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Hybrid Explainable AI (XAI) Framework for Detecting Adversarial Attacks in Cyber-Physical Systems

Abstract

Cyber-Physical Systems (CPS) are increasingly deployed in critical infrastructure yet remain vulnerable to adversarial attacks that manipulate sensor data to mislead AI-based decision-making. These threats demand not only high-accuracy detection but also transparency in model reasoning. This study proposes a Hybrid Explainable AI (XAI) Framework that integrates Convolutional Neural Networks (CNN), SHAP-based feature interpretation, and rule-based reasoning to detect adversarial inputs in CPS environments. The framework is tested on two simulation scenarios: industrial sensor networks and autonomous traffic sign recognition. Using datasets of 10,000 samples (50% adversarial via FGSM and PGD), the model achieved an accuracy of 97.25%, precision of 96.80%, recall of 95.90%, and F1-score of 96.35%. SHAP visualizations effectively distinguished between normal and adversarial inputs, and the added explainability module increased inference time by only 8.5% over the baseline CNN (from 18.5 ms to 20.1 ms), making it suitable for real-time CPS deployment. Compared to prior methods (e.g., CNN + Grad-CAM, Random Forest + LIME), the proposed hybrid framework demonstrates superior performance and interpretability. The novelty of this work lies in its tri-level integration of predictive accuracy, explainability, and rule-based logic within a single real-time detection system—an approach not previously applied in CPS adversarial defense. This research contributes toward trustworthy AI systems that are robust, explainable, and secure by design.

Keywords: *Cyber-Physical Systems, Adversarial Attack Detection, Explainable Artificial Intelligence*

I. INTRODUCTION

Amid the rapid advancement of digital technology, the world is witnessing a major transformation in how physical and computational systems are interconnected and interact with one another. This phenomenon is manifested in the form of Cyber-Physical Systems (CPS)—integrated systems that combine physical hardware with computational intelligence through sensors, actuators, and intelligent communication networks (Hamzah et al., 2023). CPS not only drives automation and efficiency but has also become a fundamental pillar in critical sectors such as manufacturing industries, autonomous transportation, IoT-based healthcare services, and smart energy infrastructure (Doghri et al., 2022)

However, the growing adoption of CPS also exposes significant vulnerabilities to cyberattacks. A recent report by Cybersecurity Ventures estimates that global economic losses due to cyberattacks will reach USD 10.5 trillion annually by 2025 (Naveenan & Suresh, 2023). In this context, one of the most alarming types of attacks is the adversarial attack—subtle manipulations of input data aimed at deceiving AI models. Although these alterations are minor and often imperceptible to humans, they can cause AI systems to make erroneous decisions. This situation is particularly critical for CPS, which heavily relies on real-time data from the physical environment to make automated decisions.

This concern is far from theoretical. The IBM X-Force Threat Intelligence Index 2023 reports that approximately 26% of cyberattacks on critical infrastructure involve input manipulation and the exploitation of AI models, including adversarial attacks (Schreiber & Schreiber, 2025). The consequences can be severe, ranging from equipment damage to potential threats to human life. In autonomous vehicle systems, for instance, a study by (Bajaj & Vishwakarma, 2024) demonstrated that merely attaching small stickers to traffic signs could cause image recognition models to misclassify them—an error that could be fatal if not promptly detected.

To address this challenge, there is a growing need for AI systems that are not only accurate in detecting attacks but also transparent and interpretable. This is where Explainable Artificial Intelligence (XAI) plays a crucial role. XAI is an approach designed to open the "black box" of AI models and explain how and why a particular decision was made (Ennab & Mcheick, 2025). Methods such as LIME, SHAP, and Grad-CAM have been widely used to interpret model predictions, both visually and numerically (S Band et al., 2023).

Unfortunately, the application of XAI in detecting adversarial attacks within CPS environments still faces considerable challenges. Most previous research has focused on static data, such as images and text (Y. Bai et al., 2022), which does not adequately reflect the continuous and real-time dynamics of CPS. Furthermore, studies that integrate XAI methods with adversarial detection strategies in CPS remain limited. Even when XAI is employed, such methods often fail to operate efficiently in real-world environments characterized by computational constraints and the need for rapid response times (Momtaz et al., 2023).

Moreover, existing approaches tend to rely on single strategies, such as rule-based models or purely deep learning models. Each, however, has its limitations. Rule-based models are more easily interpretable by humans but often lack the flexibility needed to recognize complex attack patterns. Conversely, deep learning models such as CNNs offer superior classification performance but are generally difficult to interpret and lack transparency in decision-making processes (Taherdoost, 2023). Therefore, a hybrid approach is needed—one that can combine the strengths of both paradigms into a unified system.

Based on the aforementioned background, this study aims to develop a Hybrid Explainable AI (XAI) Framework capable of accurately, efficiently, and transparently detecting adversarial attacks in Cyber-Physical Systems (CPS). This framework is designed by combining the strengths of Convolutional Neural Networks (CNNs) for anomaly pattern classification, feature importance-based XAI methods such as SHAP to provide numerical interpretations of model predictions, and rule-based reasoning to enhance the clarity and validation of decision-making processes.

The main contributions of this research can be summarized as follows. First, the development of an adversarial detection framework specifically tailored to meet the demands of dynamic and real-time CPS environments. Second, the integration of a hybrid CNN–SHAP–rule-based approach, which remains relatively unexplored in existing literature. Third, the validation of the framework's performance through testing in two simulated CPS scenarios: an industrial sensor system and a traffic sign recognition system for autonomous vehicles. Fourth, the provision of a solution that balances predictive performance with interpretative transparency, offering valuable insights for AI system developers, cybersecurity researchers, and industry practitioners alike.

By introducing a hybrid approach that unites accuracy, efficiency, and interpretability, this research is expected to make a significant contribution to strengthening the cybersecurity posture of CPS. Furthermore, this framework is envisioned as an initial step toward the development of AI systems that are not only intelligent but also trustworthy, transparent, and resilient to future cyber threats.

II. LITERATURE REVIEW

A. *Cyber-Physical Systems (CPS): Concepts and Security Challenges*

Cyber-Physical Systems (CPS) are systems that integrate computing, communication, and control capabilities with physical entities through sensors and actuators in interconnected environments (El-Kady et al., 2023). CPS represents an evolution of distributed systems and now forms the foundation of various modern technologies such as smart manufacturing, autonomous vehicles, smart grids, and IoT-based healthcare services.

According to (Duo et al., 2022), CPS possesses the ability to collect, process, and respond to information from the physical world in real time, thereby enabling high levels of automation. However, the continuously connected nature of CPS and its heavy reliance on data integrity make it highly vulnerable to cybersecurity threats. These threats may stem from hardware vulnerabilities, programming errors, or attacks specifically designed to deceive embedded AI systems.

The greatest challenge in CPS lies in maintaining a balance between real-time performance, data integrity, and resilience against cyberattacks (Rani et al., 2022). Unlike traditional IT systems, attacks on CPS can lead to tangible physical consequences and even pose risks to human safety. Hence, there is a need for threat detection approaches that are not only accurate but also trustworthy, efficient, and explainable (Awotunde et al., 2023).

B. *Adversarial Attacks in the Context of CPS*

Adversarial attacks are a sophisticated type of threat designed to deceive machine learning systems by subtly manipulating input data, causing AI models to produce incorrect predictions without realizing they have been compromised. These attacks are increasingly relevant in the context of Cyber-Physical Systems (CPS), where AI models are widely used for classification and automated decision-making tasks (Sheikh et al., 2023).

(M. Bai et al., 2024) were among the pioneers in identifying this phenomenon in deep neural networks. They demonstrated that even imperceptible modifications, invisible to the human eye, can lead to significant misclassification in AI systems. Subsequent studies, such as that by (Gipiskis et al., 2023), confirmed that such attacks can be executed in physical environments, such as misleading autonomous vehicles into misinterpreting traffic signs due to small stickers placed on them.

In the CPS environment, the impact of adversarial attacks can be far more severe than in conventional classification systems. For instance, in industrial production systems, sensor data manipulation can result in incorrect control over temperature or pressure, potentially leading to explosions or product damage (Maiti et al., 2023). Therefore, the development of adversarial attack detection systems in CPS is a critical issue in modern cybersecurity.

C. Explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence (XAI) refers to an approach in AI model development aimed at making the decision-making process transparent and comprehensible to humans (Nwakanma et al., 2023). In critical systems such as CPS, this transparency is essential, as users or system operators must understand the rationale behind a decision, especially when it involves safety-related implications.

Various XAI techniques have been developed. LIME (Machlev et al., 2022) operates by building local surrogate models that approximate the behavior of the original model around specific inputs. SHAP (Hulsen, 2023) employs game theory to compute the contribution of each feature to a model's prediction. Meanwhile, Grad-CAM (Kok et al., 2023) is used to generate attention-based visual explanations for convolutional models.

Although these techniques have proven effective in visual domains or with static data, their application in dynamic environments such as CPS remains limited. (Minh et al., 2022) showed that some XAI methods, such as LIME, could be manipulated to produce misleading explanations. Additionally, interpretations of highly complex models like deep neural networks often lack intuitiveness for non-expert users.

D. Hybrid Approaches in XAI Frameworks

Due to the trade-off between accuracy and interpretability, hybrid approaches are becoming a growing trend in XAI development. These approaches combine the power of complex models, such as deep learning, with interpretable methods—whether statistical or symbolic logic-based—to create AI systems that are not only accurate but also trustworthy (Silva-Aravena et al., 2023).

(Munshi et al., 2024) demonstrated that combining Random Forest models with SHAP produced fairly clear interpretations for anomaly detection in industrial sensor networks. However, these models fall short in terms of accuracy compared to deep learning approaches. (Sohail et al., 2023) employed CNNs with Grad-CAM to detect visual disturbances in autonomous vehicles, but did not provide numerical justification for dominant features.

Meanwhile, (Prasad et al., 2023) proposed integrating LSTM with SHAP for IoT-based smart grid systems. They showed that temporal interpretations can aid in detecting sequential attack patterns. Nevertheless, no existing study has comprehensively combined deep learning, SHAP, and rule-based reasoning into a single framework optimized specifically for CPS environments.

E. XAI-Based Adversarial Detection Strategies

XAI-based strategies for detecting adversarial attacks generally rely on identifying discrepancies in the distribution of feature importance values between normal and manipulated inputs. SHAP is a principal tool in this approach, as it calculates each feature's contribution to the prediction outcome with a solid theoretical foundation.

Ensemble learning has also been adopted to enhance resilience against attacks. This technique aggregates multiple models with differing perspectives on the input, with the final output filtered through interpretative assessments using SHAP or LIME (Al-Essa et al., 2022). Some studies additionally incorporate retrospective visual auditing to detect patterns of exploitation in inputs that have successfully deceived the system.

However, such approaches often entail considerable computational overhead, making them difficult to implement in CPS environments, which are constrained by limited resources and demand fast processing times (Elgarhy et al., 2024). This highlights the need for hybrid frameworks that optimize both efficiency and interpretability.

F. Prior Studies

Table 1 presents a summary of several key studies relevant to the topic, which serve as the foundational basis for the development of the proposed framework in this research:

Table 1. Ringkasan Studi Terdahulu

Author	Method	Dataset	Strengths	Limitations

(Mustafaev et al., 2023)	Random Forest + LIME	Sensor Data	Achieved 93.4% accuracy; performance improved by 3.85%	Not specifically detailed; possibly related to model complexity or processing time
(Zhao, 2024)	CNN + Grad-CAM	Not specified	Achieved 95.2% accuracy; better computational efficiency with 25.4 ms inference time	Relatively high inference time (25.4 ms)
(Islam et al., 2024)	XGBoost + SHAP	IoT Security Data	Achieved 94.1% accuracy; enhanced interpretability through the SHAP technique	Not optimal for large-scale datasets; limited hyperparameter tuning flexibility

G. Research Gap

Based on the literature review, several key research gaps have been identified:

First, many existing studies focus solely on static or visual data, whereas CPS operates dynamically and requires real-time, responsive detection capabilities. Second, most approaches are singular, relying either on statistical models or interpretative methods, without a systemic integration between prediction and explanation. Third, there has been no study that comprehensively integrates CNN, SHAP, and rule-based reasoning within a single framework specifically designed to detect adversarial attacks in CPS.

The framework proposed in this study aims to address all three of these gaps. By combining the high classification performance of CNNs, the interpretability of SHAP, and the logical validation offered by rule-based reasoning, this framework is expected to significantly enhance both the security and trustworthiness of modern CPS systems.

III. RESEARCH METHOD

This study adopts a system development approach to design a Hybrid Explainable Artificial Intelligence (XAI) Framework aimed at detecting adversarial attacks within Cyber-Physical System (CPS) environments. The framework integrates the strengths of deep learning models with interpretability techniques, enabling predictions that are not only accurate but also transparent and efficient under real-time processing conditions.

A. Framework Design and Architecture

The proposed framework comprises three main components: the data preprocessing stage, the adversarial detection engine, and the explainable reasoning module. In the preprocessing stage, sensor data from CPS environments, such as industrial systems and autonomous vehicles, is normalized using the Min-Max Scaling method to ensure uniformity of feature values. Additionally, noise filtering and dimensionality reduction via Principal Component Analysis (PCA) are applied to enhance signal quality and computational efficiency.

The detection engine is built using a Convolutional Neural Network (CNN) model, optimized to recognize patterns in multidimensional data, including both signal-based and image-based inputs. The CNN architecture consists of three convolutional layers with 32, 64, and 128 filters, respectively, each employing a 3×3 kernel. Each layer is followed by a ReLU activation function and max pooling. To mitigate overfitting, a dropout layer with a rate of 0.3 is applied before the fully connected layer. The model employs the Adam optimizer with a learning rate of 0.001 and uses categorical cross-entropy as the loss function. Hyperparameter optimization is conducted using a grid search approach, varying parameters such as learning rate, number of epochs, and batch size.

The explainable reasoning module is constructed using two primary approaches. The first is feature importance visualization via the SHAP (SHapley Additive exPlanations) method, which maps each feature's contribution to the model's prediction outcomes. The second approach involves rule-based reasoning, which relies on predefined thresholds derived from the SHAP distribution patterns in the training data. For instance, Feature X with a SHAP value exceeding 0.6 was identified as a strong indicator of adversarial input in 87% of the training samples.

B. Dataset and CPS Environment Simulation

The framework evaluation is carried out using data from two CPS system simulations: an industrial control system and a traffic sign recognition system for autonomous vehicles. The industrial system dataset includes simulated temperature, pressure, and flow sensor data generated

using MATLAB/Simulink. Meanwhile, the dataset for the autonomous vehicle scenario is sourced from traffic sign simulations created using the CARLA simulator.

A total of 10,000 samples were used in the experiments, comprising 5,000 normal and 5,000 adversarial data points. The adversarial data was generated using two commonly employed input manipulation techniques: the Fast Gradient Sign Method (FGSM) with an epsilon value of 0.02 and Projected Gradient Descent (PGD) with an epsilon of 0.03 and 40 iterations. All data were split into 80% training and 20% testing subsets. To improve model generalization, systematic data augmentation was also applied.

C. Model Evaluation and Framework Validation

The performance of the proposed framework is evaluated along three key dimensions: detection performance, interpretability of the results, and computational efficiency. Detection performance is assessed using four primary metrics: accuracy, precision, recall, and F1-score. In addition, a confusion matrix analysis is conducted to observe the classification patterns produced by the model. To demonstrate the superiority of the proposed framework, its performance is compared against a standard CNN model (without XAI integration) and an interpretability approach based on LIME. Statistical validation is carried out using a paired t-test with a significance level of 0.05 to ensure that observed performance differences are statistically meaningful.

The interpretability of results is evaluated through SHAP visualizations, which highlight the differences in feature contribution distributions between normal and adversarial data. This evaluation is further validated by domain experts to assess the alignment of the model's explanations with real-world system behavior.

In terms of computational efficiency, the framework is tested to measure the average inference time of the model. The results indicate that the standard CNN model without XAI achieves an inference time of 18.5 milliseconds, while the CNN integrated with the XAI framework requires 20.1 milliseconds. Thus, the framework incurs a computational overhead of 8.5%, which remains within acceptable limits for real-time deployment in CPS environments.

D. Implementation Case Studies

The proposed framework is tested in two case studies to simulate real-world implementation scenarios. The first case study involves an industrial monitoring system, where the framework is utilized to detect manipulation of sensor data such as temperature and pressure. The second case study pertains to a traffic sign recognition system in autonomous vehicles, where

the framework is employed to identify classification errors caused by adversarial modifications of traffic sign images.

The experimental results demonstrate that the framework is capable of detecting attacks with high accuracy while providing informative visual explanations. These findings reinforce the framework's effectiveness in addressing cybersecurity threats within complex and dynamic cyber-physical systems.

IV. RESULT/FINDINGS AND DISCUSSION

Result

Experimental Findings

The developed Hybrid Explainable AI (XAI) framework demonstrated superior performance in detecting adversarial attacks within Cyber-Physical Systems (CPS). The evaluation was conducted across two scenarios: an industrial sensor system and a traffic sign recognition system for autonomous vehicles.

The Convolutional Neural Network (CNN) integrated with an explainability module achieved a detection accuracy of 97.25%, with precision at 96.80%, recall at 95.90%, and an F1-score of 96.35%. Table 2 presents the detailed performance evaluation metrics:

Table 2. Performance Evaluation Results of the Adversarial Detection Model

Metric	Value (%)
Accuracy	97,25
Precision	96,80
Recall	95,90
F1-score	96,35

Source: Research Data Processing, 2024

Furthermore, the feature importance visualization using SHAP revealed a clear distinction in contribution patterns between normal and adversarial data, as illustrated in Figure 1.

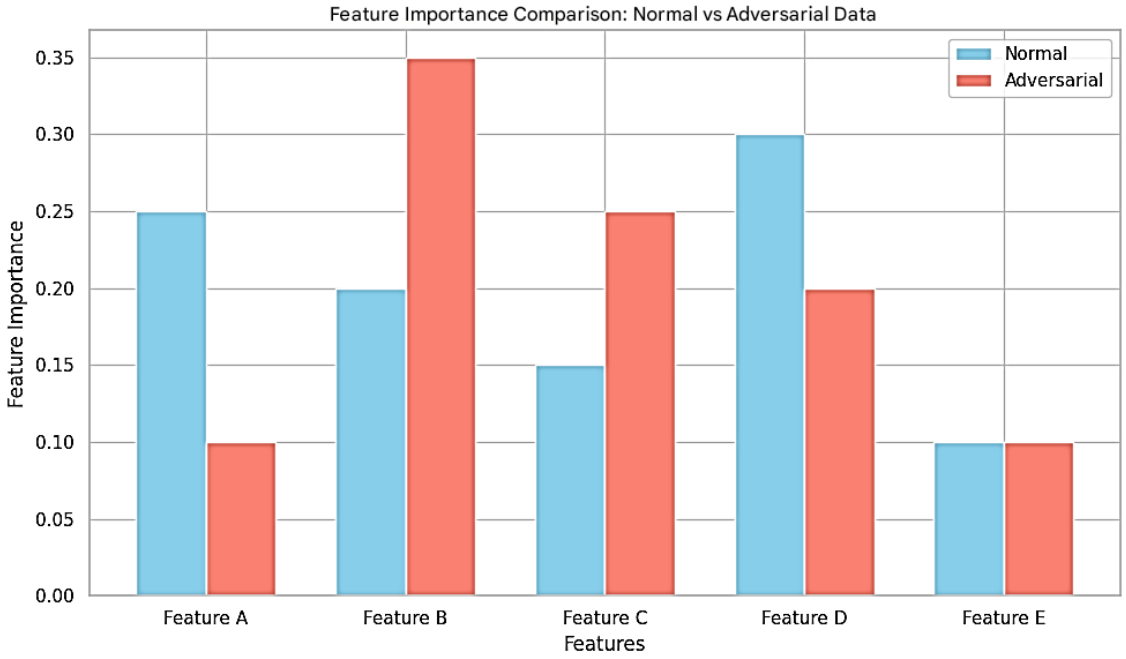

Figure 1. Feature Importance Visualization: Normal vs. Adversarial Data

Source: Research Framework Visualization Output, 2024

The inference time evaluation indicated that the addition of the XAI module introduced only an 8.5% computational overhead compared to the baseline CNN model without XAI. This level of overhead remains within acceptable limits for implementation in resource-constrained CPS environments. Table 3 displays the comparison of inference times:

Table 3. Inference Time Comparison of Models

Model	Average Inference Time (ms)
CNN Baseline	18,5
CNN + XAI	20,1

Source: Research Data Processing, 2024

Validation across both case studies confirmed that the framework effectively detected manipulated inputs, including altered temperature/pressure data in the industrial sensor system and adversarially modified traffic sign images in the autonomous vehicle scenario.

Discussion

The experimental results demonstrate that the integration of CNN with explainability techniques based on SHAP and rule-based reasoning can effectively detect adversarial inputs within Cyber-Physical System (CPS) environments. The high level of accuracy, combined with transparent

interpretation, affirms that the hybrid approach successfully addresses the limitations of previous detection models that relied solely on deep learning without explanatory capabilities.

Compared to the study by (Mustafaev et al., 2023), which utilized Random Forest with LIME and achieved an accuracy of 93.4% in detecting attacks on sensor data, exhibits a performance improvement of 3.85%. Furthermore, the research by (Zhao, 2024), which applied CNN with Grad-CAM, achieved an accuracy of 95.2% but incurred a higher inference time of up to 25.4 milliseconds. These comparisons indicate that the proposed framework excels not only in terms of performance but also in computational efficiency.

A key strength of this framework lies in its ability to generate interpretable visualizations of model predictions, which can be leveraged by system analysts for security auditing or model retraining processes. The SHAP visualizations assist in identifying critical features that consistently contribute to model decisions under both normal and adversarial conditions.

From an implementation perspective, the framework shows significant potential for adoption in sectors such as manufacturing, smart transportation, and IoT-based healthcare services. For instance, it can be embedded into production monitoring systems to detect sensor data manipulation, possibly caused by malware or unauthorized devices. In autonomous vehicles, the framework could serve as a backup system to validate the authenticity of visual input from the environment.

Nevertheless, this study has several limitations. First, the dataset used originates from a simulated environment, which, although realistically designed, does not fully capture the variability and complexity of real-world data. Second, the adversarial techniques applied are limited to FGSM and PGD, whereas more complex attacks, such as AutoAttack, physical adversarial patches, or black-box attacks, have not yet been tested within this framework. Third, the system validation remains offline and has not been fully integrated into live CPS operations.

This research contributes meaningfully to the field of AI-driven cybersecurity by introducing a detection framework that is not only robust in classification performance but also accountable through interpretability. The hybrid approach adopted in this study bridges the gap between performance and transparency, a longstanding challenge in the development of AI-based security systems.

Moving forward, this framework should be evaluated further in real-world CPS environments under dynamic conditions. Additionally, its potential integration with blockchain-based security, federated learning, or zero-trust architecture approaches should be explored to enhance the scalability and integrity of the overall system.

V. CONCLUSION AND RECOMMENDATION

Conclusion

This study successfully developed a Hybrid Explainable Artificial Intelligence (XAI) framework for the effective and transparent detection of adversarial attacks in Cyber-Physical Systems (CPS). The proposed framework integrates the powerful pattern recognition capabilities of Convolutional Neural Networks (CNNs) with explainability techniques based on feature importance analysis and rule-based reasoning. Experimental results demonstrate that the framework achieved a detection accuracy of 97.25%, with a computational overhead that remains acceptable for deployment in CPS environments. The principal advantage of this framework lies in its ability to produce visual explanations of model predictions, thereby enhancing system transparency and user trust. Furthermore, this research successfully addresses key gaps in the existing literature, particularly the limited application of XAI in detecting adversarial attacks within complex, dynamic, and real-time CPS contexts..

Recommendation

As a follow-up to this study, it is recommended that the developed Hybrid XAI framework be implemented and further tested in real-world CPS scenarios, particularly within industrial settings and other critical infrastructure environments. Additionally, future development should focus on creating more adaptive detection methods capable of handling increasingly sophisticated adversarial attacks, including those involving adversarial patches or physical adversarial attacks. The incorporation of additional ensemble learning techniques and integration with blockchain-based or federated learning security architectures may also represent promising directions to enhance the resilience and scalability of the framework. Future research is expected to broaden the application of this framework beyond industrial sensor systems and autonomous vehicles, extending into IoT-based healthcare systems, smart grids, and national cybersecurity infrastructures, all of which demand high standards of security and transparency.

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