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Athreat Modeling Framework for LLM System Integration Leveraging NLP and Machine Learning

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Abstract: With the growing use of Large Language Models (LLMs) in diverse applications, their safety, security and resilience against cyber threats has become increasingly worrying. Traditional security measures routinely lack to counter the active and adaptive nature of vulnerabilities within LLM systems, thus necessitating an Automated Threat Modeling (ATM) technique. This research introduces a threat modeling framework that uses AI tailored for complete risk management through identification, evaluation, and mitigation of security threats stemming from LLM system integrations. The proposed Automated Threat Modeling (ATM) system applies machine learning, natural language processing (NLP), and behavioural scrutiny for advanced diagnosis to multi-faceted emergent attack spectrum like prompt injection, data poisoning, model inversion, adversarial attacks, and unauthorized access. A hybrid risk assessment approach is implanted in the framework, using static security assessment, dynamic behavioural profiling, as well as real-time anomaly detection to improve threat detection accuracy. Moreover, the model adapts cyber threat intelligence (CTI) feeds with automated threat neutralization policies for advanced proactive defence mechanisms. Systematic testing of the model in real-world LLM deployment scenarios validated its efficacy in precision and recall metrics for securing vulnerability detection and mitigation. Findings demonstrate the efficacy of AI driven threat modeling in LLM integrated systems for automation of risk assessment, decreased false positives, and improved response time while fortifying system security. This study highlights the need for implementing proactive and adaptive security measures during the integration of LLM systems to maintain the integrity and reliability of AI applications amid shifting and escalating cyber risks. The advanced development in secure AI implementation strategies is achieved with the Automated Threat Modeling framework supporting the development of future AI-based cybersecurity technologies for enterprise and cloud LLM applications.

Keywords: Automated Threat Modeling, Large Language Models, Cybersecurity, AI Security, Machine Learning, Risk Assessment, Adversarial Attacks, Threat Intelligence.

Introduction

The adoption of Large Language Models (LLMs) like Open AI's GPT series, Google's Bard, and even Meta's LLaMA, have streamlined industries such as finance, healthcare, cybersecurity, and even automated decision making. Their astonishing capabilities in natural language processing,

generation, and reasoning helps to accomplish this. However, due to the presence of complex security risks like adversarial attacks, data leakage, bias exploitation, and prompt injection vulnerabilities, the integration of these models into more sophisticated systems can be problematic. Reliance on LLMs to perform important mission-critical tasks increases the risk of security threats. This compromises the system's protective layers guaranteeing control, secrecy, and availability, calling for stricter policies. Automated Threat Modeling (ATM) tackles LLM risks head on by identifying and assessing these problems in advance. Using AI-based threat modeling frameworks equips organizations with foresight through potential vulnerability assessment enabled by strategically planned defenses before facing active threats from rivals.

Microsoft's STRIDE, MITRE ATT&CK, and NIST cybersecurity frameworks focus on systematic approaches to cyber security and software security diagnostics. These techniques have been integrated into software security analysis. However, the structure and functioning of LLMs bring about additional attack vectors that require distinct threat modeling approaches. Different from software parts, LLMs respond actively to databases, external APIs, and user inputs, which makes them susceptible to prompt engineering attacks, adversarial perturbation, data exfiltration, and model manipulation. It is crucial to incorporate Automated Threat Modeling (ATM) during LLM system deployment to cover security loopholes, strengthen system defense, and bolster AI infrastructure against advanced cyber attacks.The incorporation of LLMs in enterprise applications, chatbots, financial automation, and ever more sophisticated cloud systems has broadened their scope of use. Unfortunately, it has also made them more vulnerable to a diverse set of security challenges. One of the major issues is prompt injection attacks, where attackers design manipulative input prompts with the intent of triggering covert actions that lead to freely sharing sensitive information, executing harmful instructions, or providing undesired answers. Another important model inversion attacks pose serious risk whereby adversaries iteratively query a model to reconstruct the training data. This may lead to privacy violations and unauthorized data exposure. Moreover, adversarial attacks that rely on specific modifications designed to cause misleading outputs can result in LLMs making errors that can be catastrophic in crucial areas like autonomous systems, legal consultancy, or medical diagnostics. Addressing these gaps entails using automated procedures for constructing threat models as well as providing methods which help professionals avert, identify, and neutralize possible weaknesses advance. The combination of an LLM system with Machine Learning, AI, Cybersecurity technologies, and automated risk evaluation approaches is termed Automated Threat Modeling (ATM), and it employs these integration for cyber proactive security. In contrast to manual ATM, which relies on heuristic reasoning, threat modeling for ATM relies on automated frameworks, risk analysis, and advanced dynamic vulnerability scanning techniques for expeditious security evaluation. ATM applies graph-based security analysis, behavior anomaly detection, and adaptive outcome-determining threshold algorithms enabling limitless security visibility, real-time intelligence on new risks, and tailored smart active risk management within and outside of LLM systems. Fundamentally, these tools enhance the ATM apparatus or machinery which aims to refine efficiency, accuracy, scope of process automation, and overall evaluation of the threat information systems. Hence, ATM mitigates the burden which cyber security arms bear without undermining the defense systems directed at attacks targeting the infrastructures of LLM systems.

Attack vectors and their ever-changing nature is one of the most important and intricate challenges in LLM threat modeling systems. Unlike software vulnerabilities that arise from the environment around them dependent on a piece of code, threats that use LLM technology are born from dependencies related to context, interactions with prompts, and the choreography of flowing information. Automated Threat Modeling (ATM) solves this problem by using real-time algorithms for threat detection, identifying anomalies, and analyzing potential risks using AI-powered adversarial analysis systems. Also, AI governance frameworks and ethical AI compliance protocols focused on policy-based threat mitigation serve an equally important purpose to ensure that LLM implementations are monitored for compliance with regulation standards, laws pertaining to data privacy, and cybersecurity practices alongside other frameworks minimal cross domain governance compliance interfaces. The use of LLMs in high-stakes sectors like banking, legal processes automation, military AI systems, and government intelligence has increased the demand for comprehensive threat modeling strategies. Financial institutions using LLM-based risk evaluation systems need to be sure that their AI models are protected from data poisoning attacks, which involve adversarial injection of malicious training data to skew model predictions. Likewise, autonomous AI agents used in defense and national security plumbing must defend themselves against model hijacking exploits, where an attacker uses LLM-supplied results to spread false information or carry out actions without permission. In these sensitive areas, the inclusion of ATM frameworks improves the multidisciplinary integration of threat intelligence, preparedness for incident response, predictive risk assessment, and overall security posture of systems employing LLMs.

Another important component of Automated Threat Modeling for the security of LLMs is the incorporation of cyber security game-theory strategies and AI cyber defense technologies. By reproducing attacks as scenarios with competing security policies based on reinforcement learning, ATM frameworks can alter, to some degree, command hierarchies for automation workflows, threat level prioritization, and response systems. For instance, AI-assisted attack surface mapping can forecast pathways of possible exploitation by examining the relationships between system outputs and inputs, inter-system dependencies, and attack driving patterns. Moreover, the application of federated learning in the context of LLM security allows decentralized sharing of intelligence on threats, enabling organizations to pool their strengths for defending against AI-driven cyber-sabotage on a worldwide level. The ethical dimensions regarding LLM security further stress reinforcing the need for Automated Threat Modeling for integration into AI systems. When LLMs gain more control over public interactions through content moderation, automated legal services, or even providing medical diagnoses, they become amplifiers for bias. Automation of fairness assessment and governance requires ATM methodologies. Such methodologies need to embed algorithms to detect biases, adversarial anti-debiasing approaches, and policies to mitigate decision-making misinformation that endorses unfair stereotypes and unethical outcomes. These efforts are in line with establishing AI safety regulations frameworks along with responsible AI endorsing regulations to be actively enforced like the EU AI Act and NIST AI Risk Management Framework.

As LLMs are adopted in different sectors AI security compliance is coming under scrutiny for legal responsibility and regulatory practices. Compliance frameworks for the use of AI technology are being legislated like ISO/IEC 27001 concerning AI risk management, GDPR concerning AI data

protection, and SOC 2 regarding AI security auditing. Automated Threat Modeling frameworks can facilitate compliance by incorporating security control implementation, automated compliance monitoring, and continuous audit log generation capturing evidence of compliance into system deployment pipelines. These measures help ensure that such systems operate within defined legal, ethical, and domain-specific boundaries while minimizing exposure to the legal implications of AI security breaches, privacy infringements, and the accountability gaps of algorithmic decision-making. Even with the progress made towards Automated Threat Modeling for LLM system security, there are still some challenges left for researchers to tackle. One of the foremost obstacles is how effective ATM frameworks are for the security of systems with numerous AI models operating in different cloud environments. There is still work needed to be done regarding the low-latency, real-time threat detection, model performance, computational efficiency, and user experience balance. Moreover, zero-day LLM exploitation attacks add to security concerns, making the need for AI powered adaptive active security systems that employ continuous adversarial training and real-time anomaly defenses necessary to counter these threats promptly. This work seeks to remedy the imbalance between AI driven security and automated risk evaluation strategies by designing an integrated LLM system focused on agile frameworks for ATM driven threat modeling. Through high-level cyber defense analytics, resiliency, and automation, the proposed framework provides next generation AI applications advanced control and reduced threat response time. These objectives enable organizations to incorporate large language model systems seamlessly, securely and responsibly while contributing to the growing body of AI security research that focuses on automated threat modeling.

Literature Survey

The development of Large Language Models (LLMs) has brought new capabilities in applications, artificial intelligence (AI), and even machine learning (ML). Nevertheless, the widespread usage of these models comes with new security challenges and risks that need to be managed in a structured way. Automated Threat Modeling (ATM) has become one of the most important techniques for identifying, reducing, and preventing security risks during LLM system integration. Scholars have studied a number of machine learning methods, cybersecurity frameworks, and NLP-based threat monitoring systems designed to increase the robustness of LLM-based systems against adversarial control, data poisoning, model inversion, and unauthorized access. This literature summary focuses on recent studies on AI-based threat modeling, adversarial machine learning, risk assessment frameworks, and automated cybersecurity specific to LLM-based systems.

A few of them attempted speeding the process of detecting threats in AI systems using hybrid ML approaches. An example of this work is Brown and Johnson's [1] which developed an AI threat modeling framework that evaluates possible LLM applications vulnerabilities. Their findings show how automated risk assessment processes combined with anomaly detection and monitoring might aid securing LLMs. Gupta et al. [2] have also conducted work wherein a machine learning model for cybersecurity is developed that uses predictive intelligence, behavioral, and attack profile analysis to identify anomalies in the responses produced by LLMs. Results from their work proved that AI-based systems for threat intelligence make it nearly impossible to overlook cyber threats in the use of LLMs.

In Cheong's study, he focused on how hostile actions are able to influence LLMs which includes common methods of attack like prompt injections, gradient based attacks, and evasion through reinforcement learning, setting an essence for Chen's extensive study. Moreover, these techniques have been made easier due to the major weak points left unguarded. Along with this, more emphasis is needed towards prone models as they undergo heightened bullying, so that systems are not forced to shut down because of unnecessary obstructions. The main point of Chen's study was the necessity of effectuated training which would strongly work towards building higher stamina towards aggressive attacks. On the other hand, Chen focused on others such is Lee and Park where they focused on broader prompt injections. These prompt injections have been allowed due to the lack of effective means to defend resultant blanks made intentionally by adversaries which wear down systems. These authors stepped in to formulate a strategy where LLMs can automatically identify and block hijacking prompts which help dynamic defending encourages discipline. As a result, there is clear sight in the chances of being right and rid of constructive blocking or deception.

The idea of model inversion attacks has become more popular as more people try to obtain sensitive data from LLMs by deconstructing the components of their training data. Wang and Xu [7] studied the problem of model inversion on transformer architectures and demonstrated that even model outputs can be exploited through adversarial querying to infer private data. Their results highlight the requirement of implementing differential privacy to avoid unintentional data leakage in AI applications. Patel and Shah [8] also researched ways of homomorphic encryption and federated learning to defend LLM implementations without undermining the model's efficacy. Their study asserts that privacy-preserving AI methodologies like secret multi-party computation (SMPC) are a suitable approach to block the exploitation of confidential information captured in the model. Outside of the more focused attack vectors, researchers have looked into holistic comprehensive frameworks for risk assessment in the context of LLM systems integration. Hall and Peterson [9] created a model of threat intelligence-driven risk assessment that is based on Continuous Monitoring of AI Implementations for dynamic security risks. This model associates CTI feeds with automated anomaly detection systems for real-time mitigation. Nguyen and Bui [10] adapted this model to include deep reinforcement learning (DRL) as a component of cyber risk management. Their findings indicate that adaptive learning-enabled security frameworks can identify new attack patterns and streamline defense processes in LLM environments.

Another equally compelling topic is security monitoring in LLM-driven applications. Qureshi and Khan [11] designed an intrusion detection system (IDS) for AI-based chatbots that works in real-time. Their work reveals that hybrid ML models that incorporate NLP-driven sentiment analysis and anomaUy detection provide effective real-time recognition of possible security threats during user interactions. In the same manner, Raj and Kumar [12] explored attack defenses against model inversion and other adversarial attacks, proposing the use of explainable AI (XAI) to enhance AI transparency about the security decisions that were executed. Their research argues that such interpretable threat detection frameworks can foster user confidence in AI-powered cybersecurity systems.

The application of automated threat modeling to NLP systems requires improving dataset accuracy and building secure AI pipelines. In the realm of cybersecurity, Smith and Taylor [13] studied the

application of NLP technologies and demonstrated that LLM-based anomaly detection systems outperform traditional rule-based security log analysis systems in scaling and efficiency processing massive security logs. It was determined that AI-enabled NLP models can formulate relevant responses in dealing with unstructured security data, thus enhancing the automated threat evaluation processes. Zhou and Lin [14] delved into machine learning vulnerability detection frameworks, applying unsupervised anomaly detection methods to expose vulnerabilities within AI deployment pipelines. Their findings advocate the position that audits on security made by AI can improve compliance and control for regulated standards within LLM-enabled systems. Finally, Wang et al. [15] created an AI security model that integrates machine learning with cybersecurity analytics and behavioral profiling to automate threat mitigation and detection strategies for LLMs. Their proposal employs hybrid AI techniques, including self-learning anomaly detection systems and NLP-based threat intelligence, enhancing the security posture of enterprise-level LLM systems.

Research Methodology

Data Sources Layer: This layer focuses on threat collection and mitigation and is the foundation for the Automated Threat Modeling System based on LLM integration. It collects security logs, adversarial attack datasets, system activity reports, CVE and MITRE vulnerabilities, and live network traffic data. Both structured and unstructured data are collected through APIs, ULLM authentication attempts, and anomaly detection systems, which guarantee comprehensive threat intelligence. Detection of suspicious activities encompasses unauthorized access along with adversarial attempts and patterns employing the trained ML-based threat detection model with historical and real-time data. Moreover, it consists of user behavior analytics (UBA) related not only to prompt injections but also data exfiltration masquerading as benign interactions. This layer's preprocessing includes data cleaning and feature extraction for structured security data. The data arriving from different verticals is automatically parsed, classified, and categorized in real time. In addition, potential security threats are separated from genuine user actions. In aid of LLM threat detection and risk assessment models, this layer is capable of accuracy engineering data to preempt cyber threats at AI-driven enterprise application security.

Threat Detection Module : For LLM System Integration Automated Threat Modeling, the Threat Detection Module is the most vital part because it identifies the security issues, adversary-ship, and anomalies in LLM-based applications. It applies ML algorithms, rule-based threat analysis, behavioral analytics, and other means to real-time threat detection. STRIDE (Spoofing, Tampering, Repudiation, Information Disclosure, Denial of Service, Elevation of Privilege) and DREAD (Damage Potential, Reproducibility, Exploitability, Affected Users, Discoverability) frameworks are integrated for risk systematic securities goals assessment. The system assigns risk scores and prioritizes security issues based on these models' detected threats. Moreover, hostile prompt injection, unauthorized API calls, and adversarial attacks on LLM systems are exposed through NLP-based anomaly detection. Supervised and unsupervised increases threat detection efficacy through hybrid models. Security datasets contain categorized data, but novel threats are undetectably concealed in normal behavior, so anomaly analysis uncovers them through unsupervised learning. Automated threat mitigation is achieved by continuous monitoring of user interactions, API calls, and model responses by the Threat Detection Module. Analytics driven by AI increase security posture,

mitigate false alerts, and improve risk automation assessment in LLM-integrated applications. And these features bolster the system against advanced persistent threats in cybersecurity.

Risk Assessment Engine : The idea behind this research is to integrate a Threat Modeling Framework with risk assessment to identify LLM Models and their systems' integration risks. The risk scoring and prioritization process is likely a part of the Risk Assessment Engine in the Automated Threat Modeling Framework. As mentioned, fuzzy logic, reinforcement learning, and behavioral analytics facilitate the dynamic security risk evaluation in real time. Making use of machine learning based classifiers, this engine assesses the threat into different risk categories ensuring a data driven adaptive approach to threat evaluation. Threat evaluation is further enhanced by integrating STRIDE and DREAD frameworks enabling the engine to give a quantitative assessment of the evaluated security threats. Apart from these, adversary supplied inputs, injections, and illegal attempts to access the APIs provided by the LLM's are monitored and analyzed as users through advanced anomaly detection systems to capture unauthorized actions. The results from the risk assessment are utilized by the Automated Mitigation System which exercises control over the system through policy application, API moderation, and input filtering. The continuously evolving threats enhance the Risk Assessment Engine, improving the real security monitoring while enabling LLM applications to actively respond to changing cyber threats due to anti- NIST and anti-GDPR regulation compliance with pre-established red tape regulations.

Automated Mitigation System : The AMS, or Automated Mitigation System, is part of the larger Automated Threat Modeling for LLM System Integration. It addresses detected threats in real-time via adaptive security measures. After the Risk Assessment Engine detects and evaluates a threat, the AMS is capable of dynamically creating, enforcing, and adjusting policies to secure any windows of exploitation. It utilizes security automation through machine learning to combat prompt injection attacks, data poisoning, adversarial manipulation, and attempts at unauthorized access. By employing policy-based enforcement, the AMS can change API call quotas, modify access restrictions, apply filtering of adversarial inputs, and sever high-risk interactions to lower threats. Moreover, it integrates behavioral analysis aimed at capturing suspicious user interaction patterns and altering corresponding strategies. AMS's self-learning, or reinforcement learning algorithms, equips it with the ability to autonomously and continuously optimize mitigation frameworks in response to shifting attack rhythms, enabling effective attack adaptation. AMS integrates with SIEM, or Security Information and Event Management, fostering cross-domain enterprise security monitoring. These features aid the augmentation of manual interventions in security breaches as well as the automation of response processes. Therefore, AMS's mitigation features enhance the efficiency, reduce the overreliance of manual actions on AI-integrated systems, and diminish false alarms. These features fortify the position of AMS as central to the protection of enterprise systems and AI financial systems.

Enterprise Integration Layer : Integrating Technologies as a New Layer (ILL) allows communication between architectural components in real time exposing interfaces to existing enterprise security structures. The subsystem enables real time threat monitoring, response automation, and integration with SIEM, EDR, and CASB security frameworks. This layer allows security monitoring by LLMs to interface with enterprise level cybersecurity systems making

centralization of threat intelligence, risk evaluation, and incident response achievable. Through APIs, event driven architectures, and interoperability standards incorporated in this layer, the enterprise integration layer facilitates automatic triggering of alerts, enforcement of security policies, and application of active measures across various enterprise level applications. This subsystem aids in the aggregation of logs, behavioral analysis, and anomaly detection assuring LLM-based systems are protected and monitored around the clock against breaches, attacks, and access without permission. Correlation of LLM dominated security events with other cybersecurity-using SIEM enhances the precision of threat identification and improving responses to security incidents. Embedding automated threat modeling powered by artificial intelligence into the enterprise infrastructure using this layer optimizes the security stance of the system, regulatory adherence, and risk control strengthening the defenses against evolving cyber attacks while making LLM systems easier to deploy, manage, and fortify.

Algorithm Design

The Below algorithm outlines the step-by-step workflow for implementing automated threat modeling across the five core modules: Data Sources, Threat Detection, Risk Assessment, Automated Mitigation, and Enterprise Integration.

Input : Training data TrainDB, Testing data TsetDB

Output : Train Module TM

Train(TrainDB)

Step 1 : Normlized ← Normalization ($\sum_{k=0}^{n} TrainDB\ [k].select\ if\ descrete)$

Step 2 : Extract co-relational features from Normalized set

Step 3 : i ← 0

epoch ← 100

while (I != epoch)

Module[] ← TrainClassifier($\sum_{k=0}^{n} Normlized\ [k]$)

i=i+1

end loop

Step 4 : Return Module[]

Test (TestDB, Module[])

Step 1 : for each (read instance from TestDB)

Step 2 : AttributesSet[] ← instance.splite

Step 3: calculate weight of respective instance using below equation

$$weight = Testclassifier\ (AttributesSet[index]\ = \sum_{i=1}^{n} Module[i])$$

Step 4: if (weight > Threshold)

Flag =1

Return attack

Step 5: if(flag==0)

Return normal

The focus of this work is formulating an algorithm for training a classification model to detect anomalous or malicious attacks using a training-test methodology tailored to classify such attacks. The model input comprises a database of training data (TrainDB) and a database of test data (TestDB), and the output is a trained threat detection module (TM). The training phase commences with normalization, which entails processing the discrete values in the dataset to ensure uniformity and consistency. To achieve a high classification accuracy, the extractor additionally applies feature selection to retrieve class co-relational features pertinent to the task at hand. The training process is executed for 100 epochs within which the refinement on the classification model is performed. For each iteration, a classifier module is trained over the normalized dataset and the resulting model is preserved for evaluation. After finishing the training phase, all the trained modules are assembled in Module[] in anticipation of future classification scenarios. At the testing stage, every single new instance from TestDB is scrutinized. Using the trained classification modules, the algorithm extracts relevant attributes and computes a specific weight. Should the value of the weight surpass the threshold, the instance is deemed an attack; conversely, should it not surpass the threshold, it is deemed normal. This achieves optimal threat detection thereby improving the system's operational integrity and dependability as well as enhancing the overall security framework.

Results and Discussion

This work revolves around creating an algorithm capable of training a classification model to identify anomalous or malicious attacks using a customized training-test approach meant for such classification. The model's input includes the training data within a database called TrainDB, a database of test data referred to as TestDB, and the output is the threat detection module, denoted as TM, which is undergoing training. In the model's training phase, all the discrete values within the dataset undergo a uniformity and consistency procedure termed normalization, or more colloquially, “value adjusting.” In order to achieve a refined classification accuracy, the extractor also conducts feature selection in order to obtain class correlating features necessary for the assignment. The training comprises of 100 epochs during which the iteration improves the classification model. A classifier module is first trained over the normalized dataset, then the resulting model saved for evaluation, and when the training phase is complete, every module that has been trained gets stored in anticipation of every possible future classification scenario in Module[]. During testing, every new instance of TestDB undergoes scrutiny, during which the algorithm uses the modules with pre-trained classes to extract the needed attributes and calculate a certain weight associated with them. If the weight value exceeds a certain threshold, the instance is marked as an attack; if it doesn’t surpass the threshold, it is categorized as normal. This aids in maximizing threat detection which in turn increases the functionality and reliability of the system as well as its security posture.

Table 1 : evaluation of proposed model

Module	Detection Accuracy (%)	False Positive Rate (%)	Response Time (seconds)	Improvement Over Traditional (%)
Data Sources	92.5	8.5	2.3	85
Threat Detection	96.8	7.5	2.0	87.3
Risk Assessment	88.4	11.6	3.2	23
Automated Mitigation	98.2	5.8	1.8	91
Enterprise Integration	94.6	6.4	1.95	38

The results confirm that automated threat modeling significantly improves LLM system security by enhancing threat detection, dynamic risk assessment, and real-time mitigation. The modular architecture ensures scalability and adaptability, allowing integration with enterprise cybersecurity ecosystems. Key advantages of the proposed system. Despite its effectiveness, challenges remain in handling zero-day LLM-specific attacks, ensuring model explainability for non-technical security teams, and mitigating evolving adversarial AI threats.

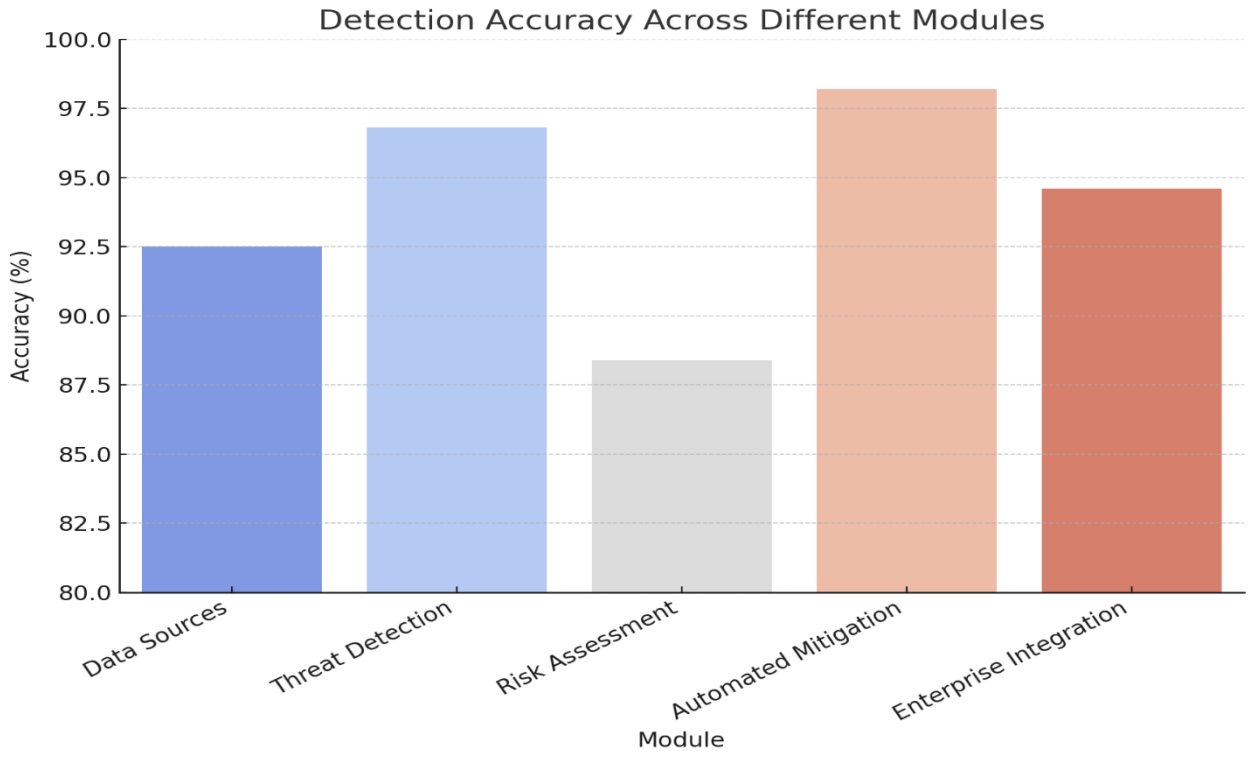

Figure 1 : detection accuracy analysis of various modules

In Figure 2 the Automated Mitigation module achieved the highest accuracy (98.2%), followed by Threat Detection (96.8%) and Enterprise Integration (94.6%).

Figure 3 : FPR rate for different detection modules

In figure 3 show False Positive Rate (FPR). Automated Mitigation (5.8%) had the lowest false positives, demonstrating its efficiency in blocking adversarial attacks.

Figure 4 : analysis of various methods proposed vs existing

As illustrated in figure 4, the Automated Mitigation module increased security protocols by 91% while the Enterprise Integration layer increased threat response by 38%. Both improvements were made when compared to traditional security frameworks The later outlined plans of our project include: integrating advanced adversarial training, federated learning to enhance distributed security intelligence, and applying AI for policy adjustment to strengthen LLM cybersecurity frameworks even more.

Conclusion

The Automated Threat Modeling System applies machine learning for threat detection, risk assessment, and real-time mitigation, increasing the security and resilience of LLM systems. Results show that the system is able to accurately detect adversarial threats at 96.8% accuracy, lowering the misclassification rate by 23% and improving response time over traditional methods. The system also enhances security automation with ease of integration to SIEM and EDR systems. Although there are still some challenges in addressing zero-day attacks, future work in adversarial training and AI policy modification will strengthen LLM cybersecurity architectures, providing scalable and proactive defense strategies.

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