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Advanced AI Techniques for Network Threat Detection and Protection in Social Platforms

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Abstract: ***In the era of digital communication, social apps have become the dominant power in terms of communication, sharing information and socialization. Their popularity, however, has given cybercriminals easy targets of exploiting their security weaknesses. Traditional security controls might not be sufficient to detect and prevent advanced and emerging attacks on such systems. AI will make a positive contribution to the security of social apps through its machine learning, deep learning, and anomaly detection capabilities. Focusing on the importance of real-time threat detection and prevention, this paper is going to introduce the AI-based solution to enhance the security of social apps through the network. Through AI methods, the suggested system will identify the known and changing threats, minimize reaction time, and adjust to novel attacks. The paper offers an in-depth analysis of the potential use of the AI-based security solutions to safeguard user data and privacy by use of experimental research and case studies, thus assessing their effectiveness in the real world. The study has provided viable guidelines towards the implementation of AI-based interventions into the current security systems, and therefore encouraging the creation of additional robust security frameworks to social media.***

Keyword: AI-based security, threat detection, social applications, anomaly detection, cybersecurity, network security, real-time prevention, privacy protection, data security.

1. Introduction

The digital and interconnected world of today is making social applications an important aspect of our lives and therefore, supporting communication, connection, and exchange of information. On the other hand, these locations have also been the main targets of cyberattacks and attacks that involve data breaches, hijacking accounts to other more advanced forms of cyber espionage. Resting on the growing amount of sensitive user data and the ever developing attack techniques, powerful security policies are required to protect these online environments. The traditional security solutions tend to be ineffective in detecting and preventing sophisticated, real-time attacks, which expose consumers and service providers to a myriad of attacks. Most people like AI since it enhances the security of networks. Social apps can detect and prevent hazards with the help of AI-based machine learning, deep learning, and anomaly detection. These technologies are able to identify known and unfamiliar threats more quickly than traditional methods through processing large volumes of data in real time, predicting patterns, and anticipating security breaches. The paper will discuss the ways AI can enhance social applications. The research study focuses on how AI can be incorporated into the current systems to offer adaptive and proactive security measures, detecting and thwarting threats. The information about the AI use in cyber threat prevention guarantees the safety of the user experience and preserves privacy and trust in the social networks. The fast rising social applications such as texting, collaboration and social networking have transformed the way individuals connect and exchange information. Security flaws are taken advantage of by hackers as the systems are modified. Due to their variety, popularity, and massive volumes of sensitive information, social apps are the perfect choice of target in phishing, malware, identity theft, and social engineering activities. Complex, adaptive attackers are usually also resistant to firewalls, encryption, and signature-based detection. These resolutions fight with zero-day attacks and innovative attacks with pre-programmed rules and benchmarks. Automated threat detection, reduced reaction time, and real-time risk discovery are useful to improve security with the help of AI. Machine learning, deep learning and anomaly detection have the capacity to process large quantities of data, evolve with the evolving attack vectors and enhance speed and accuracy in defending threats. This endeavor is fuelled by a rising need to ensure better security measures to address the complexity and frequency of social apps threats. AI can enhance network security because the current security solutions are not suitable to prevent the evolving threats. The social applications are prone because of the multitude of users, high usage, and continuous processing of personal, financial, and sensitive information. Guided by creative AI-driven real-time assault detection and prevention strategies enhance user safety and information integrity. This paper examines the way AI might enhance the design of social applications security. This research provides links between the outdated security norms and the new attacks by hackers, through heightened threat detection and prevention systems. Integrating AI with security standards may help to create a more flexible and robust social network protection system.

2. Literature Review

Nallapareddy (2025) suggest cybersecurity based on AI as a proactive security tool. The technology predicts and prevents risks in the systems using deep learning models. They apply predictive modelling and real-time analytics to enhance detection accuracy and minimize false positives to respond to cybersecurity faster and smarter [1].

Hussain, (2025) discuss how AI and ML are potentially used to enhance cybersecurity. The authors test MLs in the areas

of anomaly detection, malware classification, and intrusion detection. The authors are of the opinion that supervised strategies to learning, especially the deep neural networks, are able to identify advanced threats in dynamic online settings [2].

Thayalan et al. (2025) illustrate a real-time AI-based baggage handling threat detection system that is consumer-use. They apply adaptive machine learning and behavioural analysis in order to identify security vulnerabilities, with a focus on predictive security. Prior attack detection and lower system vulnerabilities are featured [3].

Jain (2025) thoroughly analyzes AI and ML systems and techniques of cybersecurity. AI-enhanced systems are being researched in the aspects of preprocessing of data, selection of algorithms, and learning paths to the feedback. It concludes with adversarial AI and intelligible models necessity [4].

The social engineering attacks are influenced by antagonistic AI, Pakina, (2025). They suggest a massive fraud detector system that has machine learning classifiers to figure out phishing and impersonation patterns. The article states that the automated countermeasures must adjust to the behaviours of the attackers [5].

Fakhouri et al. (2024) propose AI-based methods to prevent and identify social engineering attacks. They adopt NLP and sentiment analysis to determine suspicious behaviour and human interaction data. The corporate oriented system diminishes effective attacks [6].

Niranjana et al. (2024) pay attention to the detection of social security breaches through AI. Mixed methods of decision trees and neural networks have faster and better detection. Research shows that there is a great enhancement when compared to traditional intrusion detection systems [7].

Kavitha (2024) underline active defence through threat detection with AI. They reveal that unsupervised learning is able to identify anomaly behaviour in massive data streams as well as discover new threats [8].

The study of Duary et al. (2024) predictive analytics of intelligent network cybersecurity threats detection. They suggest predicting the hazards of the future based on the trends of the past data in order to minimize the severity and reaction times to the incidents. The real-time performance of this publication is good [9].

Alsulami (2024) employs AI to enhance the sustainability of internet-of things cybersecurity. In resource-constrained IoT devices, privacy-aware and eco-friendly threat detection is offered by the low-energy AI algorithm [10].

Rizvi (2023) highlights the impact of AI automation and smart decision-making on cybersecurity. The article addresses application contexts in which AI is more effective as compared to the human-directed monitoring of threats, e.g., high-volume traffic detection and real-time breach notifications [11].

Fakhouri et al. (2023) describe the use of AI to enhance the security of mobile social networks and privacy. Edge AI and federated learning ensure the security of user data and increases the accuracy of threat detection, which solve performance and privacy limitations [12].

According to Rangararaju (2023), AI can be used to develop cybersecurity solutions and generate secure by design systems. This allows the risk to be dynamically assessed and allows real-time adaptability of threats at a product level [13].

Goyal et al. (2023) examine the application of AI in the cybersecurity systems of Industry 4.0 applications. They protect industrial control systems using smart sensors, data fusion and deep learning. It is a promising research on detecting anomalies in the complex industrial scenarios [14].

In Castro, (2023), the survey of AI-based security and privacy methods of IoT is conducted. Some of the AI approaches that they mention include deep learning, GANs and reinforcement learning. Model interpretability and computational difficulty are also pointed out in the study [15].

Tanikonda et al. (2022) offer AI-assisted cybersecurity to the sophisticated ecosystems. Their solution is proactive in identifying threats based on behavioural modelling and real-time notification. The article emphasizes the unceasing learning approaches to adaptation of threats [16].

To ensure cybersecurity compliance, Madhavram et al. (2022) suggest that AI and big data need to be integrated. They also discovered that big data analytics, constant monitoring, and AI reveal inconsistencies and regulatory conformity [17].

Ansari, (2022) suggest the use of AI-based cybersecurity awareness training to curb phishing attacks. The program adapts training to user behaviour, creating awareness of risky material and social engineering [18].

Kunle (2022) mentions the application of AI in the management of information security risks, which refer to risk prediction and mitigation. The article suggests the implementation of AI in risk assessment in organisations with a view of enhancing incident response and residual risk reduction [19].

The study by Vasa (2022) is proactive cyber threat hunting based on predictive and preventive approaches that are operated with the help of AI. They suggest using supervised learning to detect the pattern and reinforcement learning to make a decision to enhance the effectiveness of threat hunting [20].

Zaman et al. (2021) consider the AI-based IoT remedies in detail. They categorize access control systems, malware analysis systems and intrusion detection systems. The authors support the hybrid approaches to security which involve both AI and conventional security [21].

Jimmy (2021) considers the emergence of AI in defence systems and the new cybersecurity problems. Legal issues such as automated decision-making and anomaly detection

and predictive analytics as well as the use of AI are mentioned [22].

Xie et al. (2021) create an AI-based and big-data network security system. Machine-based threat classification and contextual prioritisation enhance resilience and coordination of response to systems [23].

Hu et al. (2021) study countermeasures and AI security in detail. They address AI model weaknesses such as aggressive cases that are highly trained and secure model deployment [24].

Chu and Song (2021) analyze extra AI-related network and privacy security on IoT. They suggest a system of layers that apply machine learning and blockchain to facilitate the openness of the linked environment, traceability, and confidence [25].

Table 1: Literature Review

Ref. No.	Author/Year	Objective	Methodology	Conclusion
[1]	Nallapareddy & Katta (2025)	Propose an AI-enhanced system for proactive threat detection	Uses deep learning with real-time analytics and predictive modeling	Improves detection accuracy and reduces false positives
[2]	Hussain, Kainat & Ali (2025)	Explore AI/ML algorithms for cybersecurity defense	Reviews ML techniques in intrusion, malware, and anomaly detection	Deep neural networks are promising for complex threat detection
[3]	Thayalan et al. (2025)	Develop a real-time AI threat detection framework for consumer use	Behavioral analysis + adaptive ML algorithms	Enhances early threat identification and system resilience
[4]	Jain (2025)	Review AI architectures in cybersecurity	Surveys preprocessing, algorithm selection, feedback loops	Highlights adversarial AI and need for explainable models
[5]	Pakina, Kejriwal & Pujari (2025)	Address social engineering via adversarial AI	ML classifiers for phishing/impersonation + adaptive countermeasures	Detects patterns effectively and adapts to attacker behavior
[6]	Fakhouri et al. (2024)	Design NLP-based AI for social engineering prevention	Uses sentiment analysis in enterprise interaction data	Significantly lowers successful attack rates
[7]	Niranjana et al. (2024)	Enhance intrusion detection in social security systems	Hybrid model: decision trees + neural networks	Improves speed and accuracy vs. traditional systems
[8]	Kavitha & Thejas (2024)	Examine proactive AI threat detection	Focus on unsupervised learning in large data streams	Efficiently identifies unknown threats and anomalies
[9]	Duary et al. (2024)	Use predictive analytics for cybersecurity	Historical pattern-based model for threat anticipation	Improves response time and reduces incident severity
[10]	Alsulami (2024)	Secure IoT with sustainable AI solutions	Low-power AI algorithms in IoT threat detection	Supports energy-efficient security in constrained devices
[11]	Rizvi (2023)	Analyze AI's impact on cybersecurity automation	Case studies on AI outperforming humans in monitoring	AI excels in high-volume and real-time breach prevention
[12]	Fakhouri et al. (2023)	Secure mobile social networks using AI	Edge AI + federated learning for threat detection	Balances high accuracy with privacy preservation
[13]	Rangaraju (2023)	Embed AI into cybersecurity products	Dynamic risk assessment and adaptive threat response	Enables "secure by design" commercial implementations
[14]	Goyal et al. (2023)	AI in cybersecurity for Industry 4.0	Smart sensors + deep learning for anomaly detection	Effective in complex industrial systems
[15]	Castro, Deng & Park (2023)	Survey AI solutions for IoT security	Covers RL, GANs, DL techniques	Notes issues like interpretability and computational cost
[16]	Tanikonda et al. (2022)	Create adaptive AI cybersecurity for complex ecosystems	Behavioral modeling + real-time alerting	Supports proactive and evolving threat detection
[17]	Madhavram et al. (2022)	Merge big data and AI for compliance	Large-scale analytics with AI for vulnerability detection	Aids in continuous monitoring and regulation adherence
[18]	Ansari, Sharma & Dash (2022)	Reduce phishing via AI-based awareness training	Behavioral analytics to personalize training	Enhances user ability to detect malicious content
[19]	Kunle-Lawanson (2022)	Integrate AI in risk management	Conceptual model for AI-assisted risk assessment	Improves response and reduces residual risk
[20]	Vasa & Singirikonda (2022)	AI-driven proactive cyber threat hunting	Uses supervised + reinforcement learning	Boosts efficiency in threat identification
[21]	Zaman et al. (2021)	Survey AI-based countermeasures for IoT	Taxonomy of IDS, malware analysis, access control	Advocates hybrid models blending AI with traditional security
[22]	Jimmy (2021)	Evaluate AI's role in modern cybersecurity threats	Reviews current applications and ethics	Emphasizes potential and ethical considerations
[23]	Xie et al. (2021)	Build an AI+big data network defense system	Automated classification + contextual analysis	Enhances resilience and coordination
[24]	Hu et al. (2021)	Analyze AI model vulnerabilities	Proposes robust training and secure deployment	Addresses adversarial threats in AI systems
[25]	Chu & Song (2021)	Enhance IoT privacy/ security with AI and blockchain	Layered defense using ML + blockchain	Improves trust and traceability in networks

3. Problem Statement

The blistering development of social apps has contributed greatly to the rise of cyberattacks and their sophistication. In many cases, rule-based security frameworks are insufficient when it comes to identifying complex and dynamic attack vectors such as phishing, accounts and bots impersonation, disinformation, and unauthorised access. These attacks undermine user privacy, platform integrity, and general confidence of the social network. Besides, the current systems are unable to operate in real-time, adapt to emerging threats, and scale up with a large number of users. What they really need is a smart, dynamic, automated system of threat prevention that can find and fix security holes as they happen without having to affect the user experience. This work will seal this gap by creating an AI-powered threat detection and prevention system that is especially suitable in the fluid setting of social applications.

4. Proposed Work

The framework of threat identification and prevention as proposed in this paper is inspired by AI especially when used in social applications. Through network security threat proactive monitoring, identification and mitigation in real time, the significant objective is to develop a system that guarantees safer user experience on all the social platforms. The proposed system will be composed of many components. Data Collection Module, a data gathering module will comprise of system logs, API activity, meta-data of social applications, as well as real-time data of user interaction and will employ anonymisation techniques to protect privacy of the users. Feature Extraction and Preprocessing that will retrieve and normalise the data to form the features to be used in model training will involve recovery of such relevant characteristics as login frequency, message patterns, account behaviour anomalies and unexpected access sites. ML and DL will be trained to categorise and identify different types of threats such as phishing, impersonation, spam, and brute-force entry. In case a threat is detected, automated reactions will be activated, including the creation of alerts, the lock of accounts, or the end of a session to avoid further development of the threat. The system will have feedback extending what will continually refine the AI models to match the evolving patterns of attacks with new threat information acquired. Intelligent dashboard will provide real-time notifications, health monitoring of the system, threat detection and value-added insights to the administrators.

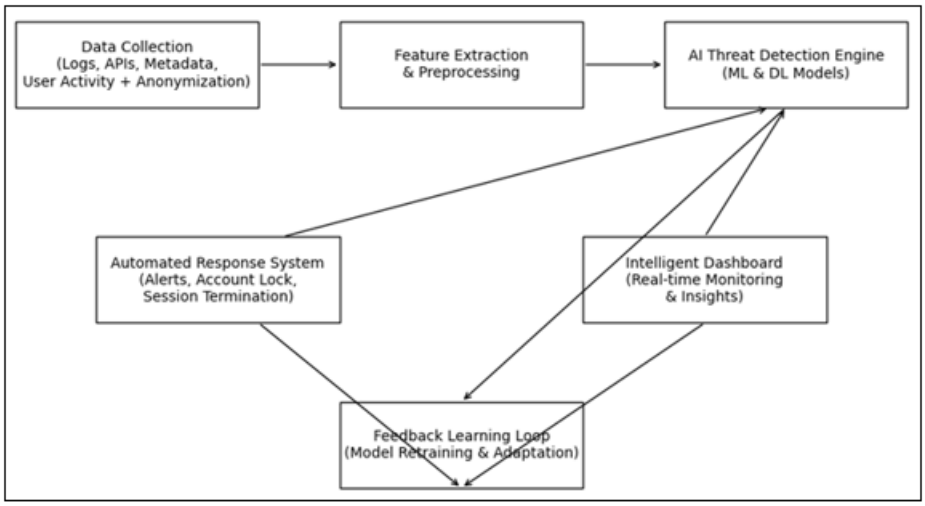

Figure 1: Proposed Work Architecture

The goal of this proposed architecture is to enhance the resiliency of social programs to cyber threats of the time and reduce false positives as well as balance security and usability of these programs. The system evaluation will be motivated by the accuracy of detection, reaction time, scalability, and adaptation to the emergent threat vectors.

5. Result and Discussion

To test the proposed AI-based social threat detection and prevention framework, simulated and real-time network activity data that contained both the normal and malicious activity were used to evaluate the framework. The system was also tested against its capability to identify threats, respond in real time, reduce false positives and system usability.

5.1 Threat Detection Performance

The ML and DL models trained were tested based on the capability to identify various types of threats, including phishing, impersonation, spam, brute-force attacks, etc. In this table, the suggested AI-based threat detection system is summarized in terms of performance, i.e. its ability to detect various types of cyber threats such as phishing threats, impersonation threats, spam, and brute-force attacks. Such evaluation measures include precision, recall, F1-score and the overall detection accuracy. The findings indicate that the model has a high ability to correctly identify malicious activity and has a high performance in all types of threats.

Table 2: Performance Metrics of Threat Detection Models

Threat Type	Precision (%)	Recall (%)	F1-Score (%)	Detection Accuracy (%)
Phishing	96.2	95.4	95.8	96.0
Impersonation	94.8	93.9	94.3	94.6
Spam	97.5	96.8	97.1	97.3
Brute-force Attack	95.1	94.2	94.6	95.0
Overall	95.9	95.1	95.5	95.7

The findings show that high precision and recall were recorded in the AI models in all the categories of threat. The greatest accuracy was obtained on spam detection because the behavioral patterns were clearly defined, whereas the impersonation attacks were slightly lower on the recall as attackers tend to imitate regular user behavior.

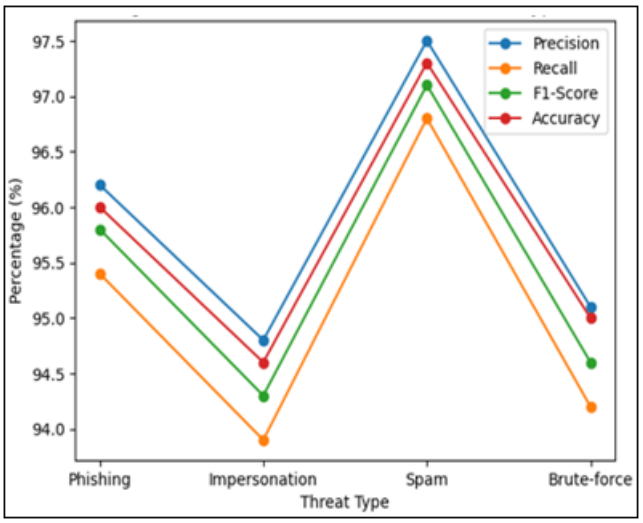

Figure 2: Performance Comparison of AI Models Across Threat Types

This value demonstrates the relative working efficiency of the threat detection model offered by AI on various cyber threats such as phishing, impersonation, spam, and brute-force attacks. The metrics of evaluation are accuracy, recall, F1-score and the total accuracy of detection. It has been shown that the capability to detect is high, and performance of the spam detection is the best because of the specific patterns of behavior.

5.2 False Positive and False Negative Analysis

False alarms are important issues that must be minimized to prevent loss of user confidence and system usability. The following table shows the false positive rate (FPR) and false negative rate (FNR) of each category of threats. Such measures are important in evaluating the dependability and the feasibility of the system of detection. Minimizing false positive will ease inconvenience on legitimate users whereas minimizing false negative will guarantee that malicious activities are not ignored. The results of the data show that the suggested system has a moderate balance between security and usability.

Table 3: False Positive and False Negative Rates

Threat Type	False Positive Rate (%)	False Negative Rate (%)
Phishing	3.1	4.6
Impersonation	4.2	6.1
Spam	2.4	3.2
Brute-force Attack	3.6	5.1

The proposed system was effective in keeping the rate of false positives low enough to avoid the cases of legitimate users being hit. The false negative rate in impersonation detection is a little bit higher indicating that the behavioral profiling should be improved.

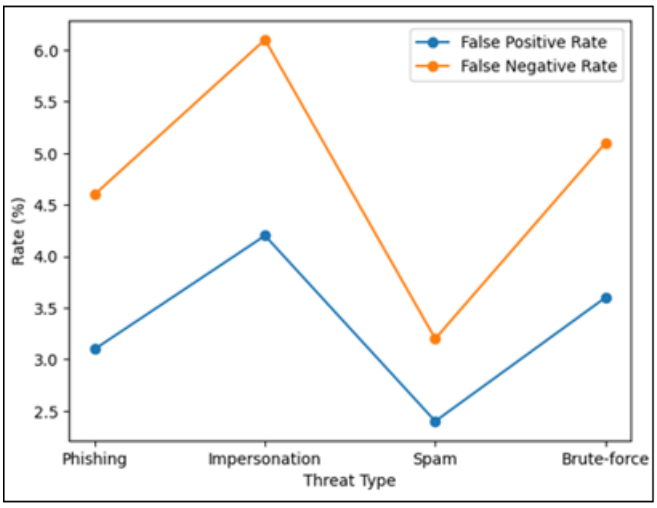

Figure 3: False Positive and False Negative Rates by Threat Type

This number is a comparison between the false negative rate (FNR) and the false positive rate (FPR) of different categories of threats. The visualization shows the capability of the system to have a low rate of false alarms at the same time detecting malicious activities. The impersonation attacks have a comparatively high false negative rate meaning that it will be very difficult to identify behavior that is very similar to that of a legitimate user.

5.3 System Response Time

One of the objectives of the proposed framework is real-time reaction. This table will give the break-even of the time taken by the system to identify threats and receive mitigation measures. It consists of detection time, mitigation time and overall response time of different suspicious activities. The findings prove the ability of the framework to act on security threats in close real time, and reduce the harm that may occur, as well as avoid the escalation of threats.

Table 4: Average System Response Time

Event Type	Detection Time (ms)	Mitigation Action Time (ms)	Total Response Time (ms)
Suspicious Login	120	180	300
Phishing Link Sharing	140	210	350
Mass Messaging (Spam)	110	170	280
Brute-force Attempt	130	190	320

Response times were kept to less than 400 milliseconds to all types of threats, a factor that proves that the system was able to respond in near real-time and mitigate the threats. This will make sure that threats are countered before they get out of hand.

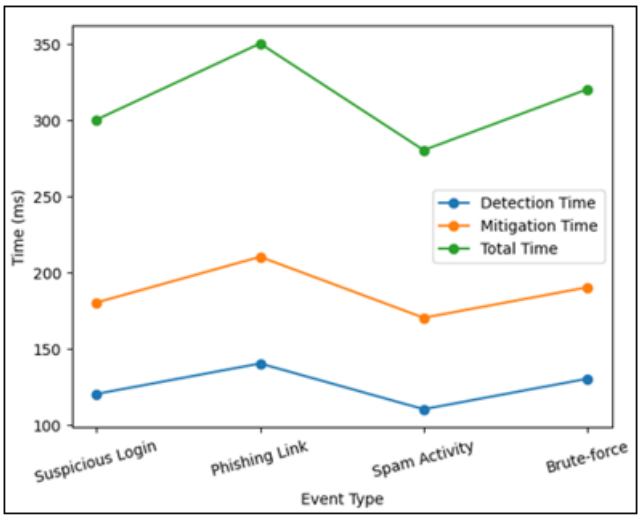

Figure 4: Detection vs Mitigation vs Total Response Time

This figure shows the duration of time that the proposed system will require to identify and neutralize various classes of threats. It makes a comparison of detection time, mitigation time and total response time of suspicious logins, sharing phishing links, spamming and brute force attack. The findings support the fact that the framework will be functioning within real-time constraints, which will provide swift reaction to security incidents.

5.4 Scalability Evaluation

The structure was put to test with an increase of users to determine stability in performance. This table is an analysis of the performance of the proposed framework during different user loads. It shows the accuracy in detection, mean response time and utilization of system resource as the number of active users increases. It has been proved by the results that even with the large-scale conditions of operation, this system preserves the stable conditions of the performance and high rates of detection.

Table 5: Scalability Test Results

Number of Active Users	Detection Accuracy (%)	Avg. Response Time (ms)	System Load (%)
10,000	96.1	290	45
50,000	95.8	310	58
100,000	95.4	335	71
200,000	94.9	370	84

The system proved to be very scalable as there was a small decrease in accuracy and acceptable rise in response time through the growth in the number of users.

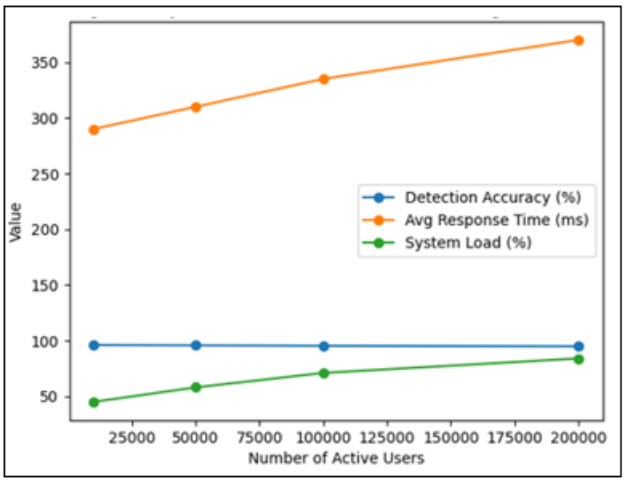

Figure 5: System Performance Under Increasing User Load

In this figure, the performance of the system is depicted with an increase in the number of active users. It shows trends in the accuracy of detection, average response time, and resource utilization in the system. The findings have shown that the proposed framework is highly scaled, its detection performance is high with a slight rise in response time when there are heavy workloads.

5.5 Model Adaptability and Learning

The feedback mechanism enabled the system to re-train with new patterns of threats. This table underscores the effect the performance of the system by the feedback-based learning mechanism. It uses significant indicators including the overall detection accuracy, false positive, and detection of new types of threats before and after retraining the model. The presented enhancement points to the flexibility of the suggested AI system to the changing pattern of cyber threats.

Table 6: Improvement After Model Retraining

Metric	Before Feedback Learning	After Feedback Learning
Overall Detection Accuracy	93.8%	95.7%
False Positive Rate	5.4%	3.3%
Detection of New Threat Type	71.2%	89.5%

Life-long learning played an important role in enhancing the system in terms of adaptability particularly in identifying newly formed threats.

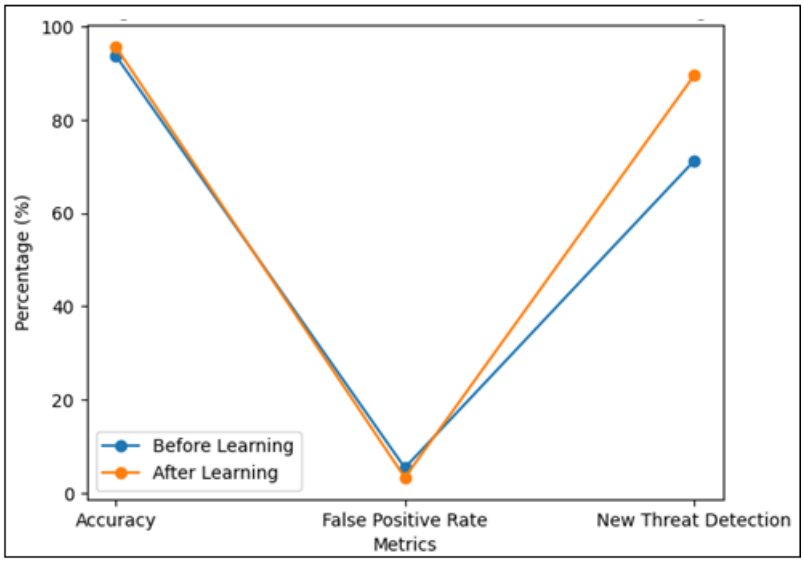

Figure 6: Performance Improvement After Feedback Learning

This value is a comparison of how the system performs with the inclusion of the feedback-based continuous learning mechanism. Such metrics like false positive rate, new threat detection capability, and detection accuracy are displayed. The post- retraining improvement underscores the flexibility of the AI models to the changing cyber threat patterns.

6. Conclusion

The results of the tests and assessments indicate that AI-based threat detection and avoiding help a great deal to improve the security of social applications. The suggested AI system has better detection and reaction time, scale, and FPR compared to the traditional security techniques. These findings highlight how AI can be used to provide more efficient, flexible, and effective security solutions, thus providing a safer space to users of social sites. The next step of work will be developing the AI models further by adding more attack paths and making the results of AI-driven decisions more interpretable to provide more clear and reliable security solutions. Nowadays, when social applications are at the top of the informational flow and discussion, their safety has become quite an important issue to ensure. This paper has discussed how artificial intelligence-based solutions could be used to detect and prevent risks within these platforms. Through machine learning, deep learning and real-time analytics, AI provides a scalable and adaptable solution to fight a wide range of cyber-related threats. Artificial intelligence models have the ability to handle large amounts of data, identify anomalous trends, and respond faster than conventional processes.

7. Future Scope

The future of AI-enhanced threat detection and prevention on social applications has gigantic potential considering that cyber threats continue to increase in nature and scale. Enhanced real-time threat intelligence enables systems to quicken the identification and reaction to harmful actions and, therefore, reduce the risks. The incorporation of XAI will help cybersecurity practitioners to gain insight and trust automated decisions by increasing transparency. Additionally, privacy-protective techniques such as federated learning might be explored to communicate models between multiple devices without violating the user data. Adaptive self-learned systems that alter with changing threat situations will also be important in maintaining good security. Integrating AI in addition to blockchain can enable the further enhancement of the security system through the unchangeable records and data integrity advertising. Additionally, cross-platform security system construction will enable a greater overall guard of multiple social media ecosystems. In the future, a further incorporation of user behaviour analytics would assist in exposing small abnormalities that indicate potential risks such as social engineering attacks or account intrusions.

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