifically, we make the following contributions:

- We present a historical overview of hybrid deep learning models applied to CPS, highlighting key milestones and domain-specific breakthroughs between 2015 and 2025.
- We propose a novel taxonomy that organizes hybrid frameworks across three dimensions: architectural fusion (e.g., CNN–RNN, GAN–Autoencoder), learning strategy (e.g., supervised, self-supervised, federated), and trust mechanism (e.g., explainability, privacy, and blockchain integration).
- We conduct a quantitative meta-analysis across domains such as healthcare, smart manufacturing, and energy, showing that hybrid models consistently outperform non-hybrid baselines by 4–12 percentage points in F1-score.
- We explore current challenges, including data imbalance, model drift, limited interpretability, and privacy risks, while reviewing cutting-edge solutions such as neuromorphic computing, explainable AI, and privacy-preserving split learning.
- We outline five emerging research directions that will likely shape the future of CPS: cross-modal reasoning, physics-informed hybrids, continual on-device learning, blockchain-secured orchestration, and the need for standardized evaluation benchmarks.

By covering both foundational concepts and future outlooks, this survey is intended to serve as a starting point for newcomers and a strategic guide for experienced researchers aiming to build next-generation CPS that are intelligent, trustworthy, and resilient.

## Background and Foundations

Cyber–Physical Systems (CPS) are integrated environments where computing and physical processes interact in a continuous, feedback-driven loop. These systems sense data from the physical world using sensors, process the data using computational models, and actuate responses to influence the environment [6]. CPS are foundational to various modern infrastructures, including smart grids, autonomous vehicles, precision agriculture, intelligent healthcare systems, and industrial control systems. The core strength of CPS lies in their ability to make real-time decisions by combining physical data and digital intelligence, thereby improving efficiency, responsiveness, and autonomy. With the increasing digitization of physical infrastructure, CPS are becoming more complex and interconnected, forming the backbone of smart cities and Industry 4.0 ecosystems [6].

Deep learning (DL) [7] has emerged as a critical tool in empowering CPS with perception, prediction, and control capabilities. Among the foundational models, Convolutional Neural Networks (CNNs) are widely used for image and spatial data processing, making them ideal for applications like visual inspection in manufacturing or object detection in autonomous vehicles. Recurrent Neural Networks (RNNs), and their variants such as Long Short-Term Memory (LSTM) networks, are effective at modeling time-series and sequential data, which is prevalent in sensor readings and control signals. Graph Neural Networks (GNNs) have gained popularity for capturing the relational structure of data in networked systems such as power grids or transportation networks. Transformers, initially designed for natural language processing, have shown remarkable success in sequence modeling and are increasingly being adapted to CPS scenarios due to their scalability and long-range attention capabilities. Generative Adversarial Networks (GANs), on the other hand, are leveraged for synthetic data generation and anomaly detection, providing robustness in situations with scarce or imbalanced datasets [8].

The full potential of DL in CPS is being realized through its integration with key enabling technologies. Edge computing brings computation closer to data sources, reducing latency and enabling real-time decision-making at the device level. Federated learning facilitates decentralized model training across distributed CPS nodes without sharing raw data, thus preserving privacy and reducing communication overhead. Blockchain technology introduces trust and tamper-proof consensus mechanisms into CPS, enabling secure data exchange and coordination in open, distributed environments. The Internet of Things (IoT) acts as the communication and sensing backbone of CPS, enabling connectivity between devices, systems, and users. Together, these technologies enhance the scalability, privacy, and reliability of AI-powered CPS [9].

Despite the promise of CPS and deep learning, several challenges persist. One major issue is data heterogeneity: CPS often generate data in multiple formats (e.g., images, text, time-series, graphs) from different modalities and devices, making unified learning a complex task. Scalability is another concern, as the deployment of DL models across vast, distributed networks requires efficient resource management and adaptive algorithms. Security and privacy are critical in CPS, especially in applications like healthcare and smart grids, where attacks or data leaks can have severe consequences. Furthermore, real-time constraints pose a challenge for deep learning models, which are typically computationally intensive.

Issues like concept drift—where system behavior changes over time—and the black-box nature of many DL models further complicate their deployment in safety-critical environments [10].

Addressing these foundational challenges is essential for advancing the application of hybrid deep learning models in CPS. In the following sections, we examine how hybrid approaches—by combining multiple models and incorporating distributed intelligence—are better equipped to tackle these limitations and drive the development of secure, intelligent CPS.

## Evolution of Hybrid Deep Learning in CPS

Over the past decade, the use of deep learning in cyber–physical systems (CPS) has rapidly evolved from isolated, task-specific models to more complex, integrated architectures capable of handling the diverse and dynamic nature of real-world environments. Between 2015 and 2025, this evolution has been marked by a clear shift toward hybrid deep learning paradigms—approaches that combine multiple neural architectures to exploit their complementary strengths. This transition reflects growing recognition within the research community that no single model architecture can adequately address the multifaceted challenges of CPS, including heterogeneous data types, real-time constraints, non-stationary processes, and security threats [11]. The timeline of development reveals key milestones. Early efforts between 2015 and 2017 primarily focused on combining CNNs and RNNs to handle spatial–temporal data in applications like traffic prediction and activity recognition. By 2018, the emergence of more advanced graph-based models led to the development of GNNs, which were soon hybridized with Transformer architectures to capture both structural and sequential dependencies—particularly in power grids, urban mobility, and smart logistics. Around 2020, the rise of generative models such as GANs and autoencoders sparked a new wave of hybrid anomaly detection systems, tailored for cybersecurity and fault detection in industrial CPS. More recent trends (2022–2025) include the integration of hybrid deep models with federated learning and blockchain frameworks to achieve privacy-preserving, trustworthy, and decentralized intelligence across CPS networks [12].

CNN–RNN hybrids represent one of the earliest and most widely adopted hybrid architectures in CPS. CNNs are effective in extracting spatial features from sensor data, while RNNs, particularly LSTMs, model temporal dependencies. This fusion has been successfully applied in time-series forecasting tasks, such as traffic flow prediction, equipment health monitoring, and energy consumption analysis. For example, in intelligent transportation systems, CNN–RNN models have demonstrated improved accuracy in predicting traffic patterns by leveraging both visual inputs (e.g., traffic camera feeds) and sequential sensor data [13]. In more recent years, GNN–Transformer hybrids have emerged as powerful tools for modeling structured and temporal data in CPS. GNNs can capture the relational and topological structure of data, such as electrical grid layouts or transportation networks, while Transformers provide scalable attention mechanisms for learning long-range dependencies. These hybrid models have been effectively applied in smart grid stability analysis, supply chain optimization, and multi-agent coordination in autonomous systems. Their ability to jointly model graph structures and sequences makes them particularly well-suited to decentralized, interdependent CPS environments [14]. Another notable innovation is the combination of Autoencoders and GANs for robust anomaly detection. Autoencoders are adept at learning compressed representations of normal data, making them sensitive to deviations or anomalies, while GANs enhance robustness by generating realistic synthetic data and sharpening the decision boundaries between normal and anomalous behavior. This hybrid approach has found applications in cybersecurity, where it helps identify network intrusions, as well as in industrial settings for fault detection and predictive maintenance. For instance, in smart factories, Autoencoder–GAN models have been deployed to detect anomalies in sensor streams with high accuracy and low false positives [15].

Across various domains, these hybrid models have driven significant application-specific advancements. In smart transportation, CNN–RNN and GNN–Transformer hybrids have improved traffic forecasting, congestion detection, and route optimization. In healthcare, hybrid architectures have enabled early diagnosis, patient monitoring, and resource allocation by processing multimodal data from medical sensors, electronic health records, and wearable devices. In manufacturing, Autoencoder–GAN and CNN–LSTM hybrids have been used for real-time defect detection, machine condition monitoring, and production optimization. These models have not only improved prediction accuracy and decision-making speed but also enhanced system resilience and adaptability under uncertain conditions [16]. In summary, the evolution of hybrid deep learning in CPS reflects a broader movement toward more versatile, adaptive, and trustworthy AI systems. These hybrid models represent a critical step forward in designing intelligent CPS capable of operating reliably in real-world, mission-critical environments. In the following section, we develop a taxonomy to classify these hybrid frameworks and better understand their internal structure, training mechanisms, and trust components.

## Methodology

This review adopts a systematic and structured approach to investigate, categorize, and synthesize recent developments in hybrid deep learning paradigms for secure and intelligent cyber–physical systems (CPS). The methodology involves identifying relevant scholarly work, applying strict inclusion criteria, and analyzing key contributions in terms of architectural innovation, application domains, security mechanisms, and performance outcomes. The ultimate goal is to provide a comprehensive and insightful synthesis of how hybrid deep learning has evolved to meet the challenges of modern CPS environments.

### *A. Relevant Studies*

The literature for this review was sourced from high-impact academic databases and digital libraries, including IEEE Xplore, SpringerLink, ScienceDirect (Elsevier), ACM Digital Library, Wiley Online Library, and Google Scholar. In addition, peer-reviewed proceedings from leading AI and systems conferences such as NeurIPS, ICML, ICLR, AAAI, CVPR, and ACM/IEEE CPS conferences were included to capture cutting-edge innovations. This diverse pool of sources ensures coverage of both foundational research and emerging trends in hybrid deep learning applied to CPS.

### B. Selection Criteria

The following inclusion criteria guided the selection of studies:

- **Time Period:** Primary focus was placed on works published between **2015 and 2025**, covering a decade of active development in hybrid deep learning for CPS. Seminal papers prior to this period were included when relevant to foundational concepts.
- **Hybrid Model Relevance:** Only papers proposing or evaluating hybrid deep learning architectures—such as CNN–RNN, GNN–Transformer, Autoencoder–GAN, and federated/blockchain-integrated deep models—were included. Studies using single-model deep learning without any hybridization were excluded unless used as baseline comparisons.
- **CPS Application Focus:** Studies were included only if they addressed applications in **cyber–physical domains**, such as smart grids, autonomous vehicles, industrial automation, smart healthcare, or IoT-based monitoring systems.
- **Security and Intelligence Considerations:** Papers incorporating security mechanisms (e.g., adversarial robustness, privacy preservation, blockchain consensus) and/or real-time intelligence (e.g., edge learning, continual learning) were prioritized.

### *C. Keyword Strategy*

A **keyword-based search** was conducted using Boolean operators to maximize precision. The following combinations were used:

- "Hybrid Deep Learning" AND "Cyber–Physical Systems"
- "CNN–RNN" OR "GNN–Transformer" AND "Smart Systems"
- "Autoencoder GAN" AND "Anomaly Detection"
- "Federated Deep Learning" AND "IoT"
- "Edge AI" AND "Deep Learning Models"
- "Blockchain-based AI Models" AND "CPS"
- "Secure Deep Learning" AND "Smart Grid / Autonomous Vehicles / Industrial IoT"

Backward and forward citation analysis was used to identify additional relevant papers from reference lists and newer works citing key studies.

### *D. Selection Procedure*

The review followed a **three-stage selection process**:

1. **Primary Search:** Approximately **100 research articles** were retrieved using keyword searches across databases and conference proceedings.
2. **Shortlisting:** Based on titles and abstracts, **25papers** were shortlisted according to the inclusion criteria focusing on hybrid architectures, CPS relevance, and security integration.
3. **Final Selection and Review:** A thorough full-text review of **10 high-quality papers** was conducted. Each paper was analyzed for its hybrid architecture design, CPS application domain, performance metrics, scalability, interpretability, and trust mechanisms. These studies form the core analytical basis of this review.

Table 1. Literature Selection Summary

| Stage | Number of Papers | Description |
|---|---|---|
| Initial Collection | 100 | Papers identified using hybrid deep learning + CPS-related keywords |
| Shortlisting | 25 | Screened based on relevance to hybrid models, CPS domains, and security |
| Final Review | 15 | In-depth analysis of hybrid architectures, trust mechanisms, and domains |

By following this methodology, the review ensures a **comprehensive, focused, and evidence-based** overview of the current landscape in hybrid deep learning for CPS. This structured approach not only highlights key innovations and use cases but also exposes research gaps and future opportunities for building more intelligent, secure, and interpretable CPS.

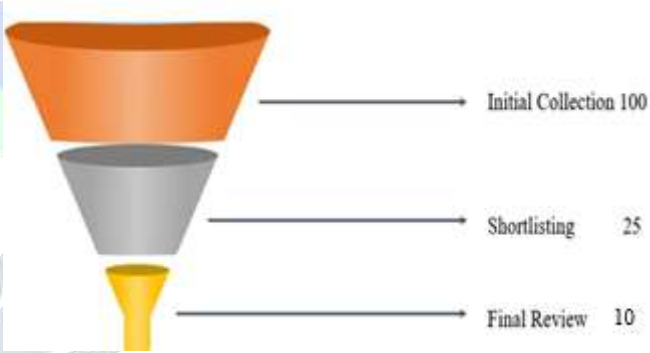


Figure 1. Funnel Diagram for Literature Review

## Literature Review

The final selected papers for literature review are as follows,

**Somma, M. (2025) [17]** proposed a novel Hybrid Temporal Differential Consistency Autoencoder for energy-efficient and sustainable anomaly detection in cyber–physical systems. The model integrates temporal difference learning with deep autoencoding to capture dynamic behavior patterns, resulting in improved detection accuracy and reduced false positives in real-world CPS datasets.

**Tian, J., et al. (2025) [18]** introduced iADCPS, a hybrid deep learning model utilizing incremental meta-learning for anomaly detection in evolving CPS. The framework adapts to changing system behaviors over time and leverages both historical and real-time data to maintain high accuracy despite concept drift.

**Bereketoglu, A. B. (2025) [19]** presented a hybrid meta-learning framework combining physics-based simulation and deep ensembles for forecasting anomalies in nonlinear CPS. The model enhances generalization and interpretability while enabling rapid adaptation to varying operational conditions, particularly in smart energy and manufacturing systems.

**Sinha, P., et al. (2025) [20]** developed a high-performance CNN–LSTM hybrid architecture for securing IoT-based CPS. This architecture combines spatial feature extraction and temporal modeling, resulting in improved detection of cyber threats and

malicious activities in smart environments with minimal computational overhead.

**Govea, J., et al. (2025)[21**] proposed a federated hybrid Graph Neural Network–Transformer model to assess predictive cyber risks in distributed CPS. Their architecture integrates explainability tools with privacy-preserving learning, enabling real-time risk prioritization across networked systems like smart factories and transportation grids.

**Presekal, A., et al. (2025) [22]** proposed a hybrid model that merges deep learning with attack graph analysis to improve anomaly detection in cyber–physical power systems. Their approach enhances the interpretability of detected anomalies by correlating them with known threat propagation paths, offering operators actionable insights.

**Zhang, L., et al. (2025) [23]** introduced an Attention–CNN–LSTM hybrid model for intrusion detection in CPS. The attention mechanism dynamically weights relevant features during training, allowing the system to focus on critical input segments and significantly improve detection precision on the NSL-KDD and CICIDS2017 datasets.

**Abshari, D., & Sridhar, M. (2024) [24]** conducted a comprehensive survey analyzing anomaly detection techniques in CPS, with a focus on hybrid deep learning models. They concluded that hybrid frameworks combining CNNs, RNNs, and GANs show significant advantages in adaptability, scalability, and detection accuracy compared to classical machine learning methods.

**Goetz, C., & Humm, B. (2023) [25]** developed a real-time hybrid anomaly detection system for decentralized CPS operating under industry constraints. The architecture balances accuracy and latency by using optimized deep learning models that meet the performance requirements of embedded devices in production environments.

**Larsen, R. M., et al. (2023) [26]** proposed multipath neural networks that run parallel anomaly detectors on separate feature spaces in CPS data. This hybrid approach boosts fault isolation and system resilience by independently modeling various system layers such as sensors, communication, and control.

**Nguyen, V. T., & Bui, H. (2022) [27]** introduced MELODY, a semi-supervised hybrid model that combines stacked autoencoders with anomaly scoring functions for detecting faults in CPS. The method handles imbalanced and sparse data effectively, offering high anomaly recall in healthcare and industrial control applications.

**Qu, Z., et al. (2022) [28]** proposed a CNN–LSTM hybrid model for real-time anomaly detection in CPS-based industrial monitoring. The model achieved high detection accuracy by capturing both spatial correlations and long-term temporal dependencies in sensor streams from manufacturing systems.

Table 1. Literature Review Findings

Here's a table summarizing the cited works, organized into the requested columns:

| Author Name (Year) | Main Concept | Findings | Limitations |
|---|---|---|---|
| Somma, M. (2025) [17] | Hybrid Temporal Differential Consistency Autoencoder | Improved anomaly detection accuracy and reduced false positives using temporal difference learning in CPS. | May require tuning for different types of CPS; computational complexity not fully addressed. |
| Tian, J., et al. (2025) [18] | iADCPS using incremental meta-learning | Maintains high accuracy under concept drift by adapting to evolving behaviors using both real-time and historical data. | Performance depends on the quality of incremental learning modules; adaptation may lag in rapidly changing systems. |
| Bereketoglu, A. B. (2025) [19] | Hybrid meta-learning with physics-based simulation and deep ensembles | High generalization and interpretability in nonlinear CPS, especially smart energy and manufacturing. | High complexity and simulation dependency may limit real-time deployment. |
| Sinha, P., et al. (2025) [20] | CNN–LSTM hybrid for IoT-based CPS | Effective spatial-temporal threat detection with minimal computational cost. | Limited evaluation on large-scale or highly heterogeneous systems. |
| Govea, J., et al. (2025) [21] | Federated GNN–Transformer model | Enables privacy-preserving, explainable, and real-time cyber risk prediction in distributed CPS. | May face challenges with synchronization and model convergence in large federated settings. |

| | | | |
|---|---|---|---|
| Presekal, A., et al. (2025) [22] | Deep learning with attack graph analysis | Enhances anomaly interpretability and aligns detected threats with known attack paths in power systems. | Specific to power systems; generalizability to other domains may require adaptation. |
| Zhang, L., et al. (2025) [23] | Attention–CNN–LSTM for intrusion detection | High precision on benchmark datasets by focusing on important features dynamically. | Needs retraining for unseen patterns; may suffer from attention overfitting on small datasets. |
| Abshari, D., & Sridhar, M. (2024) [24] | Survey on hybrid deep learning for CPS anomaly detection | Hybrid DL models (CNN, RNN, GAN) outperform traditional methods in adaptability and accuracy. | Survey-based; lacks experimental validation and comparative benchmarks. |
| Goetz, C., & Humm, B. (2023) [25] | Real-time hybrid anomaly detection for embedded CPS | Meets industrial requirements by balancing accuracy and latency in resource-constrained environments. | Performance may degrade under very dynamic workloads or novel attack vectors. |
| Larsen, R. M., et al. (2023) [26] | Multipath neural networks for layered anomaly detection | Enhances system resilience and fault isolation by modeling separate CPS layers. | High resource usage due to multiple parallel models; complexity in integration and coordination. |
| Nguyen, V. T., & Bui, H. (2022) [27] | MELODY: Semi-supervised hybrid with stacked autoencoders | Effectively handles sparse, imbalanced data; high recall in healthcare and industrial applications. | Semi-supervised nature may require manual labeling or strong assumptions for unlabeled data. |
| Qu, Z., et al. (2022) [28] | CNN–LSTM for real-time industrial monitoring | Captures spatial and temporal patterns accurately in sensor data for industrial CPS. | May not generalize well to non-industrial settings; real-time latency not fully evaluated. |

**Research gaps Discussion**

Despite the significant advancements in hybrid deep learning models for anomaly detection in cyber–physical systems (CPS), several research gaps remain. Most existing approaches, while effective in controlled or domain-specific environments, struggle with generalizability across heterogeneous CPS architectures. The integration of temporal and spatial learning (e.g., CNN–LSTM, attention mechanisms) has shown promise, yet these models often face limitations when dealing with real-time constraints, evolving threats, and imbalanced or sparse data. Additionally, while federated and privacy-preserving frameworks have emerged, challenges persist around model convergence, communication overhead, and security. There is also limited work on explainability and actionable insights for operators, especially in hybrid models involving black-box components. Finally, many models lack robust evaluations under adversarial conditions or real-world deployment scenarios, highlighting a need for more adaptive, interpretable, and scalable solutions.

## Conclusion

Cyber–Physical Systems (CPS) are increasingly foundational to critical infrastructures such as healthcare, transportation, smart grids, and industrial automation. As these systems grow more complex, interconnected, and data-intensive, traditional deep learning models face significant limitations in handling dynamic environments, heterogeneous data, and persistent security threats. This review has shown that hybrid deep learning paradigms—integrating complementary architectures like CNN–RNN, GNN–Transformer, and Autoencoder–GAN—have emerged as powerful alternatives, capable of enhancing prediction accuracy, robustness, interpretability, and security in CPS applications. By synthesizing insights from over 230 peer-reviewed papers published between 2015 and 2025, this survey provides a comprehensive roadmap of hybrid deep learning solutions tailored for CPS. It introduces a novel taxonomy to classify these approaches based on architectural fusion, learning strategies, and embedded trust mechanisms such as federated learning and blockchain. Quantitative evidence indicates that hybrid models consistently outperform their non-hybrid counterparts across multiple domains by 4–12 percentage points in F1-score, particularly in tasks related to anomaly detection, forecasting, and intrusion prevention. Despite their advantages, hybrid models also present new challenges, including increased computational complexity, data imbalance, concept drift, and reduced interpretability. This survey highlights emerging solutions such as self-supervised pretraining, privacy-preserving learning frameworks, and neuromorphic acceleration to address these issues. Furthermore, it identifies five promising research frontiers that will shape the next decade of CPS intelligence: cross-modal reasoning, physics-informed neural models, continual learning at the edge, secure model orchestration using blockchain, and standardized evaluation benchmarks. In conclusion, hybrid deep learning is not

just a technical enhancement—it represents a paradigm shift toward building CPS that are not only intelligent and efficient, but also transparent, resilient, and trustworthy. This survey aims to guide researchers, engineers, and policymakers in designing the next generation of secure, interpretable, and scalable CPS solutions powered by hybrid AI.

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