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# ARTIFICIAL INTELLIGENCE IN CYBERSECURITY RISK ANALYSIS ON NATIONAL VITAL INFRASTRUCTURE

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**Abstract** *The development of digital technology has a significant impact on increasing cybersecurity threats, especially on national vital infrastructure such as the energy, transportation, and health sectors. Cyberattacks targeting these sectors have the potential to disrupt essential public services and threaten national security. Therefore, the use of Artificial Intelligence (AI) in cybersecurity risk analysis is an urgent need. This study aims to examine the effectiveness of AI in detecting and mitigating cyber threats on vital infrastructure. The method used is a mixed methods approach that involves quantitative analysis through questionnaires on the cybersecurity team and network log data analysis using the Isolation Forest and K-Nearest Neighbors algorithms. The results show that the application of AI can increase the speed of detection and effectiveness of threat mitigation, with anomaly detection accuracy reaching 95% and an odds ratio of 2.5 in cyber threat mitigation. These findings underscore that AI has a significant contribution to strengthening cybersecurity resilience on national infrastructure. However, some challenges such as integration with legacy systems and supporting regulatory needs need to be considered for further optimization. This research contributes to practical strategies for government bodies, cybersecurity teams, and policymakers to strengthen cybersecurity frameworks by adopting AI, ensuring better protection of critical national infrastructure.*

**Keywords** Cybersecurity, Vital Infrastructure, Artificial Intelligence, Risk Analysis, Anomaly Detection

## 1. Introduction

In recent decades, national vital infrastructure such as the energy, transportation, health, and financial sectors have become increasingly connected in the digital ecosystem. The high dependence on digital technology and the internet creates significant cybersecurity risks to these infrastructures (Buchanan, 2020; Carr, 2021). Infiltration or attacks on vital infrastructure systems can have an impact on the daily lives of the wider community, and even have the potential to threaten national stability (Bada, M., & Nurse, 2019). With the development of digital technology, these threats are increasingly complex and require new adaptive approaches to ensure cybersecurity on national vital infrastructure.

The urgency of this research lies in the increasing number of cyberattacks around the world, which often target critical infrastructure to obtain major impacts

or financial gains. According to a report by Cybersecurity Ventures, cyberattacks on critical infrastructure are predicted to increase by 15% annually until 2025, reflecting an increase in risk that needs to be anticipated immediately (Bateman, 2023). The implementation of Artificial Intelligence (AI) in cybersecurity risk analysis can be one of the solutions to improve early detection and response to evolving threats (Goodman, M., & Lin, 2020)

The use of AI in cybersecurity has proven to be effective in analyzing large and complex data faster and more accurately than traditional approaches. AI is capable of detecting suspicious anomalous patterns in network traffic that are not detected by conventional methods. For example, machine learning algorithms have been used to monitor and analyze network data in real-time, identifying potential threats before a security incident occurs (Jalal, 2001). A number of cybersecurity theories also support the use of AI to assess risk, including layered defense theory and zero trust theory (Haider, 2022; Jouini, 2021).

The table below shows the latest statistics on cyberattacks on critical infrastructure in several countries, showing a significant increase over the years:

**Table 1. Cyber Attacks on Vital Infrastructure in Several Countries**

| Country | 2020 | 2021 | 2022 | 2023 |
|---|---|---|---|---|
| United States | 120 | 140 | 165 | 200 |
| English | 75 | 85 | 90 | 105 |
| Indonesia | 50 | 60 | 75 | 95 |
| Germany | 80 | 90 | 100 | 120 |

*Data: Global Cybersecurity Report, 2023 (Noble, 2021; Check Point, 2022; McAfee, 2023)*

Several previous studies have explored the use of AI in cyber risk analysis, but tend to focus on conventional information technology systems or on the small-medium business sector. For example, research by Lee and Su (2020) discusses the application of deep learning in network anomaly detection in financial companies, while (Zhang, L., Huang, Y., & Chen, 2020) study the implementation of AI for network security in the e-commerce sector (Davies, 2022). This research shows the effectiveness of AI in certain sectors, but there have not been many studies focusing on national vital infrastructure, which has different complexities and risks (Baker, 2021).

There is a gap in this research related to the limited exploration of the challenges and obstacles to the application of AI in the security of national vital infrastructure (Hall, 2021). Key challenges include the large scale, high complexity of the network, and the need for rapid response times to protect assets that are critical to the state. In addition, the integration of AI in vital infrastructure requires a special approach to ensure high data reliability and security (Jalal, 2001).

As research that fills this gap, this article offers a new approach by focusing on the development of AI-based risk analysis models tailored to national vital infrastructure. This approach will consider a variety of unique factors, such as the specific types of threats to the sector and the need to improve effectiveness and efficiency in risk mitigation (Cheng, 2022; Yang, Huang, Yang, & Yang, 2018).

The purpose of this study is to develop an AI-based risk analysis model that can improve the detection, prevention, and mitigation of cybersecurity threats on national vital infrastructure. It is hoped that this model can help significantly reduce

risk as well as provide better protection against cyberattacks on critical assets (Chan, 2009). Furthermore, this research is also expected to be able to provide practical recommendations that can be adopted by various stakeholders in improving cybersecurity resilience in this sector (Huang et al., 2020; Kim & Kim, 2014).

## 2. Method

Research Design This study uses a qualitative and quantitative descriptive design (mixed methods) with a case study approach on national vital infrastructure, such as the energy, health, and transportation sectors. The mixed methods approach allows for a deeper understanding of how Artificial Intelligence (AI) can contribute to cybersecurity risk analysis through implementation testing and risk data analysis.

Population and Population Sample in this study covers all national vital infrastructure sectors in Indonesia. The sample was purposively selected, namely the energy and transportation sectors, which represent sectors with high cybersecurity risks. The study will involve a minimum of three companies operating in the sector as case studies, with selection based on criteria such as the number of cyber incidents experienced and the level of complexity of their digital infrastructure.

**Research Instruments**

a. **Qualitative Data Collection**: In-depth interviews with cybersecurity experts, IT managers, and cybersecurity teams from each company sampled. The interview guidelines include questions about their experience with cyber threats, infrastructure readiness, as well as the application of AI in risk mitigation.
b. **Quantitative Data Collection**: A structured questionnaire given to the cybersecurity team at each company. This questionnaire measures the effectiveness of the application of AI technology in cybersecurity based on indicators such as threat detection speed, frequency of identified anomalies, and mitigation responses

**Data Collection Techniques**

a. **Participatory Observation**: The researcher will make direct observations of the cybersecurity monitoring and analysis process in the company being sampled. This technique will provide more in-depth data on workflows and challenges faced when applying AI in cybersecurity.
b. **Documentation**: Collects cybersecurity-related documents from individual companies, including incident reports, records of the use of AI in detecting threats, and records of mitigation timing and effectiveness. Documentation data will provide historical information regarding threat patterns and mitigation successes.
c. **Use of Network Data Logs**: Collects historical data from network logs for analysis using developed AI models. This data will provide attack patterns as well as potential threats that often occur.

**Data Analysis Techniques**

a. **Qualitative Analysis**: Qualitative data from interviews will be analyzed using thematic analysis methods, which allow for grouping data based on key themes

such as threat types, AI application challenges, and perceptions of AI effectiveness in cybersecurity. These findings will help identify frequent patterns as well as key barriers to AI adoption.

b. **Quantitative Analysis**: Questionnaire data and network data logs will be statistically analyzed using logistic regression methods and correlation analysis. This analysis will examine the relationship between the independent variable (AI application) and the dependent variable (cyber threat mitigation effectiveness).
c. **AI Simulation Models**: The use of machine learning algorithms (e.g., anomaly detection or attack classification) to validate risk analysis models. This simulation will be carried out using network log data to identify the effectiveness of the AI model developed in detecting threats.

**Research Table** The following is a research flow that describes the process of data collection and analysis.

**Table 2.** Research Flow

| Research Stages | Description |
|---|---|
| 1. Literature Studies | Review previous research and theories relevant to cybersecurity risk analysis. |
| 2. Sample Selection | Select a sample of the national vital infrastructure sector to be researched. |
| 3. Data Collection | Collect data through interviews, questionnaires, and observations on selected samples. |
| 4. Qualitative & Quantitative Analysis | Analyze the data obtained qualitatively and quantitatively. |
| 5. AI Model Development & Validation | Develop and validate AI models for threat detection and mitigation. |
| 6. Model Simulation | Simulate AI models to test their effectiveness in the context of cybersecurity. |
| 7. Preparation of Recommendations | Formulate recommendations based on research results to improve cybersecurity. |

**Reliability and Validity**

a. **Reliability**: The questionnaire data will be tested for reliability using the Cronbach's Alpha test to ensure internal consistency. This is important to ensure that every question on the questionnaire is reliable in measuring the effectiveness of AI implementation.
b. **Validity**: The validity of the model will be tested by cross-validation methods on the AI model developed. Cross-validation ensures that the resulting risk analysis model is reliable and generally applicable in the context of vital infrastructure

## 3. Result & Discussion

**Results of Research Analysis**

1. **Quantitative Analysis (Questionnaire)**
   a. **Descriptive Data**: From 100 respondents consisting of cybersecurity teams in three national vital infrastructure companies, the following data were obtained:
      1) Threat detection speed (scale 1-5): An average of 4.2, indicating that the threat detection speed is relatively high.
      2) Frequency of anomaly detection per week: An average of 15 cases, demonstrating the reliability of AI in identifying anomalies.
      3) Mitigation response time (in minutes): An average of 10 minutes, which is in line with the fast response time standard.
   b. **Reliability Test**: Cronbach's Alpha test is performed on a questionnaire to ensure consistency. An alpha result of 0.85 indicates that the instrument has high reliability.
   c. **Correlation Analysis**: The correlation between AI application and mitigation effectiveness was measured using Pearson correlation. The results showed a correlation value of 0.78 ($p < 0.01$), which showed a positive and significant relationship between the application of AI and the effectiveness of threat mitigation.
2. **Network Data Analysis (Log Data) with Machine Learning Algorithms**
   a. **Data Processing**: Network log data from the three companies is collected and processed using anomaly detection algorithms, namely *Isolation Forest* and *K-Nearest Neighbors* (KNN). The purpose of this analysis is to identify suspicious network activity.
   b. **Isolation Forest Results**: Out of 10,000 network log entries, the algorithm successfully identified 500 potential anomalies, with an accuracy rate of 95% based on cross-validation on historical data.
   c. **K-Nearest Neighbors (KNN):** The KNN algorithm is used to group detected activity into specific types of threats (e.g., DDoS, brute force attacks, or phishing). Of the anomalies identified, the KNN algorithm classifies 60% as potential DDoS attacks, 25% brute force, and 15% phishing, according to the pattern of threats that often occur on national vital infrastructure.
3. **AI Simulation Models for Anomaly Detection Validation**
   a. **Development of Anomaly Detection Model**: The simulation model developed is tested using network data in the last 3 months from each company.
   b. **Model Accuracy Evaluation**: The AI-based anomaly detection model developed showed results of 92% accuracy and 88% precision, with a recall of 85%, which demonstrated the model's ability to identify anomalies effectively.
4. **Logistics Regression Results**
   a. Independent variable: AI application (1 if present, 0 if none)
   b. Dependent variable: Threat mitigation success

   c. The results of logistical regression show that the use of AI has an odds ratio of 2.5 ($p < 0.01$), which means that companies that use AI have a 2.5 times greater chance of effectively mitigating cyber threats than companies without AI.
5. **Summary of Statistical Findings Based** on quantitative analysis and AI algorithms; the results show:
   a. The application of AI is able to significantly increase the speed of threat detection and the effectiveness of cyber threat mitigation on national vital infrastructure.
   b. The results of the AI model provide accurate data in the early detection and categorization of threat types, which improves the responsibility of cybersecurity teams.

**Research Discussion**

**1. The Urgency of Using AI in Cybersecurity for Vital Infrastructure**

With the increasing number of cyber threats targeting national vital infrastructure, the use of more sophisticated technologies such as Artificial Intelligence (AI) is an urgent need. Data shows that critical sectors such as energy, transportation, and health experience a significant increase in the number of attacks every year (Bateman, 2023)The speed of detection and mitigation provided by AI allows cybersecurity systems to detect threats in real-time, which is crucial to prevent disruptions to crucial public services (Goodman, M., & Lin, 2020).

The implementation of AI in cybersecurity, especially through machine learning algorithms, accelerates the process of identifying unusual patterns or potential threats in network traffic (Arora, 2020). A study from Riley, shows that companies with AI are able to respond to security incidents 2 times faster than those that rely only on manual methods. this urgency is driving the adoption of AI in protecting vital infrastructure from increasingly sophisticated threats.

**2. Effectiveness of AI Algorithms in Cyber Threat Detection and Mitigation**

AI algorithms, such as *Isolation Forest* and *K-Nearest Neighbors* (KNN), have proven to be effective in detecting anomalies that indicate potential cyber threats to vital infrastructure networks. The results of the analysis show that *the Isolation Forest* algorithm is able to identify around 500 anomalies in the network dataset, with an accuracy of 95%. AI's ability to detect unusual patterns increases the effectiveness of early detection against various types of cyberattacks, especially complex ones such as DDoS and brute force attacks (Ahn, 2024).

In addition, KNN has managed to categorize attack types with high accuracy, demonstrating the effectiveness of AI in providing specific information about the type of threat that may occur (Lee & Su, 2020; Zhang & Xie, 2021; Davies, 2022). This shows that AI is not only capable of detecting, but also facilitating faster and more accurate mitigation responses, a significant advantage in the context of cybersecurity on vital infrastructure.

**3. Limitations and Challenges of AI Implementation in Cybersecurity**

Although AI has many advantages, the challenges in applying this technology to national vital infrastructure cannot be ignored. One of the main obstacles is the complexity and scale of the network, which requires the adjustment of AI algorithms to be more compatible with this highly dynamic environment (Baker, 2021). Another

challenge is the need for AI integration with existing cybersecurity systems, which often have limitations in terms of technology compatibility.

AI implementation also faces obstacles in terms of policies and regulations. Many countries do not have specific regulations for the use of AI in cybersecurity, so there are potential risks in terms of privacy and data protection (Hall, 2021; Kumar, 2022; Wang, 2023).

**Table 3. Differences in Regulations Regarding the Use of AI**

| Country | Main Regulations | AI Usage Policy | Key Focus in Cybersecurity |
|---|---|---|---|
| **United States** | National AI Initiative Act (2020); Cybersecurity Information Sharing Act (CISA) | Encouraging the use of AI in cybersecurity, but tightening data privacy regulations. | Critical infrastructure protection, cyber attack mitigation |
| **European Union** | EU Artificial Intelligence Act (2021); General Data Protection Regulation (GDPR) | Establish ethical and security standards in AI, specifically for the processing of personal data. | Privacy protection, GDPR compliance, and data security |
| **Chinese** | National Security Law (2015); New Generation AI Development Plan (2017) | Developing AI with a freer approach, but with strict government scrutiny. | Centralized surveillance, national threat detection |
| **Japan** | Cybersecurity Basic Act (2014); AI Strategy 2020 | Govern AI with a focus on transparency and consumer protection in data usage. | Transparency and ethics in the use of AI |
| **Australia** | Artificial Intelligence Ethics Framework (2019); Security of Critical Infrastructure Act (2018) | The use of AI in cybersecurity is allowed with ethical guidelines and transparency policies. | Critical infrastructure security, compliance with ethical standards |
| **Canada** | Directive on Automated Decision-Making (2020); National Cyber Security Strategy (2018) | Regulating the use of AI in the public sector with an emphasis on impact assessment and transparency. | Cybersecurity in the public sector, AI impact assessment |
| **India** | National Cybersecurity Policy (2013); NITI Aayog AI for All Strategy (2018) | Encourage AI development without strict regulations, but with basic data protection guidelines. | Focus on AI innovation, data security development |

*Source: Report on Global AI and Cybersecurity Policies 2023 (Cheng, 2022; Huang, 2023; Ahn, 2024)*

In addition to regulations, budget constraints are also a challenge, especially in terms of costs to develop infrastructure and train experts who are able to operate AI effectively.

**4. AI's Contribution to the Effectiveness of Cyber Threat Mitigation**

This study shows that the use of AI in cybersecurity risk analysis contributes significantly to improving the effectiveness of threat mitigation on vital infrastructure. In the logistics regression test, the application of AI has an odds ratio of 2.5, which means that companies with AI have the potential to be 2.5 times more effective in mitigating cyber threats than those without AI (Fisher, 2024). This confirms the superiority of AI as a tool that can improve the overall response of cybersecurity teams.

The AI model developed shows an increase in response speed and early detection, which means AI has a direct impact on reducing the frequency of attacks that successfully penetrate the system (Goodman, M., & Lin, 2020). For example, the results of AI simulations in this study show that cybersecurity teams can respond to DDoS attacks in less than 10 minutes after detection, compared to 20-30 minutes on systems without AI (Arora, 2020).

**5. Implications and Recommendations for AI Development in Cybersecurity**

The results of this study indicate that the application of AI in cybersecurity to national vital infrastructure has a real positive impact, but still requires further optimization and development. To achieve optimization, it is recommended that companies in vital sectors invest more in the integration of AI with existing security systems, as well as provide specialized training for cybersecurity teams (Jouini, 2021).

The development of more specific regulations and collaborative efforts between the government, the private sector, and educational institutions are also needed to support the implementation of AI in this sector. These efforts will help create a stronger cybersecurity ecosystem and be prepared for the increasingly complex cyber threats of the future

## 4. Conclusion

The conclusion of this study shows that the application of Artificial Intelligence (AI) in cybersecurity risk analysis on national vital infrastructure has a significant impact in improving the effectiveness of early detection and threat mitigation. With algorithms such as Isolation Forest and K-Nearest Neighbors (KNN), AI is proven to be able to identify suspicious anomalous patterns in networks with a high degree of accuracy, reaching up to 95% on network log data. This makes a real contribution to responding to threats quickly, which is crucial in protecting critical infrastructure such as energy and transportation. The results of the logistical regression in this study also show that companies with AI application have a 2.5 times greater chance of successful threat mitigation than those who do not use AI, confirming the effectiveness of AI as an important solution in cybersecurity.

However, the study also reveals several challenges that need to be considered, including the need for better integration between AI and traditional security systems, as well as gaps in regulations governing the application of AI in the vital

infrastructure sector. This challenge indicates the need for collaborative efforts between governments, companies, and educational institutions to create supportive policies and training. These findings recommend that relevant parties continue to increase the overall use of AI technology to strengthen the resilience of national infrastructure from growing cyber threats.

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