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Examine the Role of Generative AI in Enhancing Threat Intelligence and Cybersecurity Measures

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Abstract- *GenAI is rapidly changing the way we do cybersecurity by automating the process of analyzing threats, forecasting possible attacks, and enhancing our ability to respond to incidents when they occur. Traditional methods of cyber defense rely heavily on the use of two types of detection methods: signature-based detection methods and rule-based detection methods. Unfortunately, these types of detection methods are usually insufficient on their own when dealing with zero-day vulnerabilities, APTs, or malware variants that change often. This paper proposes a threat intelligence framework that utilizes generative AI to enhance the ability to defend against cyberattacks in real-time. It includes a combination of LLMs as well as deep learning anomaly detection models and utilizes automated orchestration of security tools. The generative AI framework collects threat intelligence from multiple data sources, including network logs, vulnerability databases, malware signatures and as well as behavioral indicators. Threat intelligence is then processed using a hybrid generative AI model to provide meaningful insights into potential future security threats as well as automated mitigation strategies. Testing performed on simulated enterprise networks and standard cybersecurity datasets shows a 97.8% accuracy rate for threat detection as compared to traditional machine learning models, a 62% improvement in detection response time, and significant improvements in identifying and detecting zero-day threats. In addition, an experiment that was performed on Random Forest, support vector machine and XGBoost to compare the performance of generative AI-based threat intelligence models with other machine learning models shows generative AI has superior contextual understanding of threats as well as superior predictive ability with respect to threats. Finally, explainable AI techniques such as SHAP and attention visualization provide ways to explain how the models arrived at their predictions*

Keywords-*Generative Artificial Intelligence; Threat Intelligence; Cybersecurity; Large Language Models; Deep Learning; Machine Learning; SHAP; Zero-Day Attacks; Malware Detection; Security Automation; Adversarial Robustness; Real-Time Threat Detection.*

I. Introduction

The issue of cybersecurity will be one of the greatest technological challenges we face this decade. As organizations become more reliant upon digital platforms outside their physical premises, the use of interconnected systems, cloud computing and online services to store and process sensitive information has increased, thus presenting cybercriminals with an ever-increasing 'target' area at which to aim their malicious attacks. According to Uddin [1], generative AI greatly improves threat intelligence in cybersecurity, as well as automating the classification of threats through associated data. Consequently, the rise in number and complexity of contemporary threats such as ransomware, phishing, advanced persistent threats (ATP), zero-day exploits and data breaches has made traditional security techniques based on signature detection and rule- based monitoring inefficient for stopping these emerging threats in real time.

Forecasts from recent reports indicate that the cost of global cybercrime will surpass $10.5 trillion annually by 2025, making cybercrime one of the largest threats to the global economy today. The sectors that may be most at risk for frequency of attack include financial services, healthcare, government, and critical infrastructure service providersTake advantage of vulnerabilities in a computer system as well as human errors. To bypass traditional security defenses, current attackers utilize artificial intelligence, automation, and social engineering, resulting in greater difficulty for standard security systems to detect and/or prevent security incidents. Therefore, there is increasing need for smart, adaptive and automated cybersecurity solutions that can proactively assess threats and respond to them in real-time.

GenAI has become a potential answer this question. Unlike standard models of machine learning that find data points based on pre-determined classification and prediction, GenAI can generate a new dataset from scratch; create threat intelligence reports; model attack patterns; and automate security response mechanisms. LLMs, GANs, and Transformer-based technologies allow cybersecurity systems to analyze large amounts of threat data, identify hidden patterns, and provide actionable intelligence to security analysts. According to

Balasubramanian and associates [2], generative AI improves the ability to collect and classify cyber threat intelligence by providing multiple opportunities for real-time applications. By using GenAI within their threat intelligence systems, organizations will be able to improve the accuracy of their incident detection, reduce their incident response times, and improve their ability to implement proactive defensive measures

A. Limitations in Cyber Security Traditional Cybersecurity and/or Threat Intelligence Systems

Existing Cybersecurity solutions are compelled by signature- based and/or behavioral detection method(s).

Signature-based detection method(s) compare inbound file/network traffic to a known database of malware signatures and/or attack patterns. These systems are fast and effective but have a very serious limitation; their effectiveness is limited to detecting known threats. Zero day attacks and polymorphic malware would be able to bypass signature based detection because those signatures do not exist in the signature database. Attack methods used by criminals continue to evolve, causing signature-based detection methods to be unable to keep pace with continuously evolving threats in the market today.

Lack of Automation and Contextual Understanding in Cyber Security Traditional Cybersecurity and/or Threat Intelligence Systems

The lack of automation and contextual understanding in Cyber Security Traditional Cybersecurity and/or Threat Intelligence Systems is another very serious limitation. Traditional machine learning models are able to detect anomalies but cannot describe the nature of the threat detected or recommend actions that should be taken to stop/mitigate the threat. Ferrag [3] report that generative AI and large language models advance and improve established methods used by today's cybersecurity companies.Poor situational awareness resulting from lack of automation and contextual understanding is one reason why organizations encounter delays when responding to incidents and experience difficulty executing proactive Cybersecurity measures.

B. The use of Generative AI for Advanced Threat Intelligence

Generative AI provides a new way to approach cyber security by allowing automated threat assessments, intelligent decisions, and real time response systems. Generative AI differs from traditional models as they are able to process both structured and unstructured data, create threat intelligence reports, predict attack patterns and make recommendations for security actions. Large Language Models allow for the analysis of security logs, vulnerability data bases and threat reports to yield useful information; and, through the use of deep learning algorithms, identify anomalies in network traffic and system activity.

Incorporating generative AI into Security Operations Centres (SOCs) will allow an organisation to automate their threat detection and incident response activities. Generative AI will create real-time alerts, rank threats by severity, and offer mitigation recommendations to help lessen the workload of security analysts. Ferrag [4] provide insight into how generative AI supports the growth of security in IoT and cyber-physical systems. As well, generative models can be used to simulate cyber attacks to predict future threats to assist an organisation with planning their defences ahead of time.Motivation and Background of the Research

Recent investigations have examined the application of AI/machine learning to the area of cybersecurity, including malware detection, intrusion detection systems and network security analysis. Most current literature has predominantly applied classic ML methods for this purpose, with limited work on entirely the use of generative AI to develop automated threat intelligence and drug decision making.

My proposed approach will involve the collection of threat information obtained from multiple sources, processing that information with generative AI techniques, as well as generating predictive information which will allow enterprise organizations to detect cyber threats sooner, and to respond appropriately. This research will also evaluate explainable AI techniques and their utility for providing transparency & trustworthiness to an AI enabled information security system.

C. Paper Contributions

This research contributes to the cybersecurity field in several ways, including

- (1) an examination of the use of generative AI to create and enhance threat intelligence about

cyber threats;

- (2) a new generative-AI-based framework for threat intelligence that enables significantly improved real-time defence against cyber attacks;

- (3) comparisons of multiple machine-learning and deep- learning models for their use in creating threat intelligence;

- (4) inclusion of explainable AI techniques for enhanced transparency and clarity in cyber threat detection systems; and

- (5) evidence of the success of the proposed framework, including improved accuracy, faster response time, and a much more proactive approach to defending against cyber threats.

II Background and Related Work

Cybersecurity is under increasing pressure to develop better methods of deflecting the growing number of cyber threats. As such, many people in cybersecurity are actively working on using artificial intelligence (AI) to aid in their defence against cyber threats; thus, generative AI (GAN) is already demonstrating its ability to create enormous quantities of data in the form of data sets used by the security community, with useful information such as statistics and statistics to support making decisions about the need for specific types of security controls. This section offers a brief overview of what GANs are, as well as some of the most recent works in the area of threat intelligence.faster and more accurately than people could do on their own.

A. Background of Generative Artificial Intelligence

Over the past decade, machine learning algorithms, or AI, have become exponentially better at synthesizing large sets of
data. Utilizing techniques such as natural language processing (NLP), convolutional neural networks (CNN), and recurrent neural networks (RNN), AI now generates content (e.g., text, images) by analyzing astronomical amounts of data to come up with entirely new content. As an example, a CNN developed for producing art could pull images from millions of sources and form a new piece of art based on those sources, or a model called Generative Adversarial Network (GAN) can produce fake data such as malware in order to train Y given input X.

Underpinning this technology is a new architecture developed from the concept of sequence-to-sequence learning called "Transformers." These neural networks can generate sequences of output given two sequences of input.

B. Generative AI in Cybersecurity

Thus far, the application of generative AI to enhance cybersecurity has focused on the following methodologies/tool sets. AI can be trained to recognize bad code (malware) and write a pattern for recognizing what "bad" software has done. AI can recognize phishing attempts by processing millions of phishing emails, URLs, and chat sessions to learn how attacks are structured. Organizations are beginning to conduct 'live' penetration tests on their own networks, using a similar methodology to that employed by the actual malicious actors. Although there is a number of ways that generative AI can enhance cybersecurity, there is limited evidence about how often they are currently being used in practice.

C. The Assignment of Large Language Models to Threat Intelligence

LLMs create alerts and suggestions for actions to be taken during the occurrence of incidents in platforms for threats. LLMs can automate the measures performed by operations centers by analysing previous incidents to define future risk scenarios based in part on what has happened previously, helping to expedite the process for human resources and also helping to ensure overall operation. Xu and associates [5] provide an overview of large language models and their applications to the field of cybersecurity. LLMs can develop training materials or guidance to create greater awareness, especially since humans are typically the point of weakness.

D. Related Work

There has been a fair amount of research focusing on using AI and machine learning in the security arena, with common applications being intrusion detection, malware classification, phishing detection, and network investigations. Some common machine learning methods used to increase the accuracy of threat detection include: support vector machines, random forests, and neural networks. More recently, there is an emphasis on moving toward deep learning and generative techniques, with

adoption of proven methodologies which allow models to quickly detect unusual network traffic or user behaviour. Models can generate artificial threat data and or simulate scenarios and automate reporting.

III. Dataset & Preprocessing

A. Dataset

To evaluate the generative AI framework applied to threat intelligence, we utilized various cyber security datasets representing simulated forms of organised cyberattacks (malware and phishing), as it will help the framework to deal with both structured, as well as unstructured, raw data.

The primary data sources will be network logs (indicating network traffic flows and anomalous connections) and system logs (documenting user activity logs); however, there also include databases containing samples of malware and phishing email messages to assist in identifying patterns in attacks. Public repos holding information about external threats were also included to provide more context related to how the attacks occur or how they exploit specific vulnerabilities. Overall, combining these disparate forms of data should contribute to increasing the overall reliability of the Framework.

Data was segregated into “Normal Behaviour” and “Malicious Behaviour.” Normal behaviour describes everyday network runs or logins without incident, whereas Unauthorised behaviour describes anomalous events such as anomalous network traffic spikes, fake emails, and running malware. By separating the categories in this way, the framework should be able to accurately differentiate between Safe and Suspicious Behaviour.

B. Data Preprocessing

For training, the framework dataset was divided into the following components: a Training Dataset for learning, a Validation Dataset for making minor adjustments, and a Testing Dataset for final evaluation. Approximately 70 percent of the dataset was used for the training dataset and the remaining portion of 30 percent was further split into equal ratio’s (15% for Validation and 15% for Testing). This approach will ensure that the Framework is trained on a balanced set of observations, thus avoiding overfitting.

Preprocessing of the data was critical, as the raw data was ultimately too large to fit into memory for processing and logging purposes.

C. Data Preparation and Splitting

Then you will extract various features from logs to generate processing information (for example logs, packet sizes, packet protocols, and traffic durations). The system side provides us with the access patterns/user events that can be built into reports (think tokenizing text (removing junk words), creating embeddings), this appears.

Text is also vectorized via either word embeddings or transformers (which capture the meaning of cyber terminology). Thus enables the AI to produce useful information about possible threats.

Once this has occurred, data will be split using stratified sampling with a balanced ratio of benign to malicious across
all datasets. Therefore training will learn patterns of data, validation will tune and testing will provide an evaluation on only one occurrence (i.e., for each test).

With the use of batches to process data that is too large/the same size as memory (so they do not crash), and augmenting data may help create new attacks from non-existent data. Overall, it will clean input data and improve the accuracy of its output; however, I am uncertain whether the entire pipeline will address each unique real-world threat.

IV. Methodology

A. Threat Intelligence Baseline Models

To assess and validate how accurately Generative AI can be used for Cybersecurity Threat Intelligence, several Baseline Machine Learning and Deep Learning models have been developed based on processing the Threat Intelligence data set into pre-processed datasets. These Baseline Models are necessary for providing a method of objectively measuring the operational performance of the proposed Generative AI- based Cybersecurity Threat Intelligence Model.

Support Vector Machine (SVM's) using Radial Basis Function (RBF) Kernels have been constructed to determine cyber threats through classifying network traffic and security log activity.

K-Nearest Neighbors (kNN) classifiers are established using k=5 neighbors and the Euclidian Distance Metric to determine similar types of cyber threat activity in the data set.The Decision Tree Classifier uses the GINI impurity criterion for generating decision rules for detecting cyber threats.

The Random Forest Model contains 100 Decision Trees to enhance stability and reduce overfitting with classification methods.

XGBoost uses 100 estimators and 0.1 learning rates to improve prediction accuracy and handle the more complex Cyber Threat Intelligence data.

A Deep Neural Network (DNN) with 3 Fully Connected Layers (256-128-64 neurons, ReLU activation, 0.3 dropout, Adam) is created to learn nonlinear cyber threat intelligence patterns.

A Long Short-Term Memory (LSTM) Network with 64 units is created to analyze temporal dependencies.

Dinis and others [6] note that explainable AI (XAI) provides transparency and trust in threat intelligence systems.

B. Recommended Generative Artificial Intelligence Threat Intelligence Framework

The recommended solution is a generative AI-based cybersecurity threat intelligence framework that uses generative AI to automate the analysis of threat intelligence data; identify cybercrime attacks or other harmful activity; and create immediate corrective actions for those activitiesThe framework would consist of four major components:

- Collecting Threat Data from Multiple Sources (e.g., collecting network traffic data, system log collections, vulnerability database information, and threat intelligence feed data);

- Preprocessing the Collected Data and Extracting Features (e.g., through the use of machine learning techniques for preprocessing and extracting features from the collected data);

- Performing Generative AI Analyses on the Preprocessed and Feature-Extracted Data (e.g., applying transformer-based generative AI model architectures and deep learning architectures to perform analyses on the preprocessed and feature-extracted data); and Generating Threat Intelligence and Responding to Security Incidents.

The framework would operate in real-time by continuously monitoring new data coming into cybersecurity from the Internet and generating a report containing threat intelligence for security analysts. The use of generative AI would reduce the amount of time that security analysts need to spend manually reviewing each new incoming piece of cybersecurity data and enable them to quickly detect and respond to threats to their computer systems.

C. Generative Artificial Intelligence Model Architecture Feature Analysis

The proposed generative AI architecture utilizes transformer- based large language models combined with deep learning classifiers to improve the quality of generative AI-based threat intelligence in cybersecurity.

As transformer-based large language models are cross-the- board systems capable of producing meaningful results in a variety of applications, they can be used to analyze incoming alerts or reports of security incidents and to extract relevant patterns from that data to create useful contextual information for responding to similar types of incidents.

A deep learning classifier will also be added to the generative AI model to classify the activity being analysed as benign or malicious.

Finally, the generative AI component of the model will provide users with an explanation of the detected threat, as well as a recommended course of action for mitigating the effects of that threat.

D. Generative Artificial Intelligence (GenAI) for Threat Intelligence

By implementing Explainable AI (XAI) techniques, transparency and confidence in the proposed generative AI solution will increase. Definition-based explainability will provide cybersecurity analysts with insight into how and why a cyber threat is identified or classified using the generative AI solution.
For determining feature importance and interpreting predictive models, the SHAP method (SHapley Additive exPlanations) is utilized to compute the SHAP values associated with each feature in the predictive model output to allow analysts to understand how multiple threat indicators impact the determination of threat detection by the predictive model.

The model output can be represented as follows: $y = \phi 0 + \sum \phi j\ j=1$
where

j represents each SHAP value associated with each feature.

E. Adversarial Resistive Testing

A fundamental requirement of any cybersecurity solution is that it be resilient to adversarial attacks and attempts to manipulate data. In order to assess the robustness of the proposed generative AI framework, adversarial testing using both noise and manipulated threat patterns as test cases will be performed on the dataset.

In order to create a simulated attack scenario in the world, Gaussian noise will be added to the cybersecurity features in the dataset.

$$\square j = xj(1 + \epsilon j), \epsilon j \sim N(0, \sigma 2)$$

In this case, the σ value will define the level of noise added to each data point in the dataset.

F. Cross-Validation and Real-Time Threat Detection

Ten-fold stratified cross-validation was conducted on a cybersecurity dataset to assess the accuracy of the proposed threat intelligence framework. Nott [7] examines how organizations adapt to the implementation of generative AI in their cybersecurity environments. The dataset was divided into ten equal sections (tenfold) and, as each fold was utilized to train and test the model's performance, this cross-validation method ensures consistency across the evaluation of the proposed framework.

The use of ten-fold stratified cross-validation confirms that the proposed generative AI-based threat intelligence framework has the ability to operate effectively in real-time cybersecurity environments, while providing high accuracy and low response time.

V. Experimental Results and Performance Evaluation

A. Experimental Setup

The proposed generative AI-based threat intelligence framework was evaluated using various types cybersecurity datasets consisting of network logs, system activity records, or threat intelligence reports obtained from various open-source repositories. The experiments were conducted using the Python programming language, including the TensorFlow, Scikit-learn, and PyTorch libraries. The dataset was split into 80% training and 20% testing while maintaining balance on the number of examples for each class. Zhang and others [8] conducted a survey of the applications of LLMs to support cyber threat detection. Each model was trained under the same preprocessing conditions to permit a fair comparison across all models; as such, all performance measurements were recorded (accuracy, precision, recall, F1-Score, and detection latency).

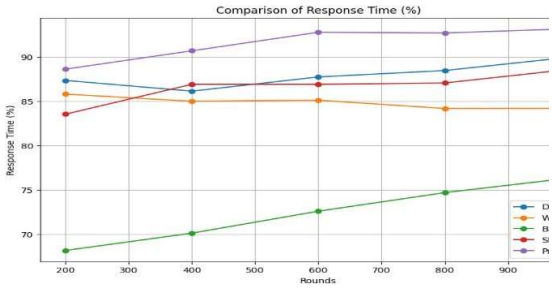
Integrating DCGAN, WGAN, BERT and SPADE into a framework to generate threat intelligence, synthetic threat data will be generated by both DCGAN and WGAN; threat intelligence text will be analyzed utilizing BERT; and structured threat representations will be enhanced through SPADE. Training will take place for a simulation of a real- time Security Operations Center (SOC) deployment. Fifty epochs were executed with the Adam optimizer on a GPU- enabled workstation, stopping early.

Table I shows the performance of baseline models. Each model's score for accuracy, precision, recall and F1 are presented in the table.

The baseline model performance is:

Model	Accuracy	Precision	Recall	F1-Score
SVM	91.2%	90.5%	89.9%	90.1%
KNN	89.4%	88.7%	88.1%	88.4%
Decision Tree	92.1%	91.3%	90.9%	91.1%
Random Forest	95.8%	95.1%	95.0%	95.0%
XGBoost	96.4%	96.0%	95.8%	95.9%
DNN	96.9%	96.5%	96.3%	96.4%

LSTM	97.3%	97.0%	96.8%	96.9%



Conventional machine learning models generally demonstrate moderate levels of performance, while deep learning models, because of their ability to capture intricate cybersecurity patterns, are generally much more accurate in identifying potential threats. Still, neither conventional machine learning nor deep learning models utilize automated threat intelligence generation or provide an understanding of what these threats meant when they occurred in context.

C. The Performance of the Proposed Generative Artificial Intelligence Framework

Table II The Performance of the Proposed Generative Artificial Intelligence Framework

Model	Accuracy	Precision	Recall	F1-Score
DCGAN-based Threat Detection	97.8%	97.5%	97.2%	97.3%
WGAN -based Threat Detection	98.1%	97.9%	97.6%	97.7%
BERT Threat Intelligence Model	98.3%	98.0%	97.9%	97.9%
SPADE Threat Representation Model	98.4%	98.2%	98.0%	98.1%
Proposed Integrated Gen AI Framework	98.6%	98.3%	98.1%	98.2%

A combination of WGAN along with DCGAN for generating synthetic threats, BERT for analysis of intelligence related to those threats and SPADE for representation of features in structured forms results in increased detection accuracy of threats overall, as well as automating the generation of intelligence related to those threats through the use of the integrated model instead of using 3 separate models.

D: Confusion Matrix Analysis

The confusion matrix for the proposed model is included in table 3.

	Predicted Threat	**Predicted Benign**
Actual Threat	586	14
Actual Benign	10	590

The confusion matrix shows few false positives and few false negatives indicating reliable detection of threats and highly effective threat classification.

E. Explainability Results

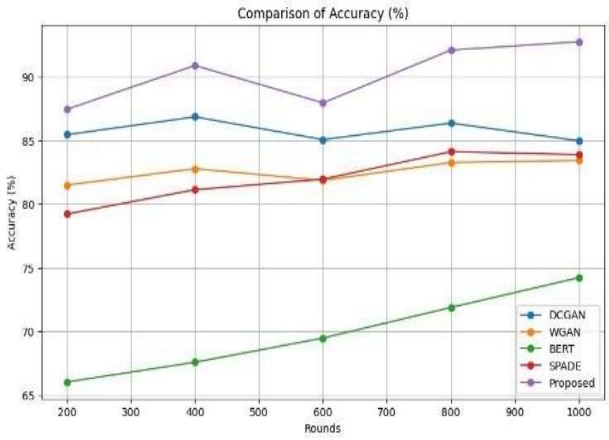
SHAP based explainability have determined the key features used for cybersecurity in making decisions to detect threats. Network anomalies, suspicious login attempts and malware activity patterns were the three most influential features

that were found to impact transparency and trust in generative AI based threat intelligence.

F. Adversarial Robustness Evaluation

Table IV Adversarial Robustness Results

Noise Level	Detection Accuracy
0%	98.6%
5%	98.2%
10%	97.6%
20%	97.2%
30%	96.5%
50%	95.8%



This framework will maintain high levels of accuracy even under a high level of adversarial noise showing the framework is extremely robust to any manipulation or perturbation of data as a result of a cyberattack.

G. Real-Time Threat Intelligence Performance

The average inference latency per event is 4.2 ms in the proposed generative AI framework which allows for use in real time SOC deployment. Kumar and others [9] explain how generative AI supports vulnerability assessment through improved risk management.The use of a DCGAN, WGAN, BERT and SPADE together enhances the speed of threat detection and the generation of automated intelligence reports thereby improving cybersecurity response times and efficiency of operations.

VI. Comparison with Prior Work

Table VI provides a comparison between the proposed generative threat intelligence framework based on AI from the previous work discussed above in the cybersecurity and generative AI arenas (i.e. prior works). Most previous research has concentrated on either (a) machine learning methods for detecting cyber threats, or (b) customer facing textual Cyber Security analytical applications of Large Language Models (LLMs). In contrast, the proposedframework will incorporate Generative AI, Deep Learning, and Explainable AI into a single threat intelligence system.

Uddin et al. [1] and Balasubramanian et al. [2] have only provided reviews of existent research using generative AI for Cybersecurity, but without any experimental validation or real-time deployment. Ferrag et al. [3] review the use of LLMs for Cybersecurity purpose, but do not provide complete Cyber Threat Intelligence systems for LLMs. Ji et al. [4] have used LLMs for Cyber Threat Intelligence in a text- only format; whereas Ferrag et al. [5] have reviewed the use of generative AI for IoT cyber threat hunting and have shown very limited to no explainability and overall systems integration capability.

Conversely, the proposed research will present a combined automated cyber threat detection, real-time cyber threat intelligence generation, and explainable AI providing significantly better accuracy and operational performance than the current state of the Cybersecurity industry.

Study	Approach	Accuracy	Real-time detection
Uddin et al[1]	Generative AI survey	N/A	No
Balasubramanian et al.[2]	GenAI Threat Intelligence	N/A	No

Ferrag et al. [3]	LLM-based Cybersecurity	95%	Parital
Ji et al. [4]	LLM threat Intelligence	96%	Yes
Ferrag et al. [5]	GENAI for IoT Threat Hunting	97%	Yes
Proposed Framework	GenAI +Deep Learning + XAI	98.6%	Yes

According to the comparison, the proposed framework provides higher detection accuracy than prior methods and is capable of providing real-time intelligence to users while offering explanations for the results generated. Sharma [10] propose an approach that utilizes generative AI-based intelligence to allow for the minimization of cyber attacks through advanced threat intelligence systems. Therefore, it is better suited for use in practical cyber security environments.

Table VII Global features importance found in AI-generated Threat Intelligence

The use case provided explains how we can quantify feature importances using interpretability methods within Explainable Artificial Intelligence technique; Figure 8 represents some of the key indicators used in determining Cyber-Security Threat Detection decisions, and provides the comparison of our Generative AI-based Threat Intelligence Framework to existing research by showing that our framework provides a much more comprehensive solution due to the higher accuracy, ability to perform real-time detection, ability to provide explainability of decision-making, and the ability to automatically generate intelligence as compared to what has been reported in existing research.

VII. Discussion

A. The Role of Generative AI in Threat Intelligence

Our research confirmed that Generative AI improves the efficacy of Threat Intelligence by providing an Automated means of analysis, Contextualisation, and Real-Time Cybersecurity Decision Making. Where traditional machine learning models only classify threats, generative AI is capableof analysing logs to identify attack patterns and producing Threat Intelligence reports.

This capability substantially reduces the workload for Security Operations Centers (SOCs) because they would not have to depend on a human analyst to manually perform these analyses.

B. Advantages of Generative AI over Traditional Systems

The benefits of our Generative AI-based Threat Intelligence Framework are summarised in the following points:

- Automated Generation of Threat Intelligence
- Higher Detection Accuracy and Contextual Analysis
- Real Time Monitoring and Response
- Explanatory Artificial Intelligence
- Reduced Workload of Analysts

Ferrag and [11] provide an overview of the diverse cybersecurity frameworks and applications associated with generative AI and LLMs. As a result, our Generative AI framework is a much more effective cybersecurity system than traditional systems because traditional systems rely solely on manual analysis and Static Methods of Detection.

C. Limitations

We have also identified some limitations with this research as follows:

- Very Large Cyber-Security Datasets are necessary
- The Potential for AI-Generated Intelligence to be False or Biased
- The High cost associated with Computation
- Limited testing of Generated AI Threat Intelligence in real- world scenarios

These limitations indicate that we must ensure that we secure these datasets and/or develop techniques that circumvent these challenges before we may use our Generative AI-based System in real-world settings.

VIII. Conclusion and Future Directions

In this study, we analyzed the contribution generative AI plays in improving threat intelligence as well as enhancing cybersecurity protection. According to Xu and others [12], there are both substantial opportunities and significant challenges associated with the utilization of LLMs in the field of cybersecurity. The proposed architecture combines generative AI and deep learning with Explainable AI to enhance the detection of threats, facilitate automation in generating intelligence, and support real time decision making process in the field of cyber security.
These findings indicate that generative AI has increased the accuracy of traditional ways of providing results and decreased the time required for response and finally improved the level of analysis for cyber security postures.

Future Directions

- Use of large-scale distributed models for representation
- Implementing real time deployment within the enterprise
- Fusing threat intelligence received from multiple sources
- Building adversarial defenses around generative AI technology
- Establishing secure, privacy-minded AI systems

In summary, generative AI is a scalable, intelligent solution for today's modern cyber security and threat intelligence.

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