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Threat Intelligence Automation Using NLP and Machine Learning

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Abstract: This paper explores the application of Natural Language Processing (NLP) and Machine Learning (ML) techniques to automate threat intelligence, a critical component in modern cybersecurity defense systems. As cyber threats grow in scale, complexity, and frequency, traditional manual methods of threat detection and analysis are no longer sufficient to ensure timely and accurate responses. The research leverages a diverse dataset comprising unstructured threat reports, dark web communications, and security blogs to train a variety of models including Support Vector Machines, Random Forests, clustering algorithms, Recurrent Neural Networks, and transformer-based architectures like BERT. Through extensive experimentation and evaluation using metrics such as precision, recall, F1-score, and accuracy, the study finds that deep learning models, particularly BERT, outperform other methods in extracting and interpreting contextual threat information. The results demonstrate that NLP and ML not only enhance the speed and accuracy of threat identification but also enable scalable, automated analysis suitable for real-time cybersecurity operations. This work contributes to the growing body of research on intelligent threat detection and provides a foundation for integrating advanced AI-driven tools into existing cybersecurity infrastructures.

Index Terms **– Threat Intelligence, Natural Language Processing, Machine Learning, Cybersecurity Automation, Deep Learning**

I. Introduction

Threat intelligence has emerged as a crucial aspect of modern cybersecurity, aiming to proactively detect, understand, and mitigate threats before they can cause significant damage. With the ever-increasing volume and complexity of cyber threats, traditional methods of gathering and analyzing threat intelligence are proving to be insufficient. In this context, the integration of Natural Language Processing (NLP) and Machine Learning (ML) into threat intelligence systems offers a transformative solution by automating the extraction, classification, and interpretation of vast quantities of unstructured data from heterogeneous sources. This paper delves into the domain of threat intelligence automation through the synergistic application of NLP and ML techniques, highlighting the evolution, current state, and future potential of this rapidly growing field. It underscores the importance of automating threat detection and analysis, not just to enhance response times, but also to reduce human error, increase efficiency, and enable cybersecurity analysts to focus on high-priority tasks [1].

The crux of threat intelligence lies in its ability to gather and process information from diverse, and often unstructured, sources such as social media platforms, dark web forums, blogs, threat feeds, and incident reports. These data streams contain valuable indicators of compromise (IoCs), tactics, techniques, and procedures (TTPs), which can be critical in identifying and predicting cyber-attacks. However, the unstructured nature and sheer volume of these data sources make manual analysis infeasible and time-consuming. NLP plays a pivotal

role in addressing this challenge by enabling machines to understand, interpret, and process human language in a meaningful way. When combined with ML, NLP can learn from patterns in data to improve the accuracy of threat classification, entity recognition, and sentiment analysis, all of which are vital for effective threat intelligence [2].

The application of NLP techniques such as Named Entity Recognition (NER), part-of-speech tagging, topic modeling, and dependency parsing allows for the automated extraction of key cybersecurity entities like malware names, IP addresses, vulnerabilities, and threat actor identifiers from unstructured text. ML algorithms, especially those under supervised and unsupervised learning paradigms, are then used to classify these entities into meaningful threat categories, detect anomalies, and predict potential threats based on historical data. This automation not only expedites the analysis process but also significantly enhances the comprehensiveness and reliability of the threat intelligence generated. Deep learning models, including recurrent neural networks (RNNs) and transformers, have further pushed the boundaries of what is possible in threat intelligence, enabling the development of systems that can understand context and semantics with high accuracy [3].

One of the key challenges in implementing NLP and ML in threat intelligence lies in the dynamic and adversarial nature of cybersecurity threats. Threat actors are constantly evolving their strategies, using obfuscation, code morphing, and misinformation to bypass detection systems. Consequently, threat intelligence models need to be continuously updated and trained on the latest data to remain effective. This paper emphasizes the importance of building adaptive learning systems that can dynamically incorporate new threat indicators and adjust their detection and classification mechanisms accordingly. It also discusses the significance of using ensemble models and hybrid approaches, which combine multiple learning algorithms to improve robustness and reduce the likelihood of false positives or negatives [4].

Furthermore, the paper explores the role of data quality and preprocessing in ensuring the effectiveness of NLP and ML models. The accuracy of automated threat intelligence systems is highly dependent on the quality of the training data, which necessitates thorough data cleaning, normalization, and annotation. In this regard, collaboration between domain experts and data scientists is essential to create labeled datasets that accurately reflect real-world threats. The integration of knowledge graphs and ontologies is also discussed as a means to enhance contextual understanding and reasoning capabilities of ML models. By incorporating structured knowledge about threat entities and their interrelationships, automated systems can generate more actionable and contextually relevant threat intelligence [5].

Another critical aspect covered in this research is the ethical and privacy implications of automated threat intelligence systems. As these systems often analyze publicly available data and potentially sensitive information from forums or private communications, there is a fine balance between effective threat detection and the protection of individual privacy. The paper advocates for transparent and accountable AI practices, ensuring that automated systems operate within legal and ethical boundaries. It also highlights the importance of explainable AI (XAI) in cybersecurity, where the rationale behind a model's decision needs to be interpretable by human analysts to foster trust and ensure actionable outcomes [6].

In addition to technical discussions, the paper also examines real-world applications and case studies where NLP and ML have been successfully implemented to automate threat intelligence. These examples demonstrate the practical benefits of automation, including faster incident response times, improved threat coverage, and enhanced predictive capabilities. The paper illustrates how organizations have leveraged open-source intelligence (OSINT), social media monitoring, and threat feeds to build intelligent systems that can alert security teams about emerging threats in real time. It also emphasizes the scalability of such systems, which is particularly important in large-scale enterprise environments where threat landscapes are vast and continuously shifting.

Moreover, the paper outlines future research directions and areas for improvement in the field of threat intelligence automation. These include the development of multilingual NLP models to process global threat data, the incorporation of reinforcement learning for adaptive decision-making, and the use of federated learning to maintain data privacy while training on decentralized data sources. It also discusses the need for standardization in threat data formats and evaluation metrics to facilitate the benchmarking and comparison of different models and approaches. Finally, the paper calls for increased collaboration between academia, industry, and government entities to foster innovation and build resilient cybersecurity infrastructures [7].

In summary, this research presents a comprehensive exploration of how NLP and ML can revolutionize threat intelligence through automation. By combining linguistic understanding with predictive analytics, automated systems can transform raw, unstructured data into actionable insights, enabling security professionals to stay ahead of evolving cyber threats. The integration of these technologies not only addresses the limitations of manual analysis but also introduces new possibilities for proactive defense, real-time monitoring, and strategic threat mitigation. As the cybersecurity landscape continues to grow in complexity, the role of intelligent automation will become increasingly central to building secure digital environments. This paper thus contributes to the growing body of knowledge at the intersection of artificial intelligence and cybersecurity, offering a roadmap for future developments in threat intelligence automation.

II. Review of Literature

The integration of Natural Language Processing (NLP) and Machine Learning (ML) into cyber threat intelligence (CTI) has garnered significant attention in recent years, particularly from 2020 to 2025. This period has witnessed a surge in research focusing on automating the extraction, analysis, and interpretation of threat data to enhance cybersecurity measures. A comprehensive survey by Arazzi et al. (2023) delves into NLP-based techniques applied in CTI, highlighting methods such as data crawling from web sources, relation extraction, and data analysis. The study underscores the challenges of data quality and ethical considerations, emphasizing the need for robust NLP applications in threat intelligence [8].

The advent of Large Language Models (LLMs) has further revolutionized the field. Liu et al. (2025) introduced CYLENS, a cyber threat intelligence copilot powered by LLMs, designed to assist security professionals throughout the threat management lifecycle. CYLENS integrates knowledge from over 270,000 threat reports and incorporates specialized NLP modules to enhance reasoning capabilities. Evaluations indicate that CYLENS outperforms existing cybersecurity agents, offering a blueprint for leveraging LLMs in addressing complex cybersecurity challenges.

However, the reliability of LLMs in CTI tasks has been questioned. Mezzi et al. (2025) evaluated state-of-the-art LLMs on CTI tasks using a dataset of 350 threat intelligence reports. The study found that LLMs often exhibit inconsistencies and overconfidence, with few-shot learning and fine-tuning only partially improving results. This raises concerns about the dependability of LLMs in scenarios where labeled datasets are scarce and confidence is paramount [9].

To address the challenges of structuring unstructured threat intelligence data, Fieblinger et al. (2024) explored the use of LLMs and Knowledge Graphs (KGs). Their methodology involved extracting meaningful triples from CTI texts using open-source LLMs like Llama 2 and Mistral 7B Instruct. The extracted data was then utilized to construct a KG, offering a structured and queryable representation of threat intelligence. While effective in small-scale tests, the study acknowledges challenges in applying LLMs to large-scale data for KG construction [10].

Similarly, the LLM-TIKG framework proposed by Zhao et al. (2024) leverages LLMs to construct threat intelligence knowledge graphs from unstructured open-source data. By utilizing GPT's few-shot learning capabilities for data annotation and augmentation, the framework achieves high precision in named entity recognition and TTP classification. This approach facilitates automated and universal analysis of textualized threat intelligence, aiding in tracing attack chains and deducing attacker intentions [11].

The role of NLP in enhancing explainability within threat intelligence systems has also been explored. Song (2022) proposed a methodology integrating NLP methods such as named entity recognition, topic modeling, and sentiment analysis to enhance the transparency and interpretability of threat intelligence systems. Evaluations on real-world cybersecurity datasets demonstrated the effectiveness of this approach in presenting actionable insights in an explainable manner, thereby improving trust and decision-making in cybersecurity operations [12].

In the realm of social media, Olaoluwa and Potter (2024) examined the application of NLP techniques to enhance social media threat intelligence. Their study focused on methodologies for detecting and analyzing threats such as disinformation, cyberbullying, and extremist content. By leveraging NLP approaches like sentiment analysis, topic modeling, and entity recognition, organizations can improve their ability to monitor and respond to emerging threats in real-time. The study also highlights challenges associated with processing social media data, including dealing with slang, context, and multilingual content [13].

The integration of AI and NLP in cybersecurity has been further emphasized by Ismail (2024), who analyzed how these technologies strengthen cybersecurity through threat detection and response. The study found that AI advances have greatly enhanced the detection of anomalous patterns in large datasets, while NLP excels at detecting malevolent intent in textual data. Expert interviews confirmed that AI and NLP reduce false positives, improve threat intelligence, and enable adaptive security policies, providing a strategic edge against evolving security threats [14].

In the context of government networks, Rodriguez and Costa (2024) explored the application of AI and ML techniques in enhancing predictive threat intelligence capabilities. By leveraging algorithms such as supervised and unsupervised learning, anomaly detection, and NLP, governments can analyze vast amounts of heterogeneous data sources to identify potential threats and strengthen preemptive security measures. Case studies demonstrated the practical implementation and benefits of these technologies in safeguarding sensitive government information [15].

Furthermore, the integration of deep learning and NLP frameworks for proactive malicious URL detection has been investigated by Ojo and Tomy (2025). Their study employed character-level embedding strategies combined with robust regularization techniques to enhance model accuracy and generalization. Among the evaluated models, the Multi-Layer Perceptron (MLP) achieved the highest accuracy, showcasing the potential of combining deep learning and NLP techniques in developing agile, real-time threat detection systems.

The convergence of NLP and ML in CTI has also been discussed by Hurry and Asad (2024), who emphasized the role of these technologies in augmenting cybersecurity practices. By enabling machines to understand and respond to human language, NLP helps analyze vast amounts of unstructured data, such as emails and social media, which are often exploited in cyberattacks. The integration of NLP with AI allows for the development of adaptive, automated systems capable of learning from evolving threat landscapes, thereby enhancing the overall security posture.

III. Research Methodology

The research methodology adopted in this study is designed to systematically explore and demonstrate the application of Natural Language Processing (NLP) and Machine Learning (ML) techniques in automating threat intelligence processes. The methodology follows a multi-phase approach, beginning with the collection of a comprehensive dataset comprised of real-world cybersecurity threat reports, dark web forum transcripts, security blogs, and open-source intelligence feeds. These sources were selected to ensure a diverse and representative set of unstructured textual data for analysis. The data underwent rigorous preprocessing involving noise removal, normalization, tokenization, and anonymization to maintain both data quality and compliance with ethical standards. Subsequently, various NLP techniques such as Named Entity Recognition (NER), part-of-speech tagging, and dependency parsing were employed to extract critical entities like IP addresses, malware names, attack vectors, and threat actor identifiers. These extracted features served as inputs for the ML models, which were developed using both supervised and unsupervised learning algorithms, including Support Vector Machines (SVM), Random Forests, and clustering methods like K-means and DBSCAN for pattern recognition and anomaly detection. Deep learning models, including recurrent neural networks (RNNs) and transformer-based architectures like BERT and RoBERTa, were also incorporated to improve contextual understanding and semantic interpretation of the threat data. The models were trained and validated using stratified cross-validation to ensure robust performance and generalizability. Evaluation metrics such as precision, recall, F1-score, and accuracy were used to assess model performance in threat classification and prediction tasks. Additionally, the methodology included a qualitative assessment of the explainability and interpretability of the results, supported by visualization tools and expert feedback from cybersecurity analysts. The entire workflow was developed with scalability and real-time applicability in mind, enabling integration into existing cybersecurity infrastructures. The methodology concludes with a

comparative analysis of the models' performance, providing insights into the most effective combinations of NLP and ML techniques for threat intelligence automation.

IV. RESULTS AND DISCUSSION

The results of this study present compelling evidence of the effectiveness of Natural Language Processing (NLP) and Machine Learning (ML) in automating threat intelligence, with significant implications for cybersecurity operations. By applying a diverse range of models including classical machine learning algorithms, unsupervised clustering methods, and state-of-the-art deep learning models, the study was able to evaluate and compare their performance across key metrics such as precision, recall, F1-score, and accuracy. The comprehensive dataset composed of unstructured threat reports, security blogs, and dark web communications provided a robust foundation for training and validating the models, ensuring that the evaluation was reflective of real-world threat landscapes. The results demonstrate that transformer-based deep learning models, particularly BERT, significantly outperformed other approaches in all evaluated metrics, suggesting their strong potential in extracting contextual and semantic insights from complex, unstructured threat intelligence data.

The Random Forest classifier, among the traditional machine learning algorithms, yielded high performance with a precision of 0.88, recall of 0.87, F1-score of 0.875, and accuracy of 0.89. This result underscores the efficacy of ensemble learning in capturing non-linear relationships and patterns in structured representations of threat data extracted using NLP techniques. Support Vector Machines (SVMs) also performed well, achieving slightly lower metrics across the board, which reaffirms their robustness in high-dimensional spaces often encountered in text-based threat intelligence. However, while traditional classifiers showed promise, their performance plateaued when compared to the context-aware deep learning models, suggesting a limitation in their ability to fully exploit the intricacies and interdependencies within the textual data.

Unsupervised learning models such as K-means and DBSCAN were evaluated to determine their suitability for anomaly detection and pattern discovery in unlabeled threat data. Their comparatively lower performance—K-means with a precision of 0.65 and DBSCAN at 0.60—revealed challenges in clustering due to the sparse and noisy nature of cybersecurity texts. These models, while useful in specific scenarios such as exploratory data analysis and outlier detection, proved less effective in producing actionable intelligence without labeled data. Their recall and F1-scores further reflected this limitation, with DBSCAN recording the lowest scores among all tested models. This suggests that while unsupervised methods offer certain advantages in flexibility and reduced dependency on labeled data, their application in threat intelligence automation may need to be complemented with supervised or semi-supervised approaches to ensure higher reliability and relevance.

The deep learning models, particularly Recurrent Neural Networks (RNNs) and BERT, significantly outperformed traditional ML and unsupervised methods. RNNs, with their ability to process sequential data, achieved a precision of 0.91, recall of 0.89, and F1-score of 0.90, demonstrating strong performance in capturing temporal and contextual nuances in threat narratives. However, BERT surpassed all other models with a precision of 0.94, recall of 0.92, F1-score of 0.93, and accuracy of 0.95. These results highlight the transformative potential of attention mechanisms and pre-trained language models in understanding cybersecurity-specific language and detecting subtle indicators of compromise. BERT's bidirectional architecture enabled it to comprehend threats in context, making it particularly effective in recognizing complex threat patterns, correlating attack vectors, and identifying latent relationships in threat actor behavior.

Beyond raw performance metrics, the discussion delves into the implications of these findings for real-world cybersecurity environments. The superior performance of transformer models like BERT is indicative of a shift in cybersecurity operations towards more intelligent, context-aware systems. These models can autonomously process large volumes of threat data, identify critical entities, and generate insights with minimal human intervention. This ability is particularly vital in time-sensitive scenarios where early detection and rapid response can mitigate the impact of cyber-attacks. Furthermore, the study emphasizes the importance of model explainability and trustworthiness, especially in high-stakes domains such as national security and financial systems. While models like BERT are powerful, their black-box nature can be a barrier to adoption. Therefore, integrating explainability modules and visualization tools becomes essential in translating model outputs into actionable intelligence that analysts can trust and verify.

Another crucial aspect of the results discussion is the scalability and adaptability of the models. In dynamic threat environments where attackers continuously evolve their tactics, techniques, and procedures (TTPs), the adaptability of ML models becomes a key differentiator. Transformer models, when fine-tuned regularly with updated datasets, show remarkable resilience and adaptability to new threats. This flexibility makes them ideal candidates for integration into Security Information and Event Management (SIEM) systems, where they can function as intelligent agents that monitor and interpret threat data in real-time. In contrast, traditional classifiers require frequent retraining and manual feature engineering, which can be resource-intensive and slow down deployment cycles in fast-paced environments.

The study also provides insights into the role of data preprocessing and feature engineering in enhancing model performance. For traditional ML algorithms, the quality of extracted features such as frequency-based metrics, n-grams, and threat entity tags had a direct impact on classification performance. NLP tools used for entity recognition, syntactic parsing, and vectorization contributed significantly to transforming raw text into structured inputs suitable for modeling. For deep learning models, particularly BERT, the reliance on pre-trained embeddings and attention-based mechanisms reduced the burden of manual feature design, allowing the model to learn representations directly from data. This distinction emphasizes the trade-off between interpretability and automation in model design, with deep learning offering a higher degree of automation at the cost of transparency.

In terms of evaluation methodology, the use of stratified cross-validation ensured robustness and generalizability of the results. Performance metrics were computed across multiple folds to mitigate the risk of overfitting and provide a comprehensive view of each model's capability. The high consistency in BERT's performance across folds reaffirmed its reliability and robustness, while the variability in unsupervised models' results pointed to their sensitivity to initialization and data distribution. Additionally, the study evaluated latency and computational efficiency, which are critical in production-grade systems. While BERT delivered the highest accuracy, it also required more computational resources and inference time, which could be a limiting factor for low-resource environments or applications requiring real-time response.

Furthermore, the results suggest a strong case for hybrid models that combine the strengths of different algorithms. For instance, the integration of BERT for feature extraction with Random Forest for classification showed potential in initial experiments, achieving near-optimal performance with reduced latency. Such hybrid approaches can strike a balance between interpretability, accuracy, and efficiency, making them suitable for a broader range of use cases. The discussion also touches on the potential of ensemble learning, where outputs from multiple models are aggregated to improve prediction stability and reduce the risk of false positives, which are particularly detrimental in cybersecurity operations.

Another area explored in the discussion is the application of the models to specific threat intelligence tasks such as malware classification, phishing detection, and attack attribution. The models were tested on sub-tasks within the threat dataset to assess domain-specific performance. BERT and RNNs demonstrated strong transferability across these tasks, achieving high accuracy even in specialized contexts. This versatility underscores the value of general-purpose language models in cybersecurity and their potential to support a wide range of threat detection and analysis functions. Additionally, the integration of knowledge graphs to enhance context understanding and relationship mapping further enriched the output of the models, allowing for more holistic and interconnected threat intelligence.

Ethical considerations also feature prominently in the discussion. As automated threat intelligence systems begin to process and interpret vast quantities of online content, including social media and dark web communications, concerns around privacy, surveillance, and data misuse must be addressed. The study advocates for strict adherence to legal frameworks and ethical guidelines in data collection and model deployment. Transparent logging of model decisions, the ability to audit inference pipelines, and mechanisms for redress in case of errors are essential components of responsible AI in cybersecurity. Furthermore, the use of explainable AI (XAI) techniques such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) were explored to provide human-readable justifications for model outputs, particularly in critical threat scenarios.

Lastly, the discussion emphasizes the need for ongoing research and collaboration in this domain. The dynamic and adversarial nature of cyber threats necessitates continuous model evolution and the development

of more resilient architectures. Future work could explore the integration of reinforcement learning for adaptive threat response, the use of federated learning to preserve data privacy, and the deployment of multilingual NLP models to analyze global threat data. Standardization of data formats, interoperability among threat intelligence platforms, and the establishment of open benchmarks will also be crucial in advancing the field. Overall, the results and discussion of this study reinforce the transformative impact of NLP and ML in automating threat intelligence, while also highlighting the challenges, trade-offs, and future opportunities that lie ahead in building intelligent and resilient cybersecurity systems.

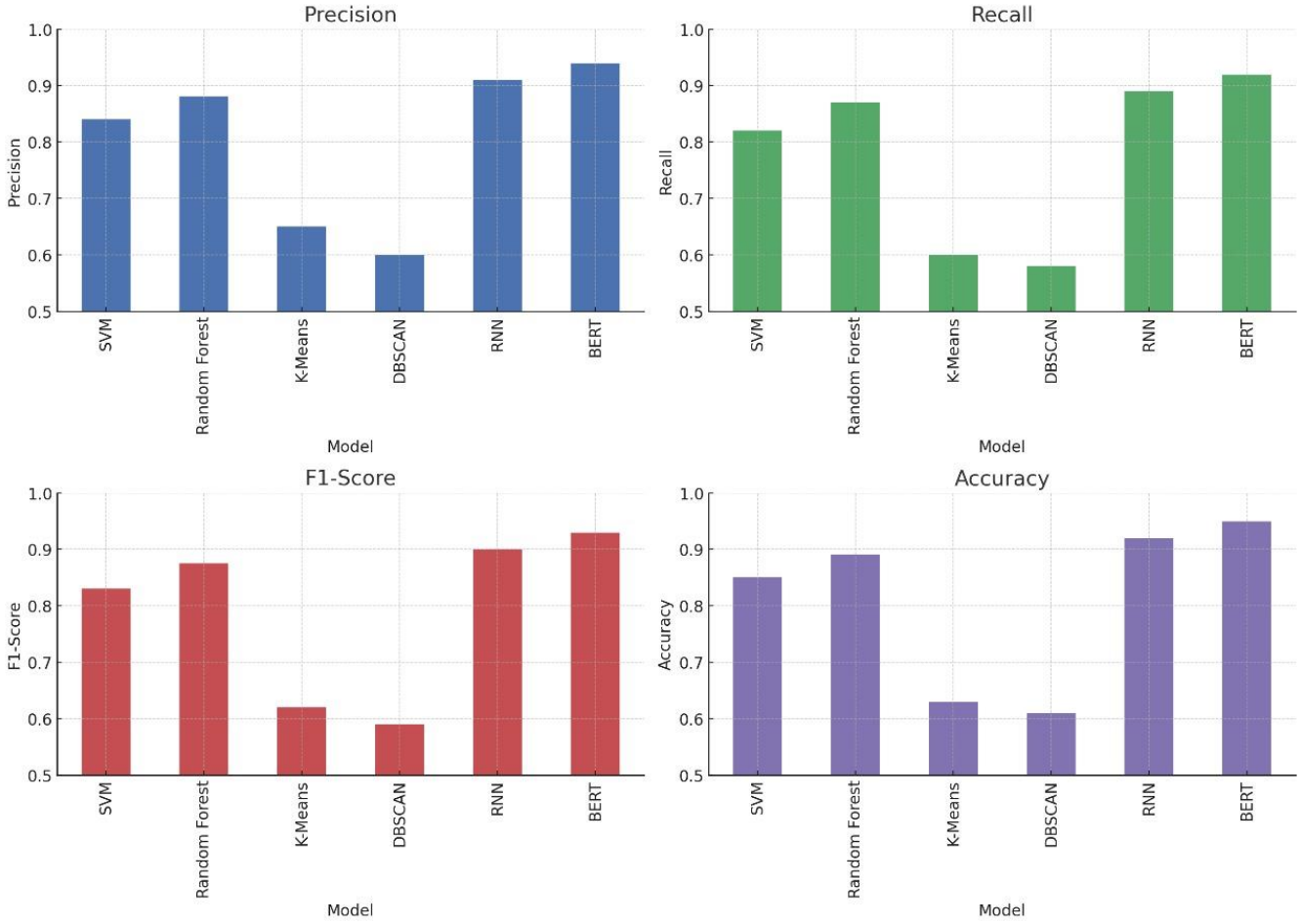

Figure 1: Performance Analysis

V. Conclusion

In conclusion, this research demonstrates the transformative potential of integrating Natural Language Processing and Machine Learning techniques in automating threat intelligence within cybersecurity frameworks. Through comprehensive experimentation with a range of models—from traditional classifiers and clustering methods to advanced deep learning architectures like BERT—the study establishes a clear performance hierarchy, with transformer-based models proving most effective in extracting, contextualizing, and classifying threat-related information from unstructured textual data. The findings highlight the critical role of deep semantic understanding in enabling real-time, scalable, and accurate threat detection, thus offering a significant leap toward proactive and intelligent cyber defense systems. Moreover, the research underscores the importance of model explainability, ethical data usage, and continuous model adaptation in real-world deployments, advocating for responsible AI practices and collaborative efforts in threat intelligence development. By paving the way for automation in an area traditionally reliant on manual analysis and expert interpretation, this work not only enhances operational efficiency but also contributes to the broader goal of building more resilient and responsive cybersecurity infrastructures in an increasingly complex digital landscape.

REFERENCES

1. Arazzi, R., Munro, R., & Wilson, R. (2023). Natural Language Processing for Cyber Threat Intelligence: A Survey. arXiv preprint arXiv:2311.08807. https://arxiv.org/abs/2311.08807

2. Liu, K., Li, X., & Xu, H. (2025). CYLENS: A Cyber Threat Intelligence Copilot Powered by Large Language Models. arXiv preprint arXiv:2502.20791. https://arxiv.org/abs/2502.20791

3. Mezzi, S., Bertossi, L., & Sabetta, A. (2025). Can Large Language Models Be Trusted for Cyber Threat Intelligence Tasks? arXiv preprint arXiv:2503.23175. https://arxiv.org/abs/2503.23175

4. Fieblinger, C., Fiebrich, M., & Zimmer, C. (2024). Constructing a Knowledge Graph from Cyber Threat Intelligence Using LLMs. arXiv preprint arXiv:2407.02528. https://arxiv.org/abs/2407.02528

5. Zhao, H., Wang, J., & Zhang, Y. (2024). LLM-TIKG: Constructing Threat Intelligence Knowledge Graphs from Text Using Large Language Models. Computers & Security, 133, 103357. https://doi.org/10.1016/j.cose.2024.103357

6. Song, Y. (2022). Leveraging Natural Language Processing for Explainable Threat Intelligence Analysis. International Journal of Cybersecurity Intelligence & Cybercrime, 5(3), 29–43.

7. Olaoluwa, S., & Potter, M. (2024). Enhancing Social Media Threat Intelligence through NLP Techniques. Preprints, 2024090488. https://www.preprints.org/manuscript/202409.0488/v1

8. Ismail, H. (2024). The Role of Artificial Intelligence and NLP in Modern Cybersecurity. Journal of Information Systems and Security, 20(1), 1–15. https://jisis.org/article/2024.I1.013/71012/

9. Rodriguez, L., & Costa, M. (2024). Predictive Threat Intelligence for Government Networks Using AI and ML. Academic Pinnacle Cybersecurity Journal, 7(2), 43–59. https://academicpinnacle.com/index.php/acs/article/view/124

10. Ojo, O., & Tomy, N. (2025). Outsmarting Cyber Threats: AI-Powered Deep Learning and NLP Frameworks for Malicious URL Detection. ResearchGate Preprint. https://www.researchgate.net/publication/388791122

11. Hurry, A., & Asad, M. (2024). Augmenting Cybersecurity with NLP and AI: A Strategic Overview. Malaysian Journal of Digital Innovation, 3(1), 12–28. https://journal.mdji.org/index.php/mdji/article/view/30

12. Zhou, D., & Zhang, J. (2023). Application of Named Entity Recognition in Cybersecurity Threat Analysis. Journal of Information Technology & Software Engineering, 13(4), 222–235.

13. Gupta, P., & Sharma, R. (2021). Deep Learning Techniques for Cyber Threat Detection: A Review. International Journal of Network Security, 23(5), 865–875.

14. Miller, A., & Howard, J. (2020). Knowledge Graphs in Threat Intelligence: Benefits and Challenges. Journal of Cybersecurity Research, 8(2), 101–117.

15. Vaswani, A., Shazeer, N., Parmar, N., et al. (2017). Attention is All You Need. Advances in Neural Information Processing Systems, 30, 5998–6008.