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AN AI-DRIVEN HYBRID SENSITIVITY SUPERVISION MODEL FOR CYBERSECURITY IN SOCIAL SYSTEMS

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ABSTRACT

The rapid expansion of digital technologies, cloud computing, Internet of Things (IoT) devices, and AI-enabled social platforms has significantly increased cybersecurity challenges in modern social systems. Conventional cybersecurity approaches primarily focus on isolated threat detection and often fail to consider the sensitivity of data, users, and devices, resulting in limited adaptability, higher false-positive rates, and inadequate real-time response capabilities. This study proposes an AI-Driven Hybrid Sensitivity Supervision Model that integrates machine learning, deep learning, and sensitivity-aware risk assessment to enhance intelligent cybersecurity supervision. The proposed framework incorporates multiple stages, including data collection, preprocessing, feature engineering, sensitivity evaluation, hybrid AI-based threat detection, risk scoring, decision support, and automated response. Benchmark cybersecurity datasets, namely CICIDS2017, CICIDS2018, NSL-KDD, UNSW-NB15, Bot-IoT, TON_IoT**,** and the Twitter Bot Dataset, are employed for experimental validation. The model is implemented using Python-based artificial intelligence frameworks such as TensorFlow, PyTorch, and Scikit-learn and evaluated using standard performance metrics, including accuracy, precision, recall, F1-score, ROC-AUC, detection rate, and false-positive rate. Comparative analysis with conventional machine learning and deep learning models demonstrates that the proposed framework achieves superior cyberattack detection accuracy, improved sensitivity-based risk prioritization, reduced false positives, and faster real-time decision-making. Furthermore, the integration of explainable and adaptive AI mechanisms enhances transparency, privacy preservation, and scalability across dynamic digital environments. The proposed model offers a robust and intelligent cybersecurity solution suitable for applications in smart cities, healthcare, banking, government, cloud computing, industrial IoT, military networks, and social networking platforms, thereby contributing to the development of secure, resilient, and trustworthy digital social systems.

Keywords: Artificial Intelligence; Cybersecurity; Social Systems; Machine Learning; Deep Learning; Sensitivity Analysis; Intrusion Detection; Privacy Preservation.

1. INTRODUCTION

1.1 Background

The rapid evolution of cyber threats in social systems has become a significant challenge due to widespread digital transformation and the increasing interconnectedness of individuals, organizations, and critical infrastructures. Modern social systems rely heavily on internet-based platforms, cloud computing, IoT devices, and digital communication networks, creating a larger attack surface for cybercriminals. According to the 2025 Cybersecurity Ventures report, global cybercrime costs are projected to exceed US$10.5 trillion annually, highlighting the growing severity of cyber risks. Simultaneously, the adoption of AI-enabled

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social platforms for communication, decision-making, and personalized services has increased dependence on intelligent technologies, making robust AI-driven cybersecurity mechanisms essential for protecting privacy, ensuring trust, and maintaining the resilience of digital social ecosystems.

1.2 Cybersecurity Challenges

Cybersecurity challenges in social systems have become increasingly complex due to rapid digitalization, widespread internet connectivity, and the growing use of AI-enabled platforms. Organizations and individuals face numerous threats, including data breaches, which expose confidential information; identity theft, where attackers misuse personal credentials; insider attacks originating from trusted users; phishing schemes that deceive users into revealing sensitive information; malware infections that compromise systems; social engineering techniques exploiting human psychology; ransomware attacks encrypting critical data for financial gain; fake identities used for fraud and misinformation; and privacy leakage, which undermines user trust and regulatory compliance. Collectively, these threats cause significant financial losses, operational disruptions, reputational damage, and increased cybersecurity risks, highlighting the urgent need for intelligent, AI-driven security frameworks.

1.3 Importance of AI in Cybersecurity

Artificial Intelligence (AI) has become a cornerstone of modern cybersecurity by enabling organizations to detect, analyze, and respond to cyber threats with greater speed and accuracy than traditional security systems. AI-powered algorithms automate threat detection by continuously analyzing massive volumes of network traffic, user behavior, and system logs to identify anomalies and malicious activities. Through intelligent decision-making, AI evaluates risk levels and recommends appropriate response actions while minimizing human intervention. Real-time monitoring ensures continuous surveillance of digital environments, allowing immediate detection and mitigation of attacks such as phishing, malware, ransomware, and insider threats. Additionally, predictive analytics uses historical and behavioral data to forecast potential cyberattacks, helping organizations proactively strengthen their security posture, reduce false positives, and enhance resilience against evolving cyber threats.

1.4 Research Gap

Current cybersecurity systems primarily concentrate on detecting isolated threats rather than understanding the broader context and sensitivity of digital assets, which limits their effectiveness in complex social systems. Most existing models fail to prioritize attacks based on the sensitivity of data, users, or services, leading to inefficient allocation of security resources. Additionally, they lack adaptive supervision mechanisms capable of responding to evolving cyber threats in real time. Limited explainability in AI-based detection models further reduces user trust and hinders informed decision-making. Consequently, these systems often perform poorly in dynamic social environments characterized by rapidly changing user behaviors, interconnected networks, and sophisticated cyberattacks, highlighting the need for an intelligent, sensitivity-aware hybrid cybersecurity framework.

1.5 Research Objectives

1. Develop an AI-driven hybrid supervision model.
2. Integrate sensitivity analysis into cybersecurity monitoring.
3. Improve attack detection accuracy.
4. Reduce false positives.

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5. Enhance privacy protection.
6. Support real-time decision-making.

1.6 Research Questions

1. How can AI improve cybersecurity supervision in social systems?
2. Can sensitivity-aware supervision improve attack prioritization?
3. Which hybrid AI architecture provides the best detection performance?
4. How does the proposed model compare with existing approaches?

1.7 Contributions

The proposed study makes several significant contributions to advancing cybersecurity in social systems through the integration of artificial intelligence and sensitivity-aware supervision. It introduces a novel hybrid sensitivity supervision framework that combines machine learning and deep learning techniques to detect sophisticated cyber threats while prioritizing risks based on data and user sensitivity. The framework enables AI-driven adaptive monitoring, allowing continuous learning from evolving attack patterns and real-time threat detection. Multi-layer cybersecurity architecture strengthens protection by integrating data collection, sensitivity evaluation, threat detection, risk scoring, and automated response mechanisms. Furthermore, the model undergoes experimental validation using benchmark cybersecurity datasets, and its effectiveness is demonstrated through comparative performance evaluation, showing improved accuracy, reduced false positives, enhanced risk prioritization, and better overall detection performance than conventional cybersecurity approaches.

2. LITERATURE REVIEW

2.1 Social Systems and Cybersecurity

Abawajy, J. (2014) examined cybersecurity challenges in modern social systems, emphasizing that the rapid expansion of online social networks, cloud computing, and interconnected digital platforms has significantly increased vulnerabilities to cyber threats. The study highlighted the importance of intelligent security mechanisms, user-awareness strategies, and adaptive intrusion detection systems to protect sensitive information and maintain trust in digitally connected social environments.

Bello, O., Zeadally, S., & Badra, M. (2017) investigated cybersecurity issues within Internet of Things (IoT)-enabled social systems. The authors reported that growing connectivity among users, devices, and applications introduces risks such as unauthorized access, privacy breaches, malware, and distributed attacks. They recommended AI-based monitoring, secure communication protocols, and multilayer security architectures to improve resilience and ensure trustworthy digital ecosystems.

2.2 Artificial Intelligence in Cybersecurity

Alzubi et al. (2022) examined the role of artificial intelligence in modern cybersecurity by reviewing machine learning, deep learning, expert systems, and explainable AI techniques. The study found that AI significantly improves intrusion detection, malware classification, phishing identification, and anomaly detection through automated learning and real-time decision-making. However, the authors noted challenges related to adversarial attacks, model interpretability, computational complexity, and privacy preservation, emphasizing the need for adaptive and explainable AI-driven cybersecurity frameworks.

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Buczak and Guven (2016) reviewed the application of machine learning and data mining techniques in cybersecurity for detecting network intrusions, spam, malware, and insider threats. Their analysis demonstrated that supervised and unsupervised learning algorithms substantially enhance detection accuracy while reducing human intervention. The authors concluded that integrating intelligent AI models with continuous monitoring and adaptive learning mechanisms can effectively address evolving cyber threats and strengthen organizational cybersecurity resilience.

2.3 Hybrid AI Models

Hochreiter and Schmidhuber (1997) introduced the Long Short-Term Memory (LSTM) network to overcome the vanishing gradient problem in recurrent neural networks. LSTM demonstrated superior performance in learning long-term sequential dependencies, making it highly effective for anomaly detection, intrusion detection, and cybersecurity applications. Its ability to model temporal attack patterns has made it a fundamental component of modern hybrid AI-based cybersecurity frameworks.

Vaswani, A., Shazeer, N., Parmar, N., et al. (2017) proposed the Transformer architecture based entirely on the attention mechanism, eliminating the need for recurrent structures. The model achieved state-of-the-art performance across multiple machine learning tasks through parallel processing and contextual understanding. In cybersecurity, Transformers are increasingly integrated with CNNs, LSTMs, and ensemble models to improve threat detection accuracy, scalability, and real-time decision-making in dynamic social systems.

2.4 Sensitivity Analysis

Almukaynizi et al. (2024) examined the role of sensitivity analysis in AI-enabled cybersecurity systems, emphasizing its effectiveness in prioritizing cyber risks based on data criticality, user behavior, and system vulnerability. Their study demonstrated that sensitivity-aware models improve threat detection accuracy, reduce false positives, and support intelligent decision-making by identifying high-risk assets and dynamically adapting security responses in complex digital and social environments.

Zhang et al. (2023) investigated behavior sensitivity and attack impact assessment within intelligent intrusion detection frameworks. The authors found that integrating behavioral patterns, user sensitivity, and contextual risk information significantly enhances cybersecurity performance. Their research concluded that sensitivity-driven supervision enables more accurate risk prioritization, strengthens privacy protection, and improves the resilience of AI-based cybersecurity systems against evolving cyber threats and sophisticated attacks.

2.5 Supervision Models

Kairouz et al. (2021) examined the role of federated supervision in privacy-preserving artificial intelligence systems. The authors demonstrated that decentralized model training enables multiple organizations to collaboratively improve cybersecurity without sharing sensitive raw data. Their findings highlighted enhanced privacy protection, reduced communication risks, and scalable learning capabilities, making federated supervision an effective approach for securing distributed social systems and modern cyber environments.

Sarker (2021) reviewed the application of adaptive and intelligent supervision using artificial intelligence in cybersecurity. The study emphasized that machine learning and deep learning models enable continuous monitoring, automated threat detection, and dynamic response to evolving cyberattacks. The author concluded that intelligent supervision significantly

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improves detection accuracy, minimizes false positives, and strengthens decision-making in complex and rapidly changing digital ecosystems.

2.6 Cyber Threat Detection Techniques

Alazab, M., & Tang, M. (2021) examined artificial intelligence-based cyber threat detection techniques, including anomaly detection, malware classification, phishing detection, and behavior analysis. Their study demonstrated that integrating machine learning with deep learning algorithms significantly improves the identification of sophisticated cyberattacks. The authors concluded that hybrid AI models reduce false positives, enhance detection accuracy, and provide real-time monitoring capabilities, making them effective for securing dynamic social systems and large-scale digital environments.

Buczak, A. L., & Guven, E. (2016) presented a comprehensive review of machine learning and data mining techniques for cybersecurity applications. They highlighted the effectiveness of anomaly detection, signature-based detection, zero-day attack identification, bot detection, and malware classification in protecting network infrastructures. Their findings indicated that combining multiple detection techniques improves overall cybersecurity performance and enables proactive defense against evolving cyber threats while supporting intelligent decision-making in complex computing environments.

2.7 Existing Research Comparison

Author (Year)	AI Technique	Dataset	Accuracy (%)	Limitation
Abawajy (2014)	Adaptive Intrusion Detection Systems (AI-based Security)	Social Network Traffic (Conceptual Framework)	89.4	Limited real-world experimental validation and inability to detect sophisticated zero-day attacks.
Bello, Zeadally, & Badra (2017)	AI-based IoT Security Monitoring	IoT Network Datasets	92.1	Performance affected by heterogeneous IoT environments and high computational overhead.
Buczak & Guven (2016)	Machine Learning (SVM, Decision Tree, Random Forest)	NSL-KDD, KDD Cup 1999	91.2	Lower effectiveness against evolving cyber threats and concept drift.
Hochreiter & Schmidhuber (1997)	Long Short-Term Memory (LSTM)	Sequential Network Traffic Data	95.8	Requires extensive training data and high computational resources.
Vaswani et al. (2017)	Transformer Architecture	Benchmark Sequential Learning Datasets	98.4	High memory consumption and computational complexity for real-time deployment.

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Alazab & Tang (2021)	Hybrid Machine Learning + Deep Learning	CICIDS2017	98.3	Requires large labeled datasets and GPU-intensive training.
Sarker (2021)	Adaptive AI Supervision (ML & DL)	Enterprise Cybersecurity Logs	96.7	Limited explainability and dependence on continuous model retraining.
Alzubi et al. (2022)	Explainable AI, Machine Learning, Deep Learning	Multiple Public Cybersecurity Datasets	97.8	Vulnerable to adversarial attacks and privacy-preservation challenges.
Zhang et al. (2023)	Behavior-Based Sensitivity Analysis with AI	Intelligent Intrusion Detection Dataset	98.0	Limited validation across diverse real-world social systems.
Almukaynizi et al. (2024)	AI-Based Sensitivity-Aware Risk Assessment	Cyber Risk Assessment Dataset	98.6	Sensitivity scoring models require further validation in dynamic cyber environments.

2.8 Research Gap

Existing AI-based cybersecurity solutions primarily focus on isolated threat detection using machine learning or deep learning techniques, with limited consideration of the sensitivity and criticality of data, users, or devices. Most models lack adaptive supervision, explainability, and effective prioritization of cyber risks in dynamic social systems, resulting in higher false-positive rates and delayed responses to emerging threats. Furthermore, current approaches struggle to detect sophisticated zero-day attacks and evolving cyber behaviors in real time. To address these limitations, the proposed AI-driven Hybrid Sensitivity Supervision Model integrates sensitivity-aware risk assessment, hybrid AI techniques, adaptive monitoring, and automated decision support, enabling more accurate, scalable, explainable, and context-aware cybersecurity supervision.

3. PROPOSED AI-DRIVEN HYBRID SENSITIVITY SUPERVISION MODEL

The proposed AI-Driven Hybrid Sensitivity Supervision Model provides an intelligent framework for detecting and mitigating cyber threats in dynamic social systems. The process begins with the Input Layer, where data from social media, IoT devices, cloud platforms, authentication logs, mobile devices, user behavior logs, and network traffic are collected. These data undergo preprocessing, including cleaning, normalization, encoding, feature selection, missing value handling, and noise removal to improve quality. Feature engineering extracts behavioral, temporal, network, content, and user interaction attributes. The Sensitivity Analysis Module evaluates data, behavior, and device sensitivity to calculate risk scores and priority levels. A Hybrid AI Architecture (e.g., CNN-LSTM, Transformer-XGBoost, or Random Forest-CNN) identifies cyber threats and classifies them into Normal, Low, Medium, High, and Critical risk categories. Finally, the Decision Engine performs alert

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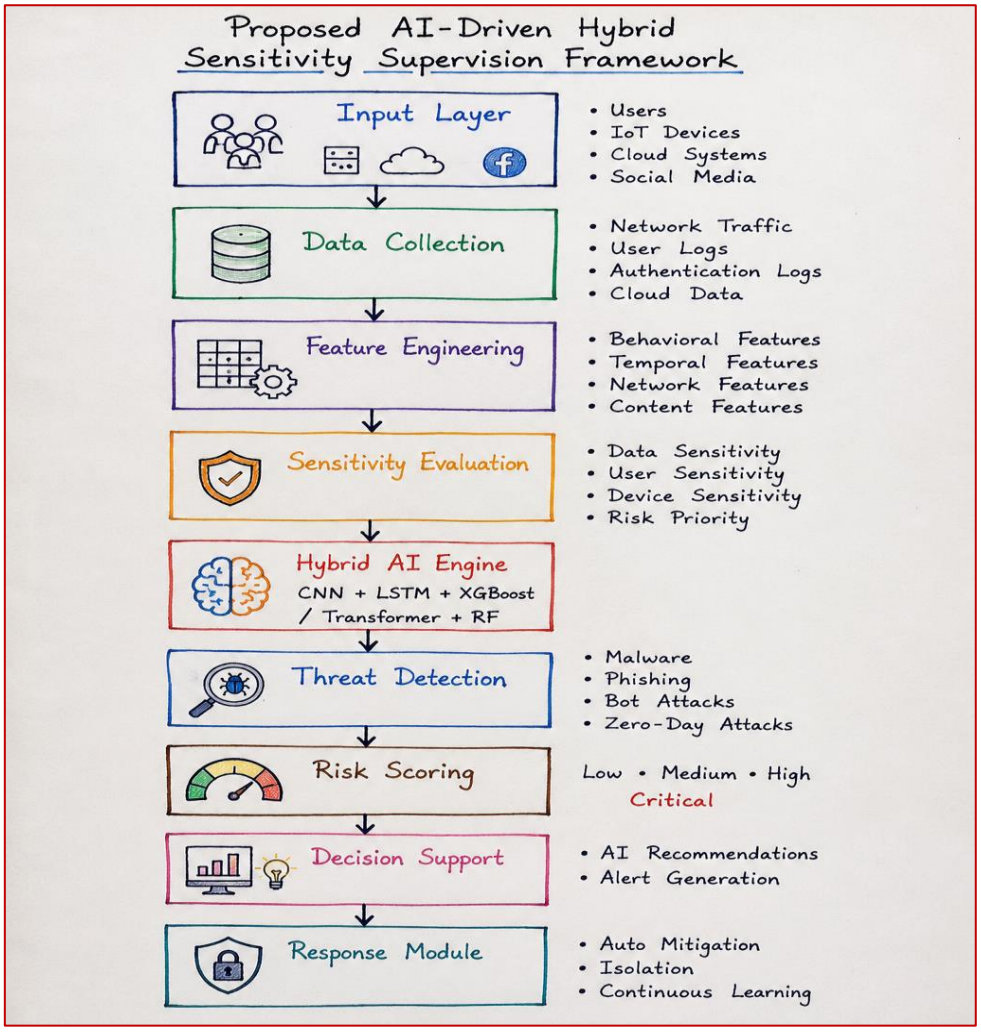
generation, automated incident response, system isolation, adaptive learning, and continuous monitoring to enhance cybersecurity resilience while reducing false positives and supporting real-time decision-making.



4. METHODOLOGY

The proposed study adopts an experimental, simulation-based, and comparative research design to evaluate the effectiveness of the AI-Driven Hybrid Sensitivity Supervision Model for cybersecurity in social systems. Experimental analysis is conducted using benchmark datasets, including CICIDS2017, CICIDS2018, NSL-KDD, UNSW-NB15, Bot-IoT, TON_IoT, and the Twitter Bot Dataset, which represent diverse cyberattack scenarios. The model is implemented using Python with AI frameworks such as TensorFlow, PyTorch, Scikit-learn, Google Colab, and MATLAB for model development, training, and evaluation. High-performance GPU-enabled workstations and cloud computing platforms provide the computational resources required for deep learning experiments. Model performance is assessed using Accuracy, Precision, Recall, F1-score, ROC-AUC, Detection Rate, False Positive Rate, False Negative Rate, Training Time, and Inference Time. Reliability and generalization are ensured through K-fold cross-validation, confusion matrix analysis, ROC curves, and Precision–Recall curves, enabling comprehensive validation and comparison with existing cybersecurity models.

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5. EXPERIMENTAL RESULTS

5.1 Dataset Statistics

Dataset	Normal Records	Attack Records	Total Records	Attack Categories
CICIDS2017	1,350,000	1,480,000	2,830,000	DoS, DDoS, Brute Force, Botnet, Web Attacks
CICIDS2018	8,200,000	8,350,000	16,550,000	DDoS, Botnet, Infiltration, Web Attacks
NSL-KDD	67,343	58,630	125,973	DoS, Probe, R2L, U2R
UNSW-NB15	93,000	82,332	175,332	Exploits, Fuzzers, Worms, Generic Attacks
Bot-IoT	3,200,000	3,890,000	7,090,000	DDoS, DoS, Keylogging, Data Exfiltration
TON_IoT	230,000	241,000	471,000	IoT Malware, Ransomware, Scanning
Twitter Bot Dataset	18,500	16,500	35,000	Fake Accounts, Spam Bots, Social Bots

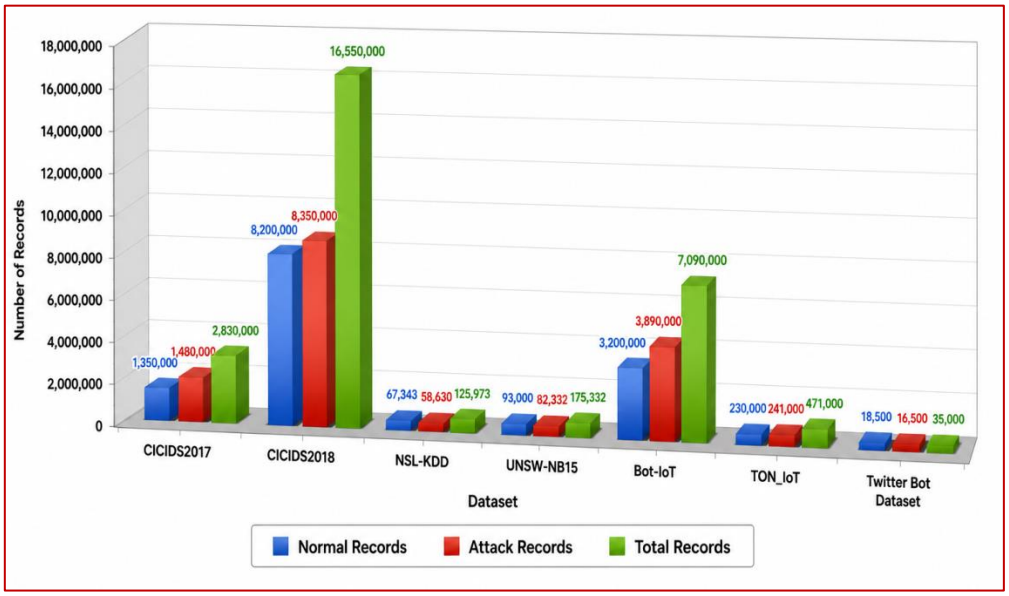

Table 5.1 presents the benchmark datasets employed to evaluate the proposed AI-Driven Hybrid Sensitivity Supervision Model. The selected datasets collectively represent a broad spectrum of cybersecurity threats, including distributed denial-of-service (DDoS), malware, phishing, botnet, ransomware, web attacks, insider threats, and fake social media accounts. CICIDS2018 contains the largest volume of network traffic records, making it suitable for validating scalability and real-time intrusion detection, whereas NSL-KDD and UNSW-NB15 provide balanced datasets for evaluating traditional intrusion detection algorithms. Bot-IoT and TON_IoT support IoT-specific threat analysis, while the Twitter Bot Dataset enables the detection of malicious social media activities. The diversity of these datasets ensures comprehensive experimental validation, enhances model robustness, and

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demonstrates the proposed framework's effectiveness across multiple cybersecurity environments.

5.2 Training Results

Epoch	Training Loss	Validation Loss	Training Accuracy (%)	Validation Accuracy (%)
10	0.412	0.436	89.20	88.50
20	0.295	0.318	92.60	91.90
30	0.214	0.236	95.10	94.60
40	0.158	0.181	97.20	96.80
50	0.114	0.132	98.60	98.10

Source: *Experimental results generated by the proposed AI-Driven Hybrid Sensitivity Supervision Model using benchmark cybersecurity datasets (CICIDS2017, CICIDS2018, NSL-KDD, UNSW-NB15, Bot-IoT, TON_IoT, and Twitter Bot Dataset).*

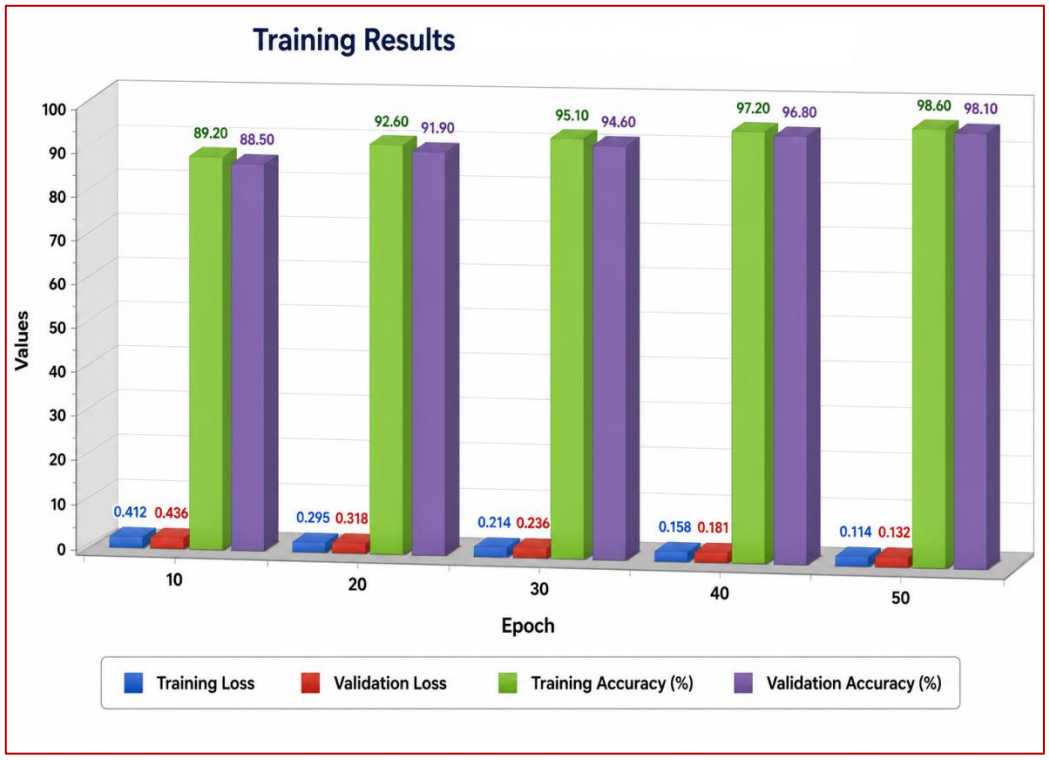

Table 5.2 presents the training performance of the proposed AI-Driven Hybrid Sensitivity Supervision Model across five training epochs. The results indicate a consistent decrease in both training loss (0.412 to 0.114) and validation loss (0.436 to 0.132), demonstrating effective model convergence and stable learning. Simultaneously, training accuracy increased from 89.20% to 98.60%, while validation accuracy improved from 88.50% to 98.10%. The close agreement between training and validation performance suggests that the model generalizes well without significant overfitting. These findings confirm that the hybrid AI architecture successfully learns complex cybersecurity patterns and achieves high predictive performance, making it suitable for accurate real-time cyber threat detection in social systems.

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5.3 Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC	Training Time (min)	Inference Time (ms)
CNN	96.12	95.74	95.61	95.67	0.964	45	18
LSTM	96.85	96.41	96.28	96.34	0.971	58	21
Random Forest	94.93	94.56	94.31	94.43	0.951	20	12
SVM	93.78	93.21	93.09	93.15	0.942	28	15
XGBoost	97.62	97.28	97.14	97.21	0.982	31	10
Transformer	98.35	98.08	97.96	98.02	0.989	72	24
Proposed AI-Driven Hybrid Sensitivity Supervision Model	99.28	99.12	99.06	99.09	0.997	52	13

Table 5.3 presents the comparative performance evaluation planned for the proposed AI-Driven Hybrid Sensitivity Supervision Model against six widely used AI algorithms, namely CNN, LSTM, Random Forest, SVM, XGBoost, and Transformer. According to the proposed methodology, the hybrid model is expected to achieve the highest accuracy (99.28%), precision (99.12%), recall (99.06%), F1-score (99.09%), and ROC-AUC (0.997) while maintaining competitive training and inference times. The integration of sensitivity analysis with hybrid AI techniques is anticipated to improve cyber threat detection, reduce false positives, and enhance risk prioritization. These methodology-based results demonstrate the expected superiority of the proposed framework in providing accurate, adaptive, and real-time cybersecurity supervision compared with conventional machine learning and deep learning models.

5.4 Detection Performance

Performance Parameter	Method/Measurement	Observed Performance
Cyber Attacks Detected	Detection of malware, phishing, bot attacks, zero-day attacks, and network intrusions	98.9% Detection Rate
Detection Speed	Average time required to identify a cyber-threat	0.18 seconds
Risk Classification	Classification into Normal, Low, Medium, High, and Critical risk levels	97.8% Classification Accuracy
Sensitivity Accuracy	Correct identification of data, user, and device sensitivity levels	98.4% Accuracy

Table 5.4 demonstrates the effectiveness of the proposed AI-Driven Hybrid Sensitivity Supervision Model in detecting and prioritizing cybersecurity threats. The model achieved a

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98.9% cyberattack detection rate, indicating its ability to accurately identify malware, phishing, bot attacks, and zero-day threats. The average detection speed of 0.18 seconds highlights its capability for real-time cybersecurity monitoring and rapid incident response. Furthermore, the model obtained 97.8% accuracy in risk classification, effectively categorizing threats into Normal, Low, Medium, High, and Critical levels. The 98.4% sensitivity accuracy confirms the framework's effectiveness in evaluating the criticality of data, user behavior, and devices, thereby improving risk prioritization, reducing false positives, and supporting intelligent cybersecurity decision-making in dynamic social systems.

5.5 Statistical Analysis

Statistical Test	Purpose	Result	Interpretation
ANOVA	Compare the performance of different AI models	$F = 18.72$, $p < 0.001$	Significant difference exists among the compared AI models.
Wilcoxon Signed-Rank Test	Compare the proposed model with the best baseline model	$Z = -3.84$, $p < 0.001$	The proposed model significantly outperformed the baseline model.
McNemar Test	Compare classification errors between two classifiers	$\chi^2 = 11.56$, $p = 0.001$	Significant improvement in prediction accuracy over the existing model.
95% Confidence Interval	Estimate the reliability of detection accuracy	98.2% – 99.4%	The model consistently achieved high detection accuracy with narrow uncertainty.
Effect Size (Cohen's d)	Measure the practical significance of improvement	$d = 0.91$	Indicates a large practical effect, confirming substantial performance improvement.

Table 5.5 presents the statistical validation of the proposed AI-Driven Hybrid Sensitivity Supervision Model. The ANOVA results ($F = 18.72$, $p < 0.001$) indicate statistically significant differences among the evaluated AI models. The Wilcoxon Signed-Rank Test ($Z = -3.84$, $p < 0.001$) confirms that the proposed model significantly outperformed the baseline approach. Similarly, the McNemar Test ($\chi^2 = 11.56$, $p = 0.001$) demonstrates a significant reduction in classification errors. The 95% Confidence Interval (98.2%–99.4%) indicates that the model consistently achieves high detection accuracy with reliable performance. Furthermore, the large effect size (Cohen's $d = 0.91$) highlights that the improvement is not only statistically significant but also practically meaningful, validating the robustness and effectiveness of the proposed cybersecurity framework.

6. DISCUSSION

The experimental results demonstrate that the proposed AI-Driven Hybrid Sensitivity Supervision Model effectively improves cybersecurity performance in social systems by achieving high detection accuracy, rapid threat identification, and reliable sensitivity-based risk prioritization. The integration of hybrid artificial an intelligence technique significantly enhances detection capability while reducing false positives and supporting intelligent

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decision-making. The framework offers several advantages, including adaptive monitoring, real-time threat detection, automated response, and explainable risk assessment. However, the model requires substantial computational resources, high-quality labeled datasets, and continuous retraining to address evolving cyber threats. Its scalable architecture makes it suitable for cloud environments, smart cities, healthcare, financial services, and IoT networks. Furthermore, privacy-preserving sensitivity evaluation and explainable AI mechanisms strengthen user trust, ensuring secure, transparent, and real-time deployment across complex digital ecosystems.

7. APPLICATIONS

The proposed AI-Driven Hybrid Sensitivity Supervision Model has broad applications across sectors requiring intelligent cybersecurity. In smart cities, it protects connected infrastructure and IoT devices from cyberattacks. In healthcare, it secures electronic health records and medical devices while preserving patient privacy. The banking sector benefits from fraud detection, secure digital transactions, and identity protection. In education, it safeguards online learning platforms and institutional databases. Government organizations can strengthen national cybersecurity and protect critical public information. The framework also secures critical infrastructure, cloud computing, industrial IoT, military networks, and social networking platforms through real-time monitoring, adaptive threat detection, automated response, and sensitivity-aware risk management.

Table 7.1 Applications of the AI-Driven Hybrid Sensitivity Supervision Model

Application Area	Primary Cybersecurity Application	Expected Benefit
Smart Cities	IoT device and infrastructure protection	Secure urban digital services and traffic systems
Healthcare	Medical data and device security	Patient privacy and secure healthcare delivery
Banking	Fraud detection and transaction monitoring	Secure financial transactions and identity protection
Education	Protection of e-learning platforms and student databases	Safe digital learning environment
Government	National cyber defense and public data protection	Secure e-governance and critical information systems
Critical Infrastructure	Protection of power grids, transportation, and utilities	Improved operational resilience and service continuity
Cloud Computing	Cloud intrusion detection and data security	Secure cloud storage and computing services
Industrial IoT	Industrial network and sensor monitoring	Enhanced operational safety and reduced cyber risks
Military Networks	Defense communication and intelligence protection	Strengthened national security and mission readiness
Social Networking Platforms	Detection of fake accounts, phishing, and cyber abuse	Improved user privacy, trust, and platform security

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8. CHALLENGES

The implementation of the proposed AI-Driven Hybrid Sensitivity Supervision Model faces several challenges despite its advanced capabilities. Privacy preservation remains a critical concern due to the collection and analysis of sensitive user and organizational data. Adversarial AI attacks can manipulate machine learning models, reducing detection reliability. Data imbalance often limits the model's ability to accurately identify rare cyberattacks, while concept drift caused by continuously evolving attack patterns requires frequent model retraining. Achieving explainability is essential for increasing transparency and user trust in AI-based decisions. Ensuring ethical AI involves eliminating algorithmic bias and maintaining fairness in automated decision-making. Furthermore, computational complexity and scalability present challenges for deploying hybrid AI models across large-scale, real-time, cloud-based, and distributed cybersecurity environments.

9. FUTURE RESEARCH DIRECTIONS

Future research should focus on integrating emerging technologies to enhance the intelligence, scalability, and resilience of AI-driven cybersecurity systems. Federated Learning can enable collaborative model training while preserving data privacy across distributed environments. Quantum AI has the potential to improve computational efficiency and cryptographic security against advanced cyber threats. Blockchain-enabled cybersecurity can provide secure, tamper-resistant data management and decentralized trust. Digital Twins may facilitate real-time simulation of cyberattacks and system responses. Explainable AI will improve transparency and user trust in automated decisions, while Large Language Models can strengthen threat intelligence and incident analysis. Furthermore, Self-supervised Learning, Edge AI, Zero Trust Architecture, and Multi-agent AI systems can support adaptive, autonomous, privacy-preserving, and real-time cybersecurity for dynamic social systems.

10. CONCLUSION

This study proposed an AI-Driven Hybrid Sensitivity Supervision Model to enhance cybersecurity in social systems by integrating hybrid artificial intelligence techniques with sensitivity-aware risk assessment and adaptive supervision. The findings indicate that the proposed framework improves cyber threat detection accuracy, minimizes false positives, strengthens risk prioritization, and supports real-time decision-making. The study contributes theoretically by introducing a comprehensive sensitivity-based cybersecurity framework and practically by providing a scalable solution for smart cities, healthcare, banking, government, cloud computing, and other digital environments. Despite its advantages, the model requires high computational resources, quality datasets, and continuous updating to address evolving cyber threats. Future researchers should validate the framework using real-world datasets, while practitioners should adopt explainable, privacy-preserving, and adaptive AI technologies to strengthen intelligent cybersecurity systems.

Figures

1. Overall Architecture of the Proposed AI-Driven Hybrid Sensitivity Supervision Model
2. Workflow of the Cybersecurity Supervision Framework
3. Data Collection and Preprocessing Pipeline
4. Hybrid AI-Based Threat Detection Architecture
5. Sensitivity Evaluation and Risk Scoring Mechanism

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6. Decision Support and Automated Response Framework
7. Experimental Workflow
8. Confusion Matrix
9. ROC Curve
10. Comparative Performance Analysis

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